UNIVERSITAT DE BARCELONA

Techniques For Estimating the Generative Multifactor Model of Returns in a Statistical Approach to the Arbitrage Pricing Theory. Evidence from the Mexican Stock Exchange

Rogelio Ladrón de Guevara Cortés

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Date:
September 2015

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PROGRAMA DE DOCTORAT D' ESTUDIS EMPRESARIALS
SUBPROGRAMA ADMINISTRACIÓ I DIRECCIÓ D'EMPRESAS
ESPECIALITAT TÈQNIQUES I ANÀLISI A LA EMPRESA

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To my daughters, wife and parents.

Acknowledgments

First of all, I want to thank the Supervisor of this Doctoral Thesis, Dr. Salvador Torra Porras, for all his time, sacrifice, compromise, support and help for the elaboration of this Thesis, which was beyond his duty as an academic and professional, but also was that corresponding to a real friend. All his strict and demanding regime, under I was forged during this time, it has been of invaluable importance to my formation as academic and professional and it has let an important print in all my academic work as well. This Thesis is as yours as mine; thanks for everything with my most sincere admiration and respect.

I also have to thank and recognize the helpful and prompt advising of academics of different countries and Universities whose expertise in some of the techniques used in this Thesis was really important to developed this research; in addition, I acknowledge all their contributions in these techniques that were the base for developing some parts of our study: to Dr. Mathias Scholz currently in the Laboratory of Computational Metagenomics, University of Trento, Italy, for all his advising regarding Neural Networks Principal Component Analysis; and to Dr. Aappo Hyvärinen, from the Department of Computer Science, University of Helsinki, for his advising concerning Independent Component Analysis.

In the same way, I want to thank Cristina Urbano at GVC-Gaesco, Spain, for the financial data provided on the Mexican Stock Exchange; without this information definitely this research had not been possible.

I would like to thank all the academic and administrative support and help of the professors and administrative staff of the Faculty of Economics and Business of the University of Barcelona, during all these years of my PhD studies, specially to: Dra. Monserrat Guillén Estany, Dr. Ramón José Alemany Leira, Dra. Esther Hormiga Pérez, Dra. Mercedes Claramunt Bielsa, Dra. Mercedes Ayuso Gutiérrez, Dr. Dídac Ramirez i Sarrio, Dr. Antonio Alegre Escolano, Dra. Maite Vilalta Ferrer, Sra. Eloísa Perez Poblador and Sra. Coloma Grandes Tribó. Moreover, I acknowledge to the Doctors who will constitute the Jury for this dissertation, for the time dedicated to review this document and for all their comments and observations.

In the personal ambit, I have to acknowledge to my dear wife, Isela Moreno Alcazar, for all her support, love, time and sacrifice that she have made in order to let me start and finish this Doctoral studies; without all your understanding, help and support I had not been able to do all this.

Thank you to my baby daughters Núria and Meritxell, for being my major motivation and force in this final stage of the elaboration of my Thesis.

I want to thank to my mother and father, Guadalupe Cortés Arellano, and Rogelio Ladrón de Guevara Domínguez, whose endless and unconditional love, help and support allowed me to realize this dream of studying my PhD in Barcelona. Both of you have been always with me in everything and without your help and support this project had not been possible as well.

Specially, I want to thank to all my friends from Spain and their families: Mia, Andreu, Fede, Carlos, Jordi Bertrán, Jordi Vilanova, Sergie, Juan Carlos, Pepito, Borja, Juan, Victor and Marc; thank you for having made me feel at home when I was so far from my house, thank you for having open the doors of your houses to me and for having shared so many special moments with you and your families. All my eternal acknowledge and friendship.

I also have to thank to all my life friends in Mexico: Samuel and Alfredo, for all their support, help and company in all the good and bad moments of my life; and to my cousins and friends Lalo, Pepe, Mauri, Ale, Vero and Bere, for all their support and help in the personal ambit during these last days of the elaboration of my Thesis.

Finally, my acknowledgment to my Institution the Universidad Veracruzana, for having allowed me to dedicate my time to accomplish my doctoral studies during the years I was in Barcelona and to finish this last stage of my dissertation.

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CHAPTER 1

Introduction.

1.1. Abstract.

This dissertation focuses on the estimation of the generative multifactor model of returns on equities, under a statistical approach to the Arbitrage Pricing Theory (APT), in the context of the Mexican Stock Exchange. Therefore, this research takes as frameworks two main issues: (i) the multifactor asset pricing models, specially the statistical risk factors approach, and (ii) the dimension reduction or feature extraction techniques: Principal Component Analysis, Factor Analysis, Independent Component Analysis and Non-linear Principal Component Analysis, utilized to extract the underlying systematic risk factors. The models estimated are tested using two methodologies: (i) capability of reproduction of the observed returns using the estimated generative multifactor model, and (ii) results of the econometric contrast of the APT using the extracted systematic risk factors. Finally, a comparative study among techniques is carried on based on their theoretical properties and the empirical results.

1.2. Object of study and context.

1.2.1. Multifactor asset pricing models and risk factors.

Understanding the behavior of financial markets has been a constant during the history of finance, specially the uncovering of the risk factors that move the markets; many approaches have been developed through the years trying to provide answers to the question of what drive the returns on equities in different stock markets. One of those approaches has been the one focused in the asset pricing models, which has tried to find the risk factors that explain the behavior of the different financial assets such as stocks.

From the beginning of the modern finance, with the portfolio theory proposed by Markowitz (1952, 1959, 1987) and market model posed by Sharpe (1963), which derived in the classical Capital Asset Pricing Model (CAPM) developed by Treynor (1961), Sharpe (1963, 1964), Lintner (1965) and Mossin (1966); both academics and practitioners, have tried to determine a systematic risk factor that explains the returns on equities in order to be able to price stocks correctly. The CAPM poses that the return on an equity is given by the systematic risk beta that moves all the stocks in the system, which corresponds to the sensitivity of the return on a specific stock to the variations of the Stock Market Index, plus the riskless inters rate and an idiosyncratic risk that affects only to that specific stock. A large amount of theoretical and empirical studies have been developed through the years focusing in the classic CAPM, its derivations and extensions, including arguments and evidence in favor and against this model[1]. However the CAPM assumes that there is only one factor of systematic risk that explains the behavior of the stocks; i.e., the market factor, which in a global and complex economy represents a naive idea.

Consequently, evolution of the financial science have resulted in other asset pricing models that have considered more than one systematic risk factor to explain the returns on equities. Perhaps the most renown alternative to the CAPM have been the Arbitrage Pricing Theory proposed by Ross (1976) and Roll & Ross (1980) which indeed considers a set of systematic factors based on two main pillars: a) a generative multifactor model of returns, and b) an arbitrage principle.

Both unifactor and multifactor asset pricing models have been widely studied in financial literature up to the present[2]; for example, under the approach of the multifactor models we can find a large amount of studies which includes extensions of the classical CAPM where other systematic risk factors, in addition to the market one, have been considered. As a result, we can broadly divide the factor models in two types: 1) the models that consider that the risk factors are observables and can be proxied by some economic or financial observable variables directly or indirectly, and 2) the models that

[1] An exhausted revision of seminal and more recent papers about the CAPM can be found in: Gómez-Bezares (2000), Fama & French (2004) and Dempsey (2013).
[2] Interested reader can find a good revision of unifactor and multifactor asset pricing models in: Gómez-Bezares (2000), Lee & Lee (2013) and Fabozzi (2013).

assume that the risk factors are unobservable and have to be estimated, via some statistical techniques, from the structure of the financial time series given by the actual quotations of the observed assets. In addition, we can find mainly the following types of systematic risk factors: a) market, b) fundamental, c) macroeconomic, d) technical, and e) statistical. Market factor is actually the one considered in the classic CAPM; fundamental factors consider financial and accounting information of the companies as additional systematic risk factors; macroeconomic factors include macroeconomic variables; technical factors put attention in technical analysis indicators[3]; and finally, the statistical approach extracts the latent systematic risk factors from the actual returns on equities observed through a period of time. As we will explain in Chapter 2, and following Zangari (2003), those factors can be classified in function of their observability; i.e., market and macroeconomic factors are considered as observable while fundamental, technical and statistical are considered as unobservable.

Each approach presents advantages and disadvantages and they are object of a continuous academic and professional discussion about the superiority of each one over the others. In fact, three of the most important international companies, that provide pricing services to the financial sector, base their models mainly in each one of these methodologies[4]. In addition, the most of the researches have given emphasis to the market, macroeconomic and fundamental risk factors to explain the returns on equities mainly in developed countries. Nevertheless, other underlying risk factors such as the statistical ones and the context of emerging markets such as the Mexican, have been out of the scope of financial research or at least have been sparsely studied[5].

In these Thesis we will focus in the statistical systematic risk factors approach which presents mainly two big differences regarding the other approaches. First, it considers that the systematic risk factors are not observable directly, but they are latent in the returns structure. Secondly, poses two separated stages in the process of identify those risk factor namely: a) risk extraction and b) risk attribution. The risk extraction

[3] Such as: Excess stock return on previous month, trading volumes, etc. (See Zangari, 2003).

[4] For example, FTSE (http://www.ftse.com/analytics/birr), uses principally the macroeconomic approach; MSCI (https://www.msci.com/), the fundamental one; and Sungard (http://www.sungard.com/), the statistical.

[5] In this sense, this Thesis tries to fill this gap in financial literature considering that, in addition to its academic and scientific value *per se,* the importance and updating of the topic can also be supported by the interest of different companies that sell services of pricing returns and risk to different uses, such as performance evaluation and risk control.

stage represents the fact of extracting those unobservable systematic risk factors that drive the returns on equities and that are latent in the observable returns structure. In this stage different dimension reduction and feature extraction techniques can be used to perform that extraction. As a result, we will have a set of systematic risk factors that explain the behavior of the stocks, but we won´t be able to identify the nature or names of them. In the risk attribution step, we will try to identify and give some meaning to those extracted factors via some additional methods such as: the association between stocks-sectors and the loading matrix, and the association of the extracted factors with some known economics or financial indicators[6].

1.2.2. Dimension reduction or feature extraction techniques.

The four techniques[7] that will be studied in this research can be considered as dimension reduction or feature extraction techniques[8], that is, statistical or computational techniques capable of, in one hand, to reduce the dimensionality of a dataset that make possible to deal with a smaller amount of variables than the original ones[9]; or on the other hand, to extract the main features or characteristics that underlie in a dataset and allow to known the latent structure of some observable variables. Considering that in the context of the Arbitrage Pricing Theory we are interested in finding systematic risk factors as independent and uncorrelated as possible, next we briefly explain each technique used in this research as well as the properties of the

[6] See Amenc & Lesourd (2003).

[7] The taxonomy and explanation of all the different existent techniques for this purpose is out of the scope of this dissertation; nevertheless, we are aware of the existence of a wide range of dimension reduction or feature extraction techniques, that could be classified under distinct approaches and can be used for these purposes. For taxonomy proposals and descriptions of some of those techniques, interested reader can consult: van der Maaten *et al*. (2009), Engel *et al.* (2011), Fodor (2002), Sarveniazi (2014), Sorzano *et al.* (2014).

[8] We chose the application of these four techniques attending a heuristic criteria that started with the classic techniques used to extract latent risk factors under a statistical approach, namely PCA and FA. Derived from the results obtained and the theoretical analysis of the properties of the extracted factors, we moved to more advanced technique that overcomes some weakness of the estimation produced by these two techniques; i.e., we used ICA in order to deal with the non-Gaussianity of the returns of the data and we used NNPCA in order to deal with the non-linearity in the extraction process. In other words, ICA considers higher order statistics in its estimation such as the kurtosis, while NNPCA incorporates the nonlinearity in the extraction process which produces non-linear components.

[9] In other words, we are interested to find those risk factors that in number are smaller than the number of directly observed factors.

component or factors extracted by each one of them, in order to justify the use of them and introduce the reader to the core of this dissertation.

The classic techniques used to extract the underlying systematic risk factors, under a statistical approach, have been Principal Component Analysis (PCA) and Factor Analysis (FA). Principal Component Analysis represents more a geometric transformation than a statistical model, where we try to reduce the total amount of observed variables in a smaller number of synthetic new variables, which are formed by a combination of the original ones. The new synthetic variables or principal components are computed by a decomposition of the covariance matrix of the observed variables, where the principal components are ranked in a descendent order according the amount of variance explained by each one of them. Those principal components have the property of be linearly uncorrelated and, in our context, they will represent the underlying systematic risk factors from the dataset.

Factor Analysis is indeed a statistical multifactor model with explicit theoretical and distributional assumptions. In this case, the model considers that the variables are the result of a linear combination of a latent structure of common uncorrelated factors, that affect all the variables, plus a specific factor that affects only to each particular variable. Those underlying factors are estimated via a decomposition of the covariance matrix as well, but in this case it divides it in two parts, one explained by common factors (communality) and one explained by the specific factors (specificity). Then, the factors extracted have the property of be linearly uncorrelated too, but common to all the variables. In our context, they will represent the systematic risk factors as well.

Implicitly or explicitly the former techniques assume the multifactor normal distribution of the data, which implies a unlikely characteristic in the financial time series, since the most common is that this kind of data are univariate and multivariate non-Gaussian distributed, due to the long tails and leptokurtic distributions[10]. Independent Component Analysis (ICA) emerges as a solution to this problem since represents a technique capable to deal with the multivariate non-Gaussianity of the

[10] See Richardson & Smith (1993), Dufour *et al.* (2003), Bai & Chen (2008), Lai *et al.* (2012), Tinca (2013), Duarte & Mascareñas (2014), Lakshmi & Roy (2012), Oprean (2012), Velásquez *et al.* (2012), Goncu *et al.* (2012), Bouri (2011) and Darushin & Lvova (2013).

variables. This technique goes beyond de correlation matrix considering higher order statistics in the estimation of the components to be extracted, which will denote a superior property: statistical independence[11]. Therefore, the independent component analysis extracts components from non-Gaussian time series that are not only linearly uncorrelated but also statistically independent which, in our context, represent more suitable systematic risk factors from a theoretically standpoint; i.e., they would be really statistically independent risk factors obtained from non-Gaussian data more suitable to introduce in a statistical approach to the APT.

Finally, the use of the Neural Networks Principal Component Analysis (NNPCA) responds to other weakness common to the three last techniques: the linear mixing of the factors estimated. That is, Principal Component Analysis, Factor Analysis and Independent Component Analysis poses that the factors and loadings of the model are result of a linear combination of those elements; however, Neural Networks Principal Component Analysis takes this mixing to the nonlinear level. In other words, we could consider this technique as an extension of the Principal Component Analysis where the extracted components are not only linearly uncorrelated but also nonlinearly too. In this case, the underlying components are nonlinearly mixed with their respective loadings via the joint effect of a nonlinear function applied to the hidden layers of weights considered in a neural network architecture used for the estimation. Consequently the systematic risk factors extracted by way of this technique will have the property of being nonlinearly uncorrelated, which theoretically represents a superior property compared to the previous components or factors; since now we would have risk factors that are not only linearly uncorrelated but nonlinearly uncorrelated too, which in a multifactor asset pricing model such as the APT would guarantee more different or independent risk factors to consider within the model[12].

[11] PCA and FA obtain linearly uncorrelated and statistically independent factors under the hypothesis of multivariate normality.

[12] We would like to remark that PCA is the only technique among those used in this study that produced the same solution independently of the number of components estimated. Conversely, FA, ICA and NNPCA will produce different results depending on the number of factors extracted due to the iterative nature of their estimation.

1.2.3. The Mexican stock market.

In order to put in context the market object of this study, we will describe briefly the Mexican Stock Market.

The Mexican Stock Market represents a very important emergent financial market which has been gradually flourishing through the years and has become in an attractive target of investment for important foreign institutional investors from different countries. Moreover, it has played a principal role in some of the financial crisis that took place in the last decades and whose effects reached the markets all around the world, such as: the Mexican Debt Crisis in 1982, the Mexican Peso Crisis (Tequila Crisis or December mistake crisis) in 1994, and obviously the Global Financial Crisis in 2008-2009, where Mexico, as an appendage of United States of America's Economy, suffered and transmitted its tremendous effects to other markets as well[13].

The Mexican Stock Exchange (BMV, by its acronym in Spanish: Bolsa Mexicana de Valores) is the only stock exchange in Mexico; it is the second larger stock market in Latin America, only after the Brazil´s BM&F Bovespa and the fifth in America. It is part of the BMV Group which is a Mexican financial services company that owns and operates also other related financial services such as: the Derivatives Exchange (MexDer), the custody institution (Indeval) and the data market provider (ValMer). The BMV is a public company from June 2008 traded in the equities market of the BMV. The trading platform (SENTRA) has been completely electronic from 1995 and from 2003, there has been access to the global market through the International Quotation System (SIC) from within the country. Currently it has alliances with the Chicago Mercantile Exchange (CME) and it is part of the Latin American Integrated Market (MILA by its acronym in Spanish) which integrates the Stock Exchanges of Colombia, Chile, Peru and Mexico. In addition to the equities market it trades debt instruments including government and corporate securities, mutual funds and warrants. The Exchange calculates 13 stock prices indexes. The major Index of the

[13] Interested reader can find a complete description of the Mexican Debt Crisis (1982), the Mexican Peso Crisis (1994) and the impact and role of Mexico in the Global Financial Crisis (2008-2009) in Rabobank (2013a & 2013b) and Cypher (2010), respectively.

BMV, the Price and Quotation Index (IPC, by its acronym in Spanish: Índice de Precios y Cotizaciones) is a capitalization weighted index of the 35 leading stocks traded in the BMV[14]. The IPC decreased to 44,692.50 index points in June from 44,703.62 index points in May of 2015. Stock Market in Mexico averaged 13,981.93 index points from 1988 until 2015, reaching an all-time high of 46,357.24 index points in September of 2014 and a record low of 86.61 index points in January of 1988 (Trading Economics, 2015). According to the World Federation of Exchanges (2015) the BMV's domestic market capitalization in 2014 was 480,245.32 million of USD, which ranks it in the 22th place worldwide; in addition, currently there are 148 listed companies.

1.3. Methodology.

1.3.1. Objectives and hypothesis.

The general objective of this Thesis is to estimate the generative multifactor model of returns on equities from a systematic risk factor statistical standpoint via the dimension reduction or feature extraction techniques: Principal Component Analysis (PCA), Factor Analysis (FA), Independent Component Analysis (ICA) and Nonlinear Principal Component Analysis (NLPCA), in order to extract the underlying systematic risk factors which will be tested in an average cross-section two stage econometric methodology of the Arbitrage Pricing Theory (APT), in the context of the Mexican Stock Exchange; once we have computed those results we will aim to compare the four techniques to the light of different criteria.

In other words, our main purpose is to carry on different extraction techniques of latent risk factors in order to:

[14] For details see: Bolsa Mexicana de Valores (2015).

1. Test the explanatory power of the generative multifactor model of returns on equities in the context of the Mexican stock market, and
2. Test the presence of relevant risk premiums associated with those underlying risk factors in the context of a statistical approach of the asset pricing model APT.

Consequently the specific objectives corresponding to each technique and the comparative study are defined as:

1. To estimate the generative multifactor model of returns on equities PCA, FA, ICA and NNPCA.
2. To build the reconstruction of the observed returns via the generative multifactor model generated by PCA, FA, ICA and NNPCA.
3. To carry on the econometric contrast of the APT using the underlying systematic risk factors extracted by PCA, FA, ICA and NNPCA.
4. To compare the four techniques in both a theoretical and empirical approach.

Therefore, we pose the following general hypothesis:

1. The generative multifactor model of returns is sensitive to the typology of the extraction technique used to extract the latent systematic risk factors.
2. The average cross-section econometric contrast methodology of the Arbitrage Pricing Theory is conditioned to the extraction technique chosen, the frequency of the data and the expression of the model (returns or excesses).
3. It exists stability in the interpretation of the latent risk factors according to the methodology used.

1.3.2. Scope and limitations.

The scope and limitations of this research regarding the APT as an asset pricing model, the statistical risk factors approach, the extraction techniques employed, and the econometric contrast methodology used, is explained in detail in the related chapters. Nevertheless, we will like to provide to the reader an overview of the principal boundaries that outline the present investigation.

Regarding the APT as an asset pricing model, we will focus only in the estimation of the generative multifactor model of returns via different techniques; however, the presence or absence of the arbitrage principle will be out of the scope of this research. Concerning the statistical approach considered, we will focus mainly in the first part of the process, i.e., the risk extraction stage; we will only propose a first attempt to the risk attribution step via some basic methodologies. About the econometric contrast of the APT using the systematic risk factors estimated via the four techniques studied, we will only make a first approach as well, using a two stage methodology, in order to evaluate the performance of this asset pricing model in the context of our research. In the first stage of the econometric contrast we estimate simultaneously, for all the system of equations, the sensitivities to the systematic risk factors (betas) extracted in each technique, then, in the second stage, we test the pricing model using an average cross-section methodology via ordinary least squares, corrected by heteroscedasticity and autocorrelation consistent covariance estimation.

1.4. Contributions.

According to the above stated and as far as we concerned, this dissertation contributes to financial research by providing empirical evidence of the estimation of the generative multifactor model of returns on equities, extracting statistical underlying risk factors via classic and alternative dimension reduction or feature extraction techniques in the field of finance, in order to test the APT as an asset pricing model, in the context of an emerging financial market such as the Mexican Stock Exchange. In addition, this work presents an unprecedented theoretical and empirical comparative study among Principal Component Analysis, Factor Analysis, Independent Component Analysis and Neural Networks Principal Component Analysis, as techniques to extract systematic risk factors from a stock exchange, analyzing the level of sensitivity of the results in function of the technique carried on.

In addition, this dissertation represent a mainly empirical exhaustive study where objective evidence about the Mexican stock market is provided by way of the application of four different techniques for extraction of systematic risk factors, to four datasets[15], in a test window that ranged from two to nine factors[16], which produced 128 models estimations, with all their corresponding phases and stages in each technique included in this Thesis, such as: a) estimation of the generative multifactor model of returns, b) simultaneously estimation of the betas, c) reconstruction of the observed returns via the estimated multifactor model of returns, d) interpretation of the estimated risk factors, e) a two-stage econometric contrast of the APT, f) comparison of the results of the four techniques under four different perspectives, etc.

[15] Attending the information availability, on one hand we built four databases two of them with a weekly frequency and the other two with a daily periodicity. On the other hand, two of them were expressed in returns on equities and the other one in returns in excesses of the riskless interest rate. More details about the datasets used in this study appears in the Chapter 3 of this dissertation.
[16] The window of test was the result of computing the number of factors to retain using nine different criteria usually applied on PCA and FA. More details about are included in Chapter 3.

1.5. Structure of the Thesis.

Finally, the structure of the Thesis is as follows. Chapter 2 presents a theoretical background of the Multifactor Asset Pricing Models as well as a proposal of taxonomy of risk factors. The Arbitrage Pricing Theory and the statistical risk factors approach, which represent the object of this Thesis, belong to this class of pricing models; thus, we will fix the standpoint of our research under the light of this classification. Considering that in following chapters, we will carry out our empiric study, the Chapter 3 describes some elements that will be common for all the techniques used; i.e., the financial market studied, the databases utilized and the methodology of the econometric contrast carried on. The following three chapters will explain each technique and present the results of the empirical study. Therefore, in Chapter 4, we will extract the pervasive systematic risk factors via the classic latent variables analysis techniques: Principal Components Analysis and Factor Analysis, using in this last case the Maximum Likelihood (ML) procedure. In Chapter 5, we will extract the underlying risk factors by way of the signal processing technique known as Independent Component Analysis, using the ICASSO methodology to estimate the independent components. In Chapter 6, we will perform the extraction using the Nonlinear Principal Components Analysis via an auto-associative neural network approach known as Neural Network Principal Component Analysis (NNPCA). Chapter 7 presents a comparative study among techniques which includes both a theoretical and an empirical approach. First, we make a theoretical matrix parallelism among techniques and a comparison of the properties of the extracted component or factors. Secondly, we compare the empirical results obtained in each technique by way of four criteria: a) accuracy in the reproduction of the observed returns, c) statistical and graphical analysis of the underlying risk structure, c) results of the econometric contrast of the APT and d) interpretation of the factors. In Chapter 8 we draw the general conclusions and pose some future lines of research. Finally, we present the references consulted and an appendix including some additional figures and tables.

Chapter 2

Multifactor asset pricing models: Taxonomy of risk factors. A review of the state of the art.

2.1. Introduction.

In the attempt to explain the equities' price formation in the stock markets, multifactor asset pricing models have been an alternative to the classic Capital Asset Pricing Model (CAPM) from the beginnings of the modern financial economics. In the financial literature we can find many theoretical and empirical studies about this topic, being the Arbitrage Pricing Theory (APT) (Ross, 1976) the most representative multifactor asset-pricing model. Following to Chan *et al.* (1998), we could set three typical uses that both academics and practitioners have made of this sort of models: a) prediction of future returns[17], b) portfolio risk optimization[18], and c) performance evaluation[19]. Nevertheless, as far as we concerned, in the literature we consider that there is not a clear and unified classification of them making the process of understanding the models, in any case some confusing, when we want to use them in empirical studies. The different approaches, theories and assumptions beneath the multifactor asset pricing models will guide us to diverse directions and methodologies when we conduct an empirical research. In order to propose an own clearer and unified taxonomy of the most relevant multifactor asset pricing models, that have been the base of the multifactor models found in financial literature, in this chapter we would try to make a brief review of them by taking account both some seminal and more recent works.

[17] See Fama & French (1997).
[18] See Rosenberg (1974), and Elton *et al.* (1997).
[19] See Elton, *et al*. (1993) and Grinblatt & Titman (1994).

2.2. Multifactor models.

Generally talking multifactor models has been an alternative to the CAPM but not a complete solution, they have some advantages over the CAPM since they represent a more generalized model[20], consider other risk factors different to the market, and do not need so restrictive assumptions such as the normality in the returns distributions and the investors' functions of utility; however they share some of its weaknesses like the linearity of their specification and the necessity of using historic data. We can distinguish three criteria to classify the multifactor models, the first attending to the value of the risk factors, the second according to the estimation of risk factors, and the third attending to the theoretical or empirical foundations of the model.

We could formulate the traditional expression of a multifactor model of returns generation as follow:

$$R_{it} = R_{ft} + \beta_{1i}F_{1t} + \beta_{2i}F_{2t} + \cdots + \beta_{ji}F_{jt} + \varepsilon_{it} \tag{2.1}$$

Where R_{it} represents the return on asset i in time t; R_{ft} the risk-free interest rate; B_{ji} the sensitivity of asset i to systematic risk factor j; F_{jt} the value of systematic risk factor j in time t common to all equities; and ε_{it} the idiosyncratic risk that only affects to asset i. This multifactor model will lie beneath the Arbitrage Pricing Model and all the different types of multivariate models that we will review next, in other words, we assume that this generative multifactor model of returns exists in the financial markets and it will allow us to obtain the APT[21].

[20] In the sense that from a multifactor model approach the market model (CAPM) can be considered as a particular case of a multifactor model where there is only one systematic risk factor represented by the market.

[21] This multifactor model of returns can be expressed alternatively as returns in excesses of the riskless interest rate whose expression is as follows: $R_{it} - R_{ft} = \beta_{1i}F_{1t} + \beta_{2i}F_{2t} + \cdots + \beta_{ji}F_{jt} + \varepsilon_{it}$

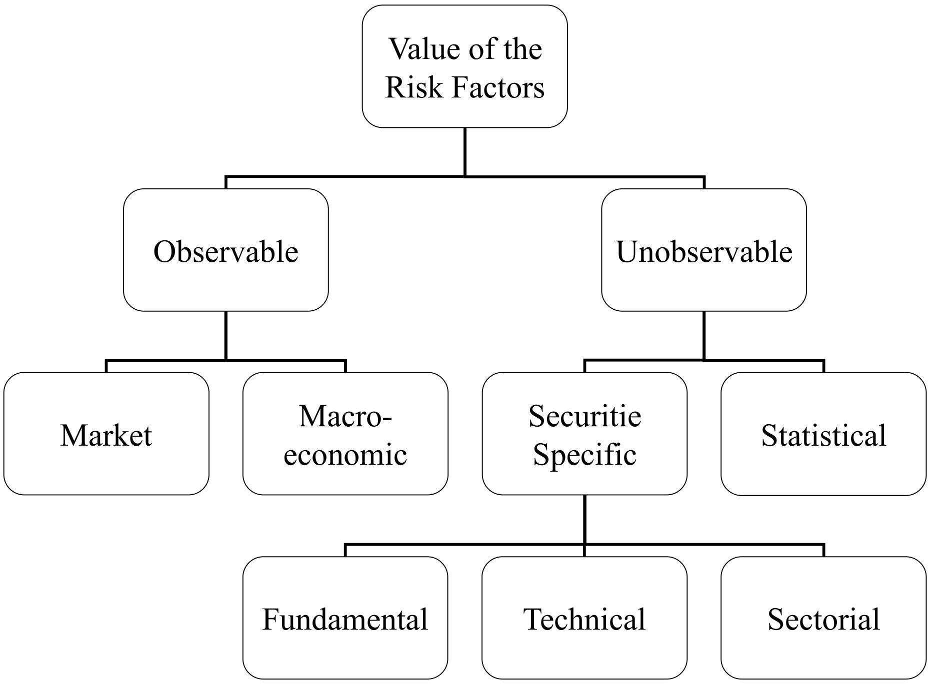
In Figures 2.1, 2.2 and 2.3, we propose a taxonomy of the multifactor models following the three criteria stated before, according to the risk factors that they consider, based on partial classifications presented in Zangari (2003) and Amenc *et al.* (2003).

2.2.1. Classification according to the value of the risk factors.

A first criterion of classification, exposed in Figure 2.1, takes account the kind of risk factor that the model assumes, so following Zangari (2003) we can make a sub-classification in this category depending on the assumed capacity to observe or not the value of the risk factors directly through some observable variables. Inside the observable factors we have market and macroeconomic factors, due to these two kinds of risks are taken from observable financial and economic indicators time series; the portfolio market for the former, and a set of predefined macroeconomic variables for the latter. The unobservable factors include fundamental, sector, technical and statistical factors. It is very important to stress the different philosophy underlying observable and unobservable approaches. The former, trust in the idea of the **value of risk factors (*Fs*)** can be observed directly through a market index or some macroeconomic time series. The latter, believe that value of risk factors can only be detected indirectly, through the securities' exposure to those set of risk factors. Security specific models will take fundamental, technical or sector attributes as the measures of those exposures (β_s) to the values of risk factors (F_s). Statistical models will calculate value of factors (F_s) and their corresponding exposures or factor loadings (B_s) simultaneously by way of multivariate techniques such as: principal component analysis and factor analysis[22].

[22] In the classical version of the statistical models PCA and FA have been the traditional statistical techniques used to estimate the generative multifactor model of returns; nevertheless, in this dissertation we will use other two more advanced techniques to perform this estimation (ICA and NNPCA), in addition to the classic techniques PCA and FA.

Figure 2.1. *Classification of multifactor models attending to the value of risk factors.*



Source: Adapted from Zangari (2003).

2.2.1.1. Market factor.

In other words we could interpret the market model practically as, the Capital Asset Pricing Model (CAPM)[23], where we trust in the existence of only one kind of systematic risk premium corresponding to the market factor, which is represented for the returns of an index market in excess of the riskless interest rate. Returns on equities will be explained by the riskless asset interest rate plus the sensitivity of each asset for being exposed to the market factor. The expression of the CAPM is as follows:

$$E(R_i) = R_f + \beta_i \cdot E(R_m - R_f), \tag{2.2}$$

where R_i is the return on equity i, R_f the riskless asset interest rate, R_m-R_f the market factor risk premium, - being R_m the return on the market index -, and finally the β_i the sensitivity of equity i to the market risk factor, in this case known as the systematic risk

[23] For a deeper study of the original works about CAPM see Sharpe (1964), Lintner (1965) and Mossin (1966).

beta[24]. If we consider the CAPM a specific case of the APT where there is only one kind of risk factor and this is observable, we can include the CAPM as a multifactor model of the market risk factor class[25]. As we can consider that market factor is observable via a market index[26], we estimate betas through a linear regression model. The CAPM has been widely contrasted, has been object of many critiques and of numerous new methodologies, either for the estimation of betas or for its econometric contrast, and has evolved in many new derivations of its original form. In financial literature we can find a large amount of theoretical and empirical studies where the CAPM has been objet of a strong academic discussion in favor and against this asset pricing model through the years; however, a revision of the state of the art of the CAPM is out of the scope of this dissertation[27]. Consequently, we will only give a short description of the CAPM's more representative variations that have led to the majority of the versions of this model that have been applied in different studies.

The consumption based CAPM includes the amount that an investor wishes to consume in the future computing a consumption beta that considers the covariance of the investor´s capacity to consume goods and services and the return of a market index[28]. The conditional CAPM or time varying CAPM is basically a variation of the static or classic CAPM where the betas and risk premiums vary over time[29]. The four moments CAPM or higher moments CAPM represents an extension of the classic CAPM where not only mean and variance are considered, but higher moments such as skewness and kurtosis[30]. The zero beta CAPM is a generalization of the classic CAPM

[24] It is important to remark that the systematic risk factor is actually the market factor represented by *(Rm-Rf)*, and beta is really the exposure of each equity to this factor; however, when using this model betas are commonly understood as if betas themselves were the systematic risk.
[25] A deeper discussion about the consideration of the CAPM as a specific case of the APT or the APT as a multibeta interpretation of the CAPM, can be found in Shanken (1982, 1985), Connor (1984) and Dybvig & Ross (1985).
[26] A discussion about the observability of the market factor and the contrastability of the CAPM can be found in the known Roll's critique (1977), Stambaugh (1982), Fama (1991) and Sharpe (1991).
[27] Interested reader can find some of the most representative earliest works in: Jensen *et al.* (1972), Fama & MacBeth (1973), Friend & Blume (1970), Blume (1971, 1975), Sharpe & Cooper (1972), Vasicek (1973), Statman (1981), Hawawini (1983), Reilly & Wright (1988), Miller & Scholes (1972), Blume & Friend (1973). Furthermore, some other representative more recent works are: Carbonell & Torra (2003), Gómez-Bezares *et al.* (2004), Fama & French (2004), Dempsey (2013), Cáceres & García (2005), Moosa (2013), Novak (2015), Saji (2014), Bilgin & Basti (2014), Kalyvitis & Panopoulou (2013), Dajčman *et al.* (2013), Eikset & Lindset (2012),
[28] For details see: Marin & Rubio (2001) and Breeden *et al.* (2014).
[29] For details see: Nieto & Rodríguez (2005), Lewellen & Nagel (2003) and Tambosi *et al.* (2009).
[30] For details see: Jurcenzko & Maillet (2002), Hwang & Satchell (1999) and Fletcher & Kihanda (2005).

where it does not exist a riskless interest rate[31]. Finally, the integration of CAPM and APT refers to attempts done to mix or unify the two main asset pricing models in finance[32]. More recently, Chiarella *et al.* (2013) developed the evolutionary CAPM (ECAPM) where they incorporate the adaptive behavior of agents with heterogeneous beliefs within the mean-variance framework.

2.2.1.2. Macroeconomic factors.

Models using these kinds of factors rely on the idea of factor risk premiums (λ_s) that affect the returns on equities can be identified using time series of predefined macroeconomic variables[33]. Although many studies have been done using this approximation, there is not a general theory about which macroeconomic measures must be used[34]. However, as Yip *et al.* (2000) point out, many of them coincide in basically four sets of macroeconomic magnitudes: change in inflation, industrial production, investor confidence and interest rates. Generally, in almost all the analyzed works the market factor is used as another macroeconomic factor too. In addition, in many of the classic works, authors have carried out multivariate techniques as principal components analysis and factor analysis, to reduce the dimensionality of the original predefined set of macroeconomics factors, in order to be able to work with a new fewer number of variables that combine the effect of all of them. Then, they estimate the sensitivities to each macroeconomic risk factor (β_s) using a cross-section or time series regression.

[31] For details see: Marin & Rubio (2001), Black (1972) and Derindere & Adigüzel (2012).
[32] For details see: Wei (1988), Connor (1984) and Srivastava & Hung (2014).
[33] Strictly speaking, since the effect of expected changes of those macroeconomic variables are already incorporated to asset prices, this approach try to estimate the surprises in those macroeconomic variables and its effect on asset returns. A deeper explanation of the model's estimation methodology that implies the obtaining of those innovations via autoregressive processes and a two-stage regression procedure can be found in the seminal studies of: Chen *et al.* (1986), Fama & Macbeth (1973), and Roll & Ross (1980). In addition a brief review about it can be consulted in Amenc & Lesourd (2003).
[34] See: Chen, *et al.* (1986), Hamao (1986), Berry, *et al.* (1988), Fama & French (1989, 1993), Chen (1991), Ferson & Harvey (1991), Pesaran & Timmermann (1995), Gangopadhyay (1996), Koutoulas & Kryzanowski (1996), and Bruno *et al.* (2002).

This approach still have been popular in more recent studies such as: Bruno, *et al.* (2002), Twerefou *et al.* (2005), Shanken *et al.* (2006), Karanikas *et al.* (2006), Evans and Speight (2006)[35], Entorf & Jamin (2007), Elhusseiny & Islam (2008), McSweeney & Worthington (2008), Mateev & Videv (2008), Javid & Ahmad (2009), Virk (2012), Leyva (2014) and Stancu (2014). This studies have carried on the macroeconomic approach to different countries and stock markets, and have used a diverse range of macroeconomic variables as risk factors, finding evidence in favor of distinct macroeconomic indicators depending on the country, the periods studied and the methodology of contrast used.

The FTSE-BIRR model.

The firm BIRR Portfolio Analysis Inc.[36] use the macroeconomic approach in its commercial models. The unexpected changes in macroeconomic variables considered as proxies of systematic risk by this model are: investor confidence (confidence risk), interest rates (time horizon risk), inflation (inflation risk), real business activity (business cycle risk) and a market index (market timing risk)[37]. Once set the value of the observable factors through the corresponding macroeconomic time series, both the exposure to each factor and its risk premiums are estimated via regressions. This model is re-estimated every month and uses monthly data from April 1992. The BIRR's core model includes five surprises in measured domestic macroeconomic factors but it can also be extended with some custom global factors. The advantage of this model is that using a much reduced number of observable factors it can explain the stocks' behavior, and control the exposure to each kind of risk in a more intuitive way; since the included variables are better known and understood by the economic theory. As well as all the macroeconomic models, they have the disadvantage of presuppose both the number and nature of factor, which can result in flawed results.

[35] In this study the authors use macroeconomic data sets but in real time.

[36] The Professors Edwin Burmeister, Roger Ibbotson, Steven Ross and Richard Roll, founded the firm BIRR Portfolio Analysis, Inc. in the late 1980's. They developed this model to analyze US portfolios for exposure to a range of macroeconomic factors. FTSE Group purchased this firm in March 2010. See FTSE-BIRR website: http://www.ftse.com/Analytics/BIRR

[37] For details of each type of risk see: Roll *et al.* (2003).

2.2.1.3. Fundamental factors.

Another trend of models has been that using fundamental variables or some security's accounting-based characteristics to explain the returns on equities such as: size, leverage, book value to market value ratio, price-earnings ratio (PER), and cash flow to market value ratio. These models emerged in the eighties and nineties as a response to complete the explanation of asset returns not given by the market factor of the CAPM[38]. It is important to remark that the main difference between fundamental and macroeconomic factors as exposed in Yip *et al.* (2000), is the **components that those models supposed to be known**. Fundamental models assume the exposures (sensitivities) to the different kinds of systematic risk (β_s) as given and estimate the risk premium (λ_s) of the security by being exposed to each class of systematic risk; whereas the macroeconomic models' philosophy is in the contrary sense, they presuppose the λ_s and estimate the β_s[39]. Thus, in this case fundamental variables will represent the exposures to each kind of systematic risk or β_s, and the model will try to estimate the factor risk premiums or λ_s by way of either a cross-section or a time series regression. Next we will expose briefly some of the most representative fundamental models.

Fama and French three-factor model or Extended CAPM.

Fama and French (1993, 1995 & 1996) proposed an extended model to explain asset returns considering two additional factors in addition to the marker factor: the book to market ratio, and the size of company, measured via its market capitalization. The formulation of this model is as follow:

$$E(R_i)-R_F=\beta_{i1}[E(R_m)-R_F]+\beta_{i2}E(SMB)+\beta_{i3}E(HML) \quad (2.3)$$

[38] See: Rosenberg (1974), Keim & Stambaugh (1986), Jaffe *et al.* (1989), Fama (1991), Chan, *et al.* (1991), Fama & French (1992, 1993, 1995, 1996, 2012), Grinold & Kahn (1999), Lakonishok *et al.* (1994), Connor (1995), Carhart (1997), Brennan *et al.* (1998), Subrahmanyam (2005), Karanikas *et al.* (2006).

[39] Strictly speaking, the lambdas have to be calculated in a first stage, following a multifactor linear generative model of returns from the values of factors (F's), which represent the elements that macroeconomic models consider as given and that can be observed.

Where $E(R_i)$ represents the expected return of asset i; R_f, the risk free interest rate; $E(R_m)$, the expected return of the market index; *SMB* (small minus big), the difference between the returns of a small capitalization portfolio and a big capitalization portfolio; *HML* (high minus low), the difference between the returns of a high book to market ratio portfolio and a low book to market ratio portfolio; and the β_s the factor loadings[40].

Although in their empirical studies this model achieves to explain the *securities* returns in a better way than the market model, they remark that the extra factors are not unique[41]. Actually, the explanatory power of other different fundamental factors has been demonstrated in several papers focused on the fundamental approach.

Carhart (1997) four-factor model.

It is practically an extension of the former model, where the momentum is added as the fourth factor. Its expression is as follow:

$$E(R_i) - R_F = \beta_{i1}\left[E(R_m) - R_F\right] + \beta_{i2}E(SMB) + \beta_{i3}E(HML) + \beta_{i4}(PR1YR) \quad (2.4)$$

Where *PR1YR* denotes the difference between the highest returns and average or lowest returns in the last year.

[40] Strictly speaking this model mix one observable factor (the market) with two unobservable variables (SMB and HML); nevertheless, it is considered the seminal or classic model under the fundamental approach.
[41] In other words, as in the macroeconomic and technical approach, the fundamental one is subject to present the error in variables problem, since if we choose other different factors to use as explanatory variables, maybe we will have different results.

The MSCI-BARRA model.

The company of support to investment processes MSCI-BARRA[42] created this model that represents one of the most commercial fundamental multifactor models in the market. This model consider that asset returns can be explained by fundamental attributes of the firm, this characteristics would represent the exposure or sensitivity (betas) to the different kinds of systematic risk, these betas are supposed to be known, and then factor returns are calculated[43].

The returns on equities follow this factor model.

$$R_{it} = \sum_{k=1}^{K} \beta_{ikt} \alpha_{kt} + u_{it} \tag{2.5}$$

Where R_{it}, is the return on equity i in excess of the riskless interest rate; β_{ik}, the factor loading or exposure of asset i to risk factor k; α_k, the return on factor k; and u_i, the specific return on equity i.

The Barra's model poses two classes of factors: industrial sector factors, that measure the differences in behavior among assets of different industry sectors; and risk indices factors, that determine the variation in performance among securities considering non-industrial factors[44]. Thus, the Barra's model considers 65 factors in total, estimating their returns monthly.

[42] MSCI and Barra joined together in 2004 when MSCI acquired Barra. Barra Inc. has been working since 1975. Morgan Stanley is the majority shareholder of MSCI Barra. See: MSCI-Barra website: www.mscibarra.com. Nevertheless, we conserve the reference to the original name of this model in order to identify it in the way of this model has been regularly named and is found in the majority of sources.
[43] For a deeper study about MSCI-Barra model see: Amenc *et al.* (2003), Sheik (1996), and Barra (1998).
[44] For the American Market, Barra had defined 52 industrial categories and the next 13 risk indices: volatility, momentum, size, size non-linearity, trading activity, growth, earnings yield, value, earnings variability, leverage, currency sensitivity, dividend yield, and non-estimation universe indicator.

This model has evolved too and different authors, members of MSCI Barra, have developed newer versions such as: Curds & Gilfedder's (2005) United Kingdom equity model[45], that represents a particular multifactor model for the British stock market; and the Hemmatti's *et al.* (2005) Barra Integrated Model (BIM)[46], that is a multi-asset class model for forecasting the risk of equities, bonds, currencies and commodities. In addition, the MSCI-Barra's research division frequently publishes recent papers about the current state of multifactor models for instance: Liu & Melas (2007), where the authors review the relationship between macroeconomic and fundamental models posing that fundamental models can be used as an approach to extract the effect of the macroeconomic factors and to understand the common factors affecting a portfolio return[47]; Miller (2006a), where the author propose an hybrid version of multifactor model combining fundamental and statistical factors[48]; and Miller (2006b) where the different kinds of factor models are revisited.

Finally, more recent studies that have used the fundamental approach are: Case *et al.* (2011), Miranyan (2012), Carrasco-Gutierrez *et al.* (2012), Stancu & Stancu (2014). In all of them different factors, methodologies of contrast, specifications of the model and results in favor or against this approach have been reported. In addition, other companies such as Northfield[49] has developed its asset pricing commercial models on this approach.

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[45] This paper refers to the newer version of the UK equity models (UKE7) but there are former versions (UKE6) that can be consulted in the MSCI website.

[46] This reference is about the newer version of the Barra Integrated Model (Version 204), former versions can be found in the MSCI Barra Website.

[47] They propose a decomposition of the fundamental factors returns into two parts: one due to macroeconomic influences and other due to sources other than macroeconomic, subsequently they split asset returns in three parts: a) a macroeconomic common factor component, b) an ex-macro common factor component and c) an specific return component. In addition, the authors distinguish two types of macroeconomic factors: a) economic variables like GDP growth, inflation, industrial production, etc., and b) market variables: like interest rate, exchange rates, commodity prices, etc. They pose that market variables are preferable to economic variables because they capture unanticipated changes in macroeconomic conditions, they are not subject to reporting lags and retrospective revisions and also, they are available at higher frequencies.

[48] The author proposes the integration of the statistical factors by way of keeping the original fundamental factor model, but extracting the statistical factors via a decomposition of the fundamental factor model's residuals. Consequently, the asset returns are divided again in three blocks: a) fundamental common factors, b) statistical common factors, and c) specific return element. Besides he carries out an empirical study on the Japanese market, where the hybrid model outdoes modestly the forecasting performance of the fundamental standard Barra's model for the Japanese market (JPE3).

[49] See Northfield website: http://www.northinfo.com/

2.2.1.4. Technical factors.

This approximation to risk factors rests on the idea of stock prices collect all the information and effects of any endogenous and exogenous source that can affect the future returns on equities. Subsequently, the standpoint of these models is that the past returns on equities can explain their future returns. The same as in fundamental models, exposures to risk factors (β_s) are represented by securities specific's characteristics named here technical factors like: excess stock returns on previous month or trading volumes; and similarly risk premiums (λ_s) will be calculated via regressions models. Studies that have focused in this approach exclusively are scarce, however we can mention the following works: Levin (1995) that uses a multilayer feedforward neural network to predict the stocks return based on its exposure to various technical and fundamental factors; Su (2006) that tests two multifactor models that include technical factors on the Chinese stock market; Bettman (2007) that consider technical factors in the context of the Australian market; and Breloer *et al.* (2014) that compare country momentum and sector momentum in global equity mutual funds.

2.2.1.5. Sector factors.

This kind of factors are the another expression of security specific factors, and follow the same philosophy that fundamental and technical designations, with the difference of sector models will approach asset's sensitivity to systematic risk factors (β_s) by the use of variables of the different industry sectors namely: energy, transportation, technology, etc. As in the technical factors, studies focused exclusively in this approach are scares, nevertheless we can mention the works of de Moor & Sercu (2010, 2011) where they compare country versus sector factors in international stock returns.

2.2.1.6. Statistical factors.

This approach share a similar standing with the technical factors, about the stock prices gather all the effects of relevant facts or economic forces that can drive the assets returns, but with a different standpoint. The philosophy of these models is that systematic risk factors can be extracted from the own structure of historical returns of a set of assets, through the statistical analysis using some reduction of dimensionality techniques. As Miller (2006b) indicates: "statistical methods can uncover relations from the patterns in records of historical returns and order them by strength." In this case, our first main objective will be uncover the pervasive systematic risk factors without taking care about the nature of the risk premiums (λ_s) or that of the sensitivities to factors (β_s), since at first sight, they will not have a clear economic interpretation once extracted. In a second step, we could try to identify them with some macroeconomic, sectorial, or fundamental variables via correlations or other techniques[50].

Unlike fundamental and macroeconomics models, here we do not presuppose as known either the sensitivities to the systematic risk factors (β_s) or the risk premium for the exposure to each kind of risk factor (λ_s); thus, both set of parameters are estimated simultaneously. We start decomposing the covariance matrix via classic multivariate, signal processing or neural networks techniques to extract the systematic risk factors and the equities' exposure (β_s) to each kind of them; then, we estimate the risk premium for each type of systematic risk (λ_s) generally through a cross-sectional regression. Statistical models have two important advantages: first, the systematic risk factors extracted are orthogonal[51]; secondly, they do not need to predefine a set of factors, i.e. the asset returns structure will generate them by way of the factor extraction techniques, making this type of factors less biased in terms of a subjective risk factors selection criterion. They have the disadvantage that the obtained factors do not have a direct

[50] The classical earliest empirical studies about the APT such as: Roll & Ross (1980), Reinganum (1981), Chen (1983), Cho *et al.* (1984), Bower, *et al.* (1984), Beenstock & Chan (1988), Connor & Korajczyk (1988) and Lehmann & Modest (1988) were done under this statistical scope focused only in the first step. Some more recent works that have been used this statistical standpoint like Gómez-Bezares (1994), and Jordan & García (2003), have made both the extraction and the later identification of factors. In addition, Amenc *et al.* (2003) present an alternative way for labelling the pervasive factors using known indicators to come back to an explicit factor decomposition from an implicit decomposition.

[51] That is completely uncorrelated each other.

economic interpretation; at first sight, each factor represents only a portfolio with sensitivity to itself equal to one, and null sensitivity to the rest of factors.

The Sungard model.

As in the case of FTSE-BIRR that bet for the macroeconomic models, and MSCI-BARRA for the fundamental ones, Sungard[52] has trust in the statistical approach for their commercial products. Their models are completely based on the Ross's Theorem of the Arbitrage Pricing Theory; they factorize the variance-covariance matrix to decompose it in the common factors and the idiosyncratic elements but using a specific statistical estimation technique, different from the classical principal components analysis and the factor analysis, that enable to work with a large data sample[53]. Depending on the country, their equity risk models consider around 20 and 25 statistical factors for getting the risk measurements; later in a second step, they look for risk attributions by apportioning fractions of the estimates to some observable variables. In other words, they decompose explicit or observable factors with the help of implicit or statistical factors, in order to explain the latter by way of the former[54]. The procedure followed by this model begins gathering a large sample of asset returns observations (including all kinds of traded assets: stocks, bonds, commodities, currencies, etc.)[55], that are grouped together for extracting the factors. The assets are clustered in homogeneous groups according to their covariance behavior; then, the returns on each group are calculated by adding the individual returns to obtain an index for each group. These indices represent the risk factors; they are constructed in such a way that they are uncorrelated and enable to compute the factor loadings, the coefficient of the specific

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[52] The original model was developed by the firm Advanced Portfolio Technologies (APT) which was founded in 1985 by Prof. John Blin and Steven Bender. This firm was acquired by Sungard in 2008 which recently (August 2015) has been acquired by Fidelity National Information Services Inc. (FIS). See Sungard website: http://www.sungard.com/ and FIS website: http://www.fisglobal.com/

[53] They use Monte Carlo simulation to probe that their technique produces a true factorial structure, solving the problem of factor analysis when working with large data samples.

[54] The interested reader can find an explanation and demonstration of their standpoint in the Sungard website. They distinguish between risk measurement and risk attribution, and remark that the popular risk models confuse these concepts, mixing them or reversing their order, subsequently they produce erroneous risk measurement and attributions.

[55] This is for avoiding the concentration ratio (number of asset over the number of time observations) "trap", consisting in having a fewer number of assets than the number of return observations. According to the APT firm, the Ross's APT theorem implies that the number of asset should be greater than the number of return observations due to the non-synchronicity of the prices frequency.

component, and later the factor risk premiums via regressions. The estimations use three and a half years of weakly returns[56].

The EM applications Inc.

In addition, other important commercial company that based its models on this approach is EM applications[57]. According to this firm (EM applications, 2015a & 2015b), we can summarize the main characteristics of the statistical factor models as follows:

1. The attribution risk in the statistical factors are not pre-specified and can be given to different macroeconomic, fundamental or user selected factors.
2. They starts with no assumptions about the factors or factor loadings and treat them both as unknown.
3. The previous values are obtained as a result of an estimation based on the securities returns.
4. Statistical factor models find independent factors that maximize the explanatory power for the security returns.
5. The flexibility of the statistical factor modes allows portfolio managers to attribute the risk to any risk factor rather than being limited to pre-specified macroeconomic or fundamental indicator that could even exclude important and relevant risk factors.

Finally, although in a smaller number, studies focused on this approach can be found in financial literature as well. A review of the state of the art on this issue is presented in Chapter 4 where we present the first techniques used for the estimation of the generative multifactor of returns under the statistical approach to the Arbitrage Pricing Theory used in this dissertation.

[56] For more details about the model procedure see Sungard website: http://www.sungard.com/solutions/risk-management-analytics/investment-risk/APT and Amenc *et al.* (2003).
[57] See EM applications website: http://emapplications.com/index.php?q=research/statistical-factor-model

2.2.1.7. Comparison among the different models.

Although it is difficult to determine which of the former multifactor models is the best, the empirical evidence of studies like Connor (1995), shows that statistical and fundamental models outperform macroeconomic models in terms of explanatory power; and that fundamentals outperform lightly the statistical ones. However, for many authors the macroeconomic models are the stronger, rather than the weaker in a theoretical and intuitive framework. Moreover, defenders of the macroeconomic models like Bumeister *et al.* (2003), pose that in addition to the intuitive interpretation of macroeconomics factors, this approach allow to account with additional information to estimate better both: risk exposures and risk premiums, and not only stock returns explaining stock returns. Nevertheless, supporters of the statistical approach such as Sungard and EM Application firms, criticize macroeconomic and fundamental models because they may present the specification error econometric problem, they do not take account variance-covariance matrix of returns and they confuse the risk measurement and risk attribution concepts. However, statistical models are very sensitive to the extraction technique used and may produce different number and structures of factors depending on the periods of time and on the number of assets[58]; in addition they have the problem of the not easy interpretation of factors. Maringer (2004) make a good summary revision of advantages, disadvantages and recommended uses of macroeconomic, fundamental and statistical models; and Miller (2006 a & b) carries out a newer comparison complementing that of Connor's (1995) classic study. Evidently each of the most famous companies selling commercial products based on the different approaches defend their own as the best solution; in that sense FTSE, MSCI and SUNGARD justify strongly the macroeconomic, fundamental, and statistical models respectively. Evidence of empirical studies has shown results supporting the three models.

[58] This is precisely one of the objectives of this dissertation.

However, the academic discussion around this issue persist until now; for example more recent studies such as Leyva (2014) contrasted the benefits of using the macroeconomic multifactor models against the others; whereas, EM Applications (2015a, 2015b) present a comparative study about the different characteristics, attributions and advantages of the macroeconomic, fundamental and statistical factors, pointing to the statistical approach as the best one. The main advantages that they state for the statistical factor model when compared with the macroeconomic and fundamental models are: a) reduced problem with missing data, b) data inputs consistent across countries, i.e., no difficulties resulting from different accounting methods or macroeconomic measurement approaches since the only input required are the securities returns, c) high-frequency data, d) no missing factors, e) no factors miss-specified, f) model flexible to attribute outputs to factors other than those the model covers. Conversely, they pointed that the disadvantage against those models is that its outputs are not directly attributable to risk factors as in the macroeconomic and fundamental models. On the other hand, Spyridis *et al.* (2012) found similar results in the application of a macroeconomic and a statistical approaches to the APT in the Athens Stock Exchanges, where both version produced partial results in favor of this asset pricing model.

On the other hand, other studies have tried to hybridize some different methods as an option to put together the advantages of each model, for instance Liu & Melas (2007) propose a model that combine fundamental and macroeconomic models, and Miller (2006a) mix the fundamental and statistical approaches. Finally, in Table 2.1 we summarize the relationship between the former models in terms of their assumptions, inputs, estimation techniques, outputs and attributions.

Consequently, according to the above stated, we consider that there is not an indisputable verdict about the absolute supremacy of any type of them over the others; nevertheless, in this research we will focus in the statistical approach since we believe that represent a better choice given the characteristics and attributes explained in this section.

Table 2.1. *Relationship among factor models.*

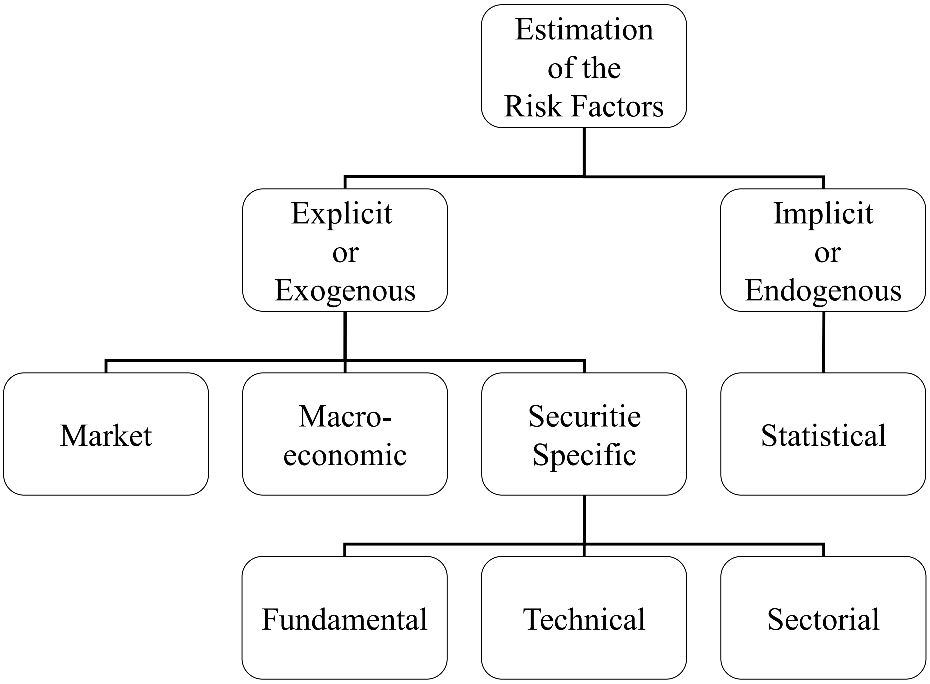
Factor model type	Assumption	Inputs	Estimation Technique	Outputs	Attribution
Market	Market factor (Market index).	Security returns and market index.	Time-series regression.	Security factor betas.	Only one factor identified with the market index pre-specified.
Macroeconomic	Macroeconomic factors (return factors) e.g. inflation and GNP growth explain all systematic risks.	Security returns and macroeconomic variables.	Time-series regression.	Sensitivity to each factor (factor loadings) are estimated. (Security factor betas.)	Only macroeconomic factors which are pre-specified.
Fundamental	Fundamental factors (e.g. P/E, P/B, Size etc.) proxy for factor loadings.	Security returns and security characteristics (Betas).	Cross-section regression.	Fundamental factors (return factors) are estimated.	Only fundamental factors which are pre-specified.
Technical	Technical factors (e.g. excess stock return on previous month, trading volumes) proxy for factor loadings.	Security returns and security characteristics (Betas).	Cross-section regression.	Technical factors (return factors) are estimated.	Only technical factors which are pre-specified.
Sector	Sector factors (e.g. energy, transportation, technology) proxy for factor loadings.	Security returns and security characteristics (Betas).	Cross-section regression.	Sector factors (return factors) are estimated.	Only sector factors which are pre-specified.
Statistical	No prejudged return factors or factor loadings. Both are estimated by statistical technique	Security returns.	1. Dimension reduction or feature extraction techniques. 2. Cross-section regressions.	Statistical Factors and Security Factors Betas. Both return factors and loadings on each factor are estimated.	Attribution to any factors (Macroeconomic, Fundamental, etc.) users select.

Source: Own elaboration adapted from Connor (1995), Zangari (2003) and EM Applications (2015a).

2.2.2. Classification according to the estimation of the risk factors.

In Figure 2.2, we mix the former classification with the one proposed by Amenc *et al.* (2003), where they propose a different categorization depending on whether the factors are extracted from the own assets returns (implicit or endogenous models) or they are estimated from external identifiable variables (explicit or exogenous). According to this classification statistical models would be the only type of implicit or endogenous model, and therefore market, macroeconomic, fundamental, sector, and technical models would be included in the explicit or exogenous category.

Figure 2.2. *Classification of multifactor models attending the estimation of risk factors.*

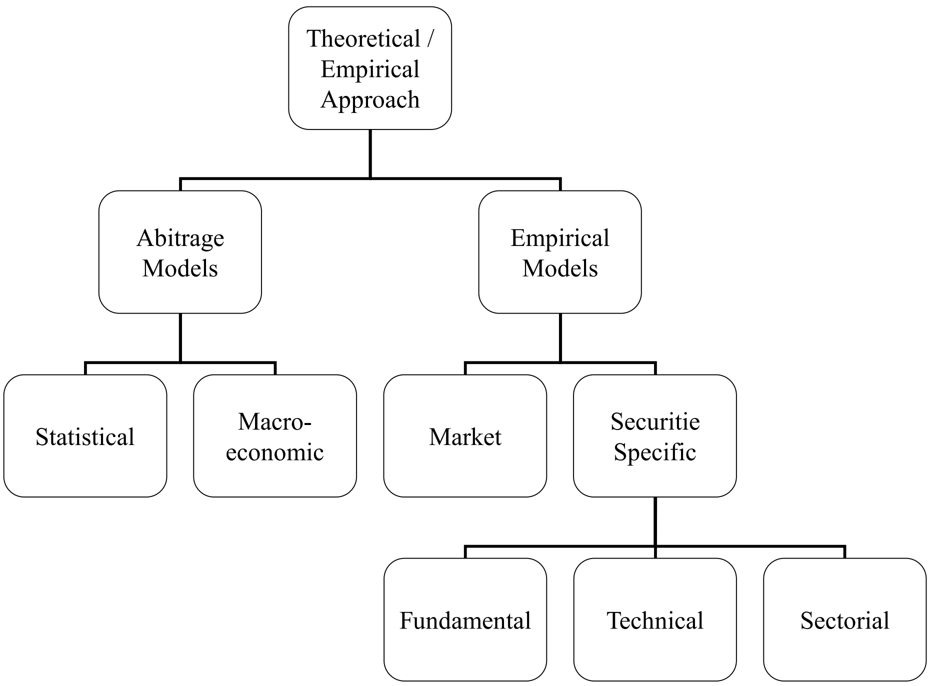


Source: Adapted from Zangari (2003) and Amenc *et al.* (2003).

2.2.3. Classification by the theoretical or empirical foundation of the model.

In Figure 2.3, we present the above explained models inside another different criterion of classification proposed by Amenc *et al.* (2003), where they divide multifactor models in two categories: those based in a financial economics concept as the arbitrage theory, and those based only on empirical considerations.

Figure 2.3. *Classification of multifactor models according to their empirical or empirical foundations.*



Source: Adapted from Zangari (2003) and Amenc *et al.* (2003).

2.2.3.1. Arbitrage models. (The Arbitrage Pricing Theory).

The Ross' (1976) Arbitrage Pricing Theory propose that returns on equities are formed by the riskless asset interest rate plus the risk premium of a set of risk factors common to all the securities, to which each individual security will have an specific exposure; and also an specific risk premium that will only affects to each equity in particular. This theory and its derived pricing model rest on two main concepts: a generative multifactor model of returns and an arbitrage argument or arbitrage absence principle[59]. The APT's pricing model equation is as follow:

$$E(R_i) = \lambda_0 + \lambda_1 \cdot \beta_{1i} + \lambda_2 \cdot \beta_{2i} + \ldots + \lambda_k \cdot \beta_{ki} \quad (2.6)$$

Where λ_0 represents the riskless interest rate, the λ_k , the risk premium associated to each different type of systematic risk factor, and the β_k , the sensitivity of equity *i* to each type of systematic risk (beta). When we use statistical models we consider that the risk factors are unobservable so, the estimation of this model implies first the extraction of the risk factors (β_s) through techniques of data reduction or feature extraction like: the classic multivariate methods of Principal Component Analysis (PCA) or Factor Analysis (FA), the signal processing technique of Independent Component Analysis (ICA), the neural networks procedures of Principal Component Neural Networks (PCNN) and other recent tools. Once we have extracted the systematic risk factors we can proceed to estimate the model parameters (λ_s) by means of a linear multiple regression or other alternative methodology of econometric contrast. Something important to remark is that in this kind of models, risk premiums (λ_s) represent attributes of the factors not of the individual securities, as we will see in the empirical models. When we use predefined macroeconomic variables in the APT-type models these λs may represent the link of securities with some aspects of the economy, consequently we would include macroeconomic factors (models) inside this category as well. Some variations of the APT model are the followings:

[59] For more details see Ross (1976), Roll & Ross (1980), Roll & Ross (1994), Gómez-Bezares (2000), Gómez-Bezares, *et al.* (1994), Marin & Rubio (2001), Amenc & Le Sourd (2003), amongst others.

Exact Arbitrage Pricing Theory (EAPT).

Strictly speaking, the original Ross' APT pricing equation has the problem of representing only an approximation of the asset pricing relation, mainly due to the problem of the impossibility of constructing a perfectly well diversified portfolio that eliminate completely the non-systematic risk in an economy with a finite number of assets. This situation could result in a miss pricing of some securities[60], prompting many authors to improve the original model by transforming the approximate pricing relation into an exact pricing relation by way of adding additional restrictions[61] or carrying out recent mathematical developments[62]. These kinds of approaches are known as Exact Arbitrage Pricing Theory.

Finally, other representative variation of the APT that have been applied on different studies through the years is the International APT, which represents an extension of this model to the international arena where it is assumed that the currency movements affect the assets factor loadings and the associated risk premiums, and it is included the joint hypothesis that the international capital market is integrated and that the APT is internationally valid[63].

[60] Nevertheless, empiric studies have shown that the pricing errors are negligible for all assets under consideration.
[61] See: Chamberlain (1983), Dybvig (1983), Grinblatt & Titman (1987), Connor (1984), Huberman *et al.* (1987), and Lehman & Modest (1988).
[62] See Khan & Sun (2003) where authors pose a tri-variate decomposition of risk: essential, non-essential and unsystematic risk.
[63] See: Dewachter *et al.* (2003), Morelli (2009) and Armstrong *et al.* (2012)

2.2.3.2. Empirical models.

As Amenc *et al.* (2003) expose, in arbitrage models the risk premiums are characteristics of the factors independently from the securities responding to the shocks of external influences; conversely, in empirical models risk premiums are associated to specific characteristics of the securities. Unlike the APT-type models empirical models do not follow strictly an arbitrage theory and do not presuppose a generative factor model of returns, their philosophy is basically the same that we explained in the fundamental factors section. This kind of models will try to explain the securities returns[64] through a decomposition using security-specific factors; i.e. specific securities attributes that are not necessarily linked to the economy in general. In other words, these models use specific securities' information instead of macroeconomic variables. The three risk factors under the security-specific sub-category in Figure 2.3 would form part of this division, because the used data are related to characteristics of particular securities namely fundamental, technical or sectorial indicators. Once again, we could classify the CAPM (market factor model) within this category as a multifactor empirical model, considering it as a particular case where there is only one security-specific factor named the beta of each equity with the market index. The firm MSCI-BARRA model would be another example of empirical models too.

[64] Strictly speaking: the risk premiums.

Chapter 3

Databases and methodology for the econometric contrast.

3.1. The Mexican Stock Exchange.

The empirical study was carried out on the Mexican Stock Exchange (BMV); for this, two aspects were taken into account: first, that very little research has been done concerning this institution; second, its relevance as an emergent financial market. Some 136 firms are listed on the BMV, its market value is about 42.86% of Mexico's GNP and its average daily operation volume exceeds 94,785 million shares, which represent a value of about 222,557 million US dollars[65]. In spite of the international financial crisis, in 2009 its main index - the Prices and Quotations Index (IPC) - achieved 32,120.47 points which represented an annual return of 48.79% in US dollars, its level of volatility during that year oscillated from 18% to 56% and the number of operations reached an all-time high of 61,024 transactions. All the foregoing conditions situated the BMV in the 26th and 21th places in the ranking of the main and emerging markets in the world, respectively in the hardest year of the financial crisis[66]. Along the last fifteen years (2000-2015) the IPC has appreciated by 504.95%, yielding an annual average return of 12.09%[67]. Nevertheless, as an emerging financial market, its volatility is high, its liquidity is low and investment is mostly concentrated in the main index equities which is mainly represented by foreign institutional investors.

[65] Figures taken from the Mexican Stock Exchange Annual Report 2013 (Bolsa Mexicana de Valores, 2013).
[66] Figures taken from the Mexican Stock Exchange Annual Report 2010. (Bolsa Mexicana de Valores, 2009).
[67] The returns are expressed in Mexican Pesos. The returns expressed in US dollars for these periods were not available. The figures were calculated with data taken from Bank of Mexico at September 14, 2015.

3.2. Description of the databases.

3.2.1. The data.

The stocks selected for this study formed part of the Price and Quotation Index (IPC by its acronym in Spanish) and represent leading companies in the industrial sectors to which they belong. Because of their importance in the Mexican Economy and their characteristics of liquidity and market value, these companies can be considered as representative of the Mexican stock market; thus, we can consider them to be characteristic securities of the BMV and the Mexican economy. Table 3.1 shows the names and sector of these shares[68].

Both the period analyzed and the shares selected reflected the availability of data among the diverse information sources consulted. Our basic aim was to build a homogeneous and sufficiently broad database, capable of being processed with the multivariate and econometric techniques used in this study.

[68] The two stocks not included in the daily databases are: CEMEXCP and KIMBERA. These stocks were not included in the weekly databases responding to information availability.

Table 3.1. *Stocks used in the study.*

No.	TICKER	Name of the Company	Sector	Sub-sector	Trade	Sub-trade
1	ALFAA	Grupo Alfa	Industrials	Capital goods	Industrial conglomerates / Holdings	Industrial conglomerates / Holdings
2	ARA*	Consorcio Ara	Industrials	Construction	House building	House building
3	AZTECAPO	TV Azteca	Telecommunications services	Communication media	Communication media	Radio & and television services
4	BIMBOA	Grupo Bimbo	Consumer staples	Food, beverage & tobacco	Food products	Production and commercialization of food products
5	CEMEXCP (1)	Cemex	Materials	Materials	Construction materials	Construction materials
6	CIEB	Corporación Interamericana de Entretenimiento	Consumer discretionary & services	Consumer services	Hotels, restaurants & leisure	Leisure facilities
7	COMERCIUBC	Controladora Comercial Mexicana	Consumer staples	Consumer staples	Consumer staples	Hypermarkets and supercenters
8	CONTAL*	Grupo Continental	Consumer staples	Food, beverage & tobacco	Beverages	Soft drinks
9	ELEKTRA*	Grupo Elektra	Consumer discretionary & services	Retailing	Specialty retail	Home furnishing retail
10	FEMSAUBD	Fomento Económico Mexicano	Consumer staples	Food, beverage & tobacco	Beverages	Diversified beverages
11	GCARSOA1	Grupo Carso	Industrials	Capital goods	Industrial conglomerates / Holdings	Industrial conglomerates / Holdings
12	GEOB	Corporación GEO	Industrials	Construction	House building	House building
13	GFINBURO	Grupo Financiero Inbursa	Financial services	Financial entities	Financial groups	Financial groups
14	GFNORTEO	Grupo Financiero Banorte	Financial services	Financial entities	Financial groups	Financial groups
15	GMODELOC	Grupo Modelo	Consumer staples	Food, beverage & tobacco	Beverages	Brewers
16	KIMBERA (1)	Kimberly-Clark de México	Consumer staples	Household & personal products	Household products	Household products / Cellulose and paper
17	PE&OLES*	Industrias Peñoles	Materials	Materials	Metals & mining	Precious metals and minerals
18	SORIANAB	Organización Soriana	Consumer staples	Consumer staples	Consumer staples	Hypermarkets and supercenters
19	TELECOA1	Carso Global Telecom	Telecommunications services	Telecommunications services	Wireless telecommunications services	Wireless telecommunications services
20	TELMEXL	Teléfonos de México	Telecommunications services	Telecommunications services	Wireless telecommunications services	Wireless telecommunications services
21	TLEVISACPO	Grupo Televisa	Telecommunications services	Communication media	Communication media	Radio & and television services
22	WALMEXV	Wal-Mart de México	Consumer staples	Consumer staples	Consumer staples	Hypermarkets and supercenters

(1) Stock not included in the weekly databases responding to information availability.

First, we chose the IPC sample used from February 2005 to January 2006; then, we constructed two return databases taking into account, as the main criterion, that the equities chosen had remained in the IPC sample during all the considered periods for which information was available[69]. In accordance with these considerations, we prepared a database made up of 20 companies and 291 weekly quotations (DBWR) ranging from July 7, 2000 to January 27, 2006; in addition, one with 22 shares that included 1,410 observations (DBDR) from July 3, 2000[70] to January 27, 2006[71]. We calculated the logarithmic weekly returns considering the assets' closing prices[72] for each Friday, in accordance with the following expression:

$$r_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right), \tag{3.1}$$

where r_{it} is the return on equity "i" in time "t"; l_n, the Neperian logarithm; P_{it}, the equity price "i" in time "t"; P_{it-1}, the equity price "i" in time "t" delayed one period.

We also built two other databases considering the returns in excess of the riskless interest rate[73]. The interest rates considered as the riskless interest rate were the average weekly and daily funding interest rates using government securities, published by the Bank of Mexico. For the weekly databases, it was necessary to convert them into the weekly equivalent to make them comparable with our returns on equities. After that, we subtracted the daily and weekly riskless interest rates from the weekly and daily

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[69] *Survival bias*: Equities that did not remain in the IPC sample throughout the entire study period, because they were unlisted, substituted, or only present for some periods, were excluded. The purpose of this criterion was to work with a strong database (from a financial point of view), considering only stocks that had survived as part of the IPC sample throughout this period of time, satisfying all the listing and maintenance requirements established by the BMV. See Gómez-Bezares *et al.* (1994).

[70] In this case, we started in July because, until 2000, the IPC sample validity was half-yearly, with the new half-yearly sample beginning in July. From 2001 to 2010, the sample validity was yearly, changing each February. Currently, it changes in the month of August.

[71] The number of assets and the periods considered were defined by the available information in accordance with the above-stated criteria. Unfortunately, since there are many gaps in the observations of several stocks in the Mexican market, it is very difficult to build a dataset of quotations which contains both a long number of observations and a large number of stocks. In our case, the 20 and 22 stocks considered represents the maximum number of shares from which we could obtain a good enough number of observations of all of them, that allowed us to build complete and homogeneous datasets for both periodicities (without missing values). This fact constitutes a very important aspect for the correct application of the extraction techniques presented. In addition, we decided to use two differently structured databases in order to test the case of weekly and daily returns as well as a larger and a smaller number of observations, according to the different studies found in literature.

[72] Although other studies have included other elements such as dividends and application rights to calculate the return on equities in addition to price variation, we could not incorporate them, as this sort of data was not available to us.

[73] The expressions of the models in returns and in excesses are presented in Chapter 2.

returns on equities, respectively, in the two databases described above. Thus, we produced two more new databases, including the same stocks and observations as in the former, but expressed as returns in excess over the riskless interest rate (DBWE and DBDE). Consequently, our study was applied to the four resulting databases, i.e., we tested the two model specifications for the two different databases.

The period analyzed in this study was considered according to the following criteria:

1. In this Thesis we are testing different techniques for extracting the underlying systematic risk factors in the context of the Mexican Stock Exchange. Principal Component Analysis and Factor Analysis which represent the classic techniques to perform that extraction, under a statistical approach of the systematic risk factors, and Independent Component Analysis and the Neural Networks Principal Component Analysis, which represent alternative techniques to achieve this objective.

2. The four techniques have an explanatory and a predictive character; however this research focuses only in the explanatory approach; that is, the potential of this technique to reproduce the observed returns on equities.

3. The period data studied has been used to extract the generative underlying structure of returns, which explains the behavior of the returns in a period that will serve as a training period in future researches, where we will try to test the predictive capacity of our models in subsequent periods of time.

4. Additionally, other reason for using this period of the dataset, was to be able to test this models in the pre-crisis periods, in order to be able to compare these results in future studies, where we will attempt to analyze the behavior of these techniques in crisis and post-crisis periods[74].

[74] Both the testing of the prediction power of the estimated models by way of the four techniques, and the comparison of the results in the crisis and post-crisis periods are out of the scope of this dissertation.

5. Finally, this period represents an interesting period of time in the Mexican political and economic spheres since represents the first six-year Presidential term of office where there was a political alternation in the Government of the Country; after more than 75 year of being ruled by the Institutional Revolutionary Party (PRI by its acronym in Spanish). This period corresponds to the Government of the first Mexican President of a different political party; Vicente Fox Quesada from the National Action Party (PAN, by its acronym in Spanish).

3.2.2. Databases descriptive statistics.

This section presents an exploratory statistical and graphical analysis of each database used in this study. For each one of them, we build: a) a figure with all the stocks plotted individually, b) the descriptive statistics and a test of univariate normality, c) the correlation matrix, d) the box plots, and e) the histograms with the normal distribution curve fit. For the sake of saving space we only present in this section some representative figures and tables related to the databases of weekly and daily returns[75]. First, in Figures 3.1 and 3.2 we present the graphics of all the stocks plotted individually corresponding to each database, respectively. Secondly, we present in Table 3.2, Figure, 3.3 and 3.4, the descriptive statistics, the boxplots and the histograms corresponding to the first database, respectively. Thirdly, in Table 3.3, Figure 3.5 and Figure 3.6 we present the analogous tables and figures of the second dataset.

In the database of weekly returns the mean of the logarithmic returns for all the stocks considered, range from -0.19% to 0.82%, and the median from 0.00% to 1.28%; in almost all the stocks both values were close. In this database GEO B represented the stock that yielded the maximum average weekly return in the considered period, and CIE B, the one that generated the major average loss. The maximum logarithmic returns among the stocks oscillated from 10.37% to 26.20%, corresponding to TELMEX L and GEO B, respectively. On the other hand, the stocks highest average weekly losses fluctuated between -11.41% (GMODELO C) and -36.09% (ALFA A). The weekly

[75] In the Section corresponding to Chapter 3 of the Appendix_2 of this dissertation, we include the figures and tables corresponding to the database of weekly excesses and the database of daily excesses, in addition to the correlation matrices of the four databases.

standard deviation ranged from 3.2% to 6.74%, which points to GMODELO C and GEO B, as the stocks with the lowest and highest volatility in the sample. Fourteen stocks present a negative skewness whereas six have a positive one, which implies that the returns of the sample reached more negative values. The twenty stocks are leptokurtic, with values higher than 3 in all the cases and reaching, in the case of TELMEX L, a maximum value of 7.78. Consequently, according to the results of the skewness and the kurtosis we can conclude that none of the stocks studied are univariate normally distributed, which will have implications on some aspects regarding the techniques used in this dissertation, as we will explain in the respective chapters. The Jarque-Bera test[76] confirms this asseveration rejecting the null hypothesis of normality at the 5% significant lever for all the stocks, except in the case of ARA*. The former results can also be observed in the boxplots and the histograms presented in Figures 3.1 and 3.2. Moreover, in the histograms we can see that the theoretical curve of the normal distribution do not fit the empirical distribution of the observed data, especially with respect to the leptokurtic shape of the distribution in almost all the variables. As a result of the temporal evolution observed in Figure 3.4, we can observe that in most of the cases there are presence of extreme values that will make difficult both, the suitable measure of the volatility and the application of certain multivariate statistical techniques.

The results of the descriptive statistics of the database of weekly excesses are very similar to those obtained in the database of weekly returns, which implies that from a statistical and graphical standpoint, there is not significant difference in both expressions of the weekly databases[77]. Both expressions share also almost all the results concerning the stocks pointed in the descriptive statistics analysis above explained, except in the case that in this database the minimum median value corresponded to CONTAL*. Likewise, the Jarque-Bera test, and the conclusions derived from the boxplots and histograms are the same[78].

[76] We are aware of the existence of other normality tests, however, we chose this because of the use of higher order moments, which will have implications in the techniques used in this study.
[77] See Table 3 of Chapter 3 in the Appendix_2.
[78] See Table 3 and Figures 1 and 2 of Chapter 3 in Appendix_2.

Finally, regarding to the correlation matrix of the four databases presented in the Appendix, we can determine that in all the cases the rates of returns are positively related, and that in almost all the cases we rejected the null hypothesis of non-correlation among the stocks, except in the case of PEÑOLES* in the weekly databases[79]. This result may be considered normal, since PEÑOLES * is a mining company specialized in the extraction on precious minerals, thus, its anticyclical behavior can be a reason of its low or non-correlation with the rest of stocks in a weekly periodicity. As stated the major correlation were detected among stocks that belong to the same economic sector. Further analysis about the correlation matrix of the databases studied is presented in Chapter 4, as preliminary test previous to the application of Principal Component Analysis and Factor Analysis.

As stated above, the results of this exploratory analysis will have implications related to the application and settings of some parameters of the extraction techniques used in the following chapters of this dissertation.

[79] See Tables 1, 2, 4, 5, 6, 7, 9 and 10 of Chapter 3 in Appendix_2.

Figure 3.1. *Line plots (Multiple Graph). Database of weekly returns.*

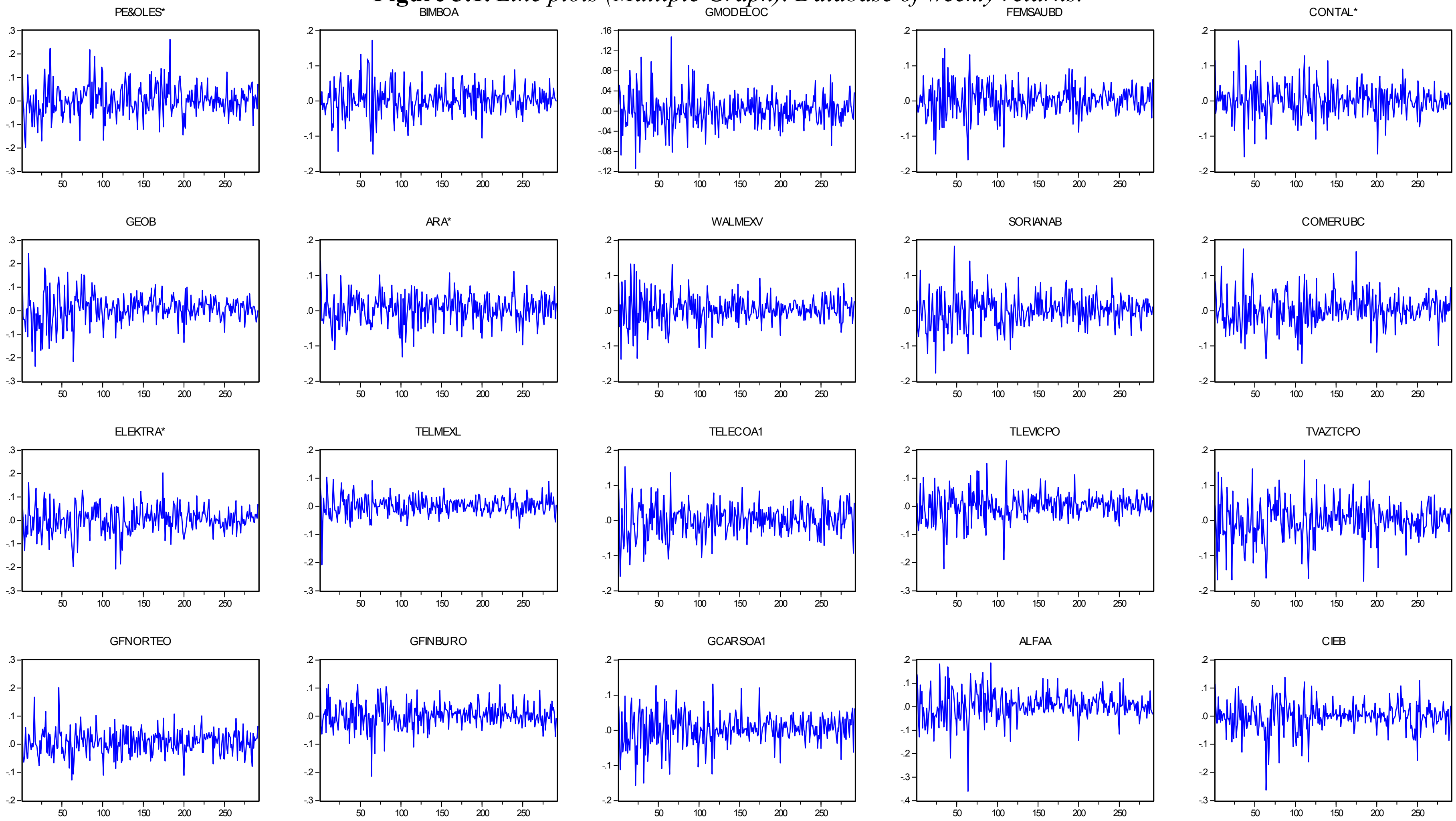


Figure 3.2. *Line plots (Multiple Graph). Database of daily returns.*

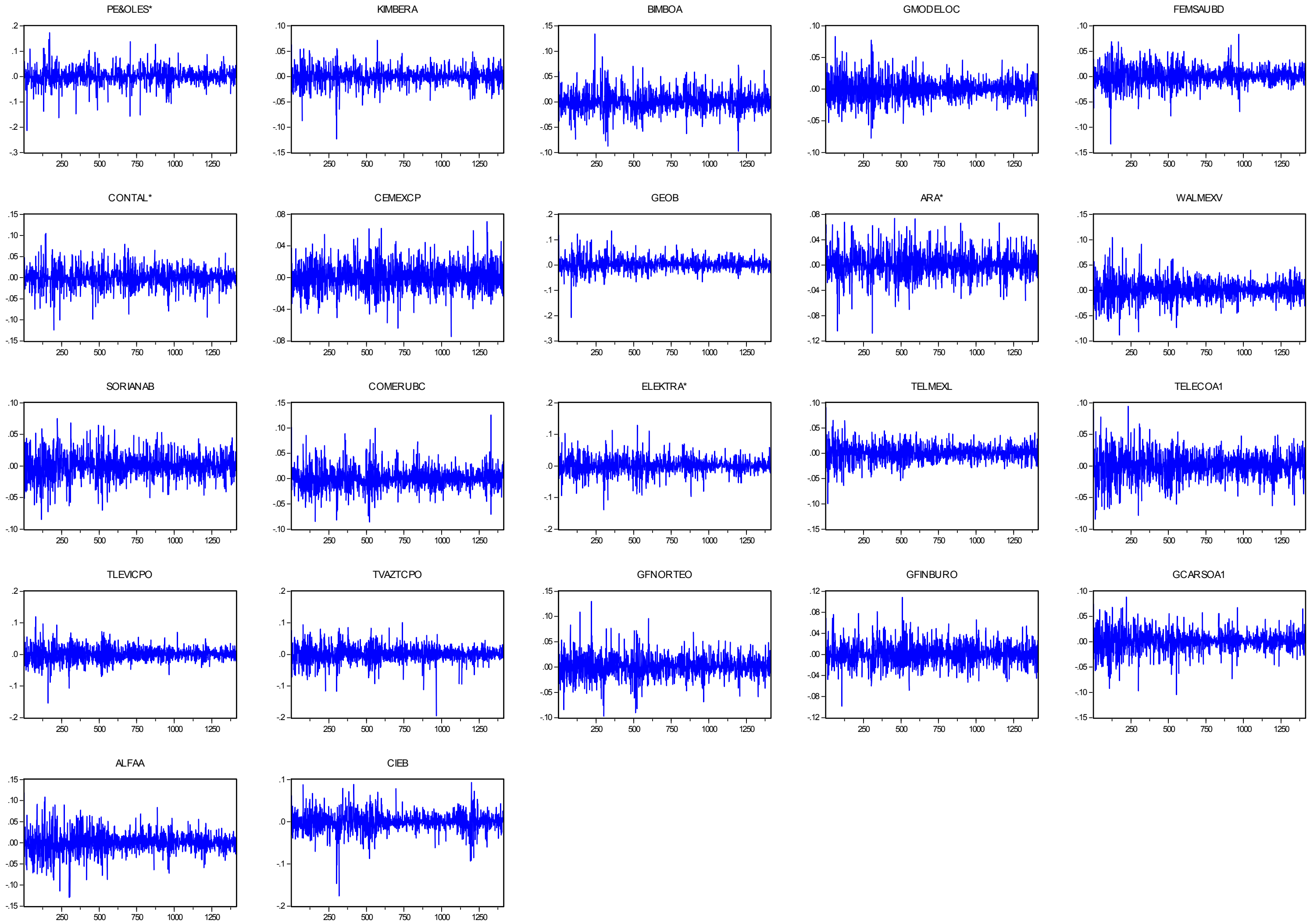


Table 3.2. *Descriptive statistics. Database of weekly returns.*

	PE_OLES_	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
Mean	0.00473	0.00316	0.00187	0.00236	0.00204	0.00819	0.00490	0.00333	0.00075	0.00226	0.00265	0.00120	0.00132	0.00090	-0.00033	0.00685	0.00246	0.00341	0.00356	-0.00195
Median	0.00000	0.00191	0.00166	0.00175	0.00000	0.01281	0.00612	0.00295	0.00000	0.00095	0.00326	0.00000	0.00247	0.00201	0.00000	0.00774	0.00308	0.00616	0.00414	0.00042
Maximum	0.26198	0.17255	0.14711	0.14883	0.17023	0.24362	0.14126	0.13302	0.18310	0.17515	0.20223	0.10370	0.15319	0.16237	0.17154	0.20164	0.11297	0.13126	0.18784	0.13822
Minimum	-0.19783	-0.15166	-0.11411	-0.16766	-0.15839	-0.23660	-0.13079	-0.13732	-0.17708	-0.14975	-0.20717	-0.20740	-0.15892	-0.22206	-0.17275	-0.12734	-0.21335	-0.15707	-0.36092	-0.26296
Std. Dev.	0.06740	0.04218	0.03214	0.04236	0.04384	0.06286	0.04060	0.03983	0.04383	0.04541	0.05687	0.03343	0.04444	0.04748	0.05275	0.04363	0.04259	0.04448	0.06189	0.05051
Skewness	0.34135	0.07769	0.31917	-0.25201	0.07159	-0.26224	-0.13353	-0.02611	-0.05328	0.13561	-0.24654	-0.57245	-0.12186	-0.39932	-0.35669	0.24866	-0.34963	-0.38022	-0.66087	-0.78432
Kurtosis	4.39484	4.77180	5.23799	4.74476	4.66921	5.12215	3.54832	4.59489	4.77280	4.46993	4.36743	7.78279	3.74571	5.74266	4.47000	4.52831	5.36087	4.30958	7.41083	6.21503
Jarque-Bera	29.24151	38.35626	65.67019	39.99115	34.03192	57.94051	4.51024	30.87516	38.24454	27.09040	25.62004	293.25403	7.46268	98.94046	32.37142	31.31952	73.50976	27.80589	257.08005	155.16387
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.10486	0.00000	0.00000	0.00000	0.00000	0.00000	0.02396	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291

Figure 3.3. *Box plots. Database of weekly returns.*

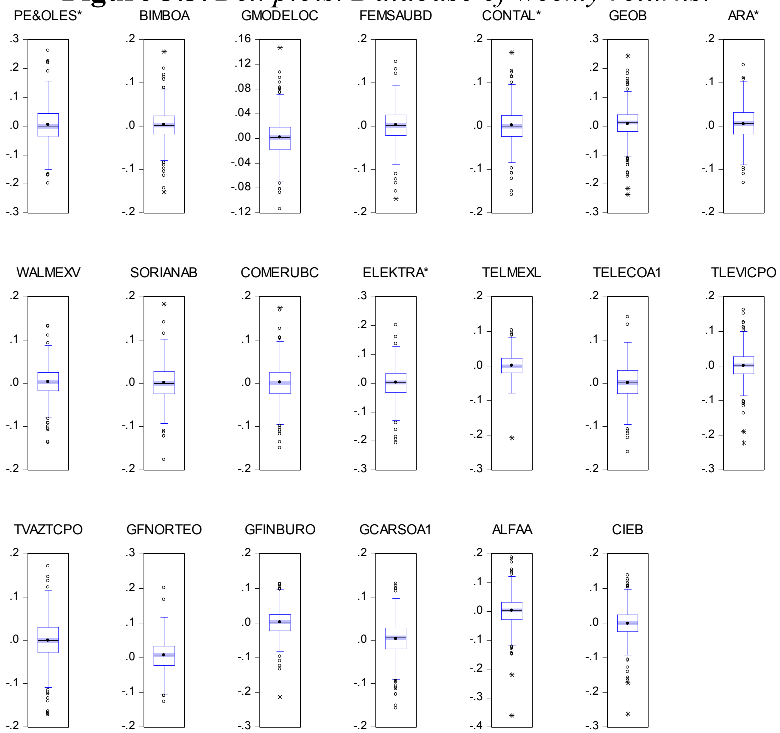


Figure 3.4. *Histograms. Database of weekly returns.*

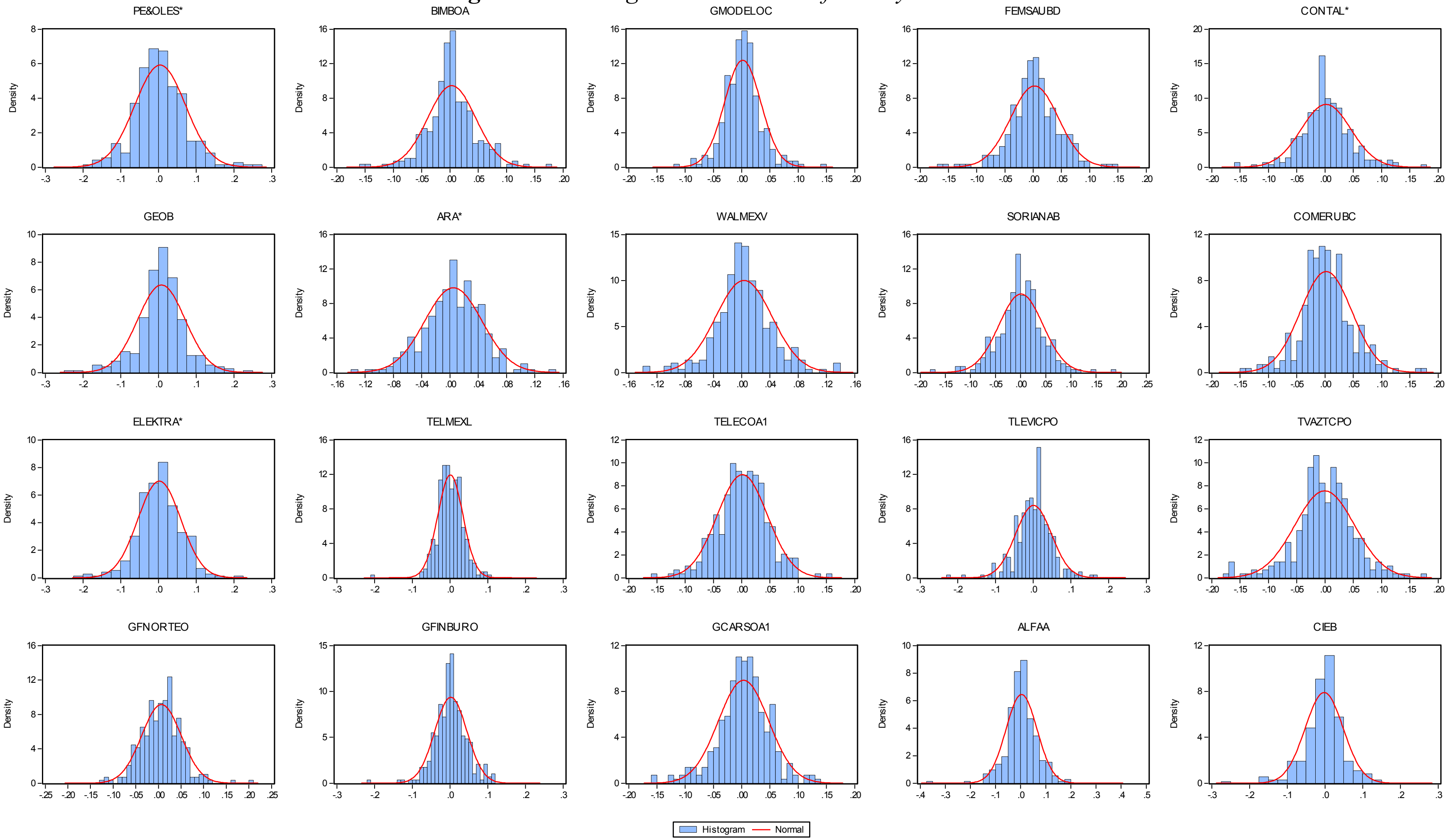


Table 3.3. *Descriptive statistics. Database of daily returns.*

	PE_OLES_	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	CEMEXCP	GEOB	ARA_	WALMEXV	SORIANAB
Mean	0.00103	0.00021	0.00065	0.00038	0.00050	0.00041	0.00077	0.00166	0.00101	0.00065	0.00017
Median	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00057	0.00000
Maximum	0.17284	0.07140	0.13416	0.08319	0.08366	0.10476	0.07069	0.13482	0.07381	0.10450	0.07505
Minimum	-0.21357	-0.12347	-0.09773	-0.07743	-0.13353	-0.12434	-0.07464	-0.20733	-0.10821	-0.08852	-0.08496
Std. Dev.	0.02946	0.01513	0.01866	0.01579	0.01747	0.02111	0.01615	0.02453	0.01895	0.01873	0.01859
Skewness	-0.37290	-0.55302	0.37402	0.17371	-0.25180	-0.19380	0.13416	-0.10538	-0.04420	0.12443	-0.08386
Kurtosis	10.16857	9.02902	7.62063	5.64679	7.19010	6.80465	4.20684	10.20437	5.93615	5.94402	4.61116
Jarque-Bera	3051.74875	2207.37871	1287.20099	418.66316	1046.36974	859.25423	89.79688	3051.90518	506.94138	512.84070	154.15882
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410

	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
Mean	0.00050	0.00053	0.00021	0.00025	0.00017	-0.00008	0.00142	0.00050	0.00071	0.00072	-0.00038
Median	0.00000	0.00018	0.00000	0.00065	0.00063	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Maximum	0.12618	0.12934	0.09048	0.09435	0.11929	0.10080	0.12981	0.10850	0.08851	0.11873	0.09308
Minimum	-0.08618	-0.13902	-0.09986	-0.08427	-0.15453	-0.19462	-0.09706	-0.09856	-0.10483	-0.12943	-0.17632
Std. Dev.	0.02044	0.02446	0.01562	0.01954	0.02197	0.02442	0.02050	0.01936	0.01921	0.02457	0.02132
Skewness	0.43065	-0.12460	-0.10181	-0.11561	-0.10524	-0.50638	0.27478	0.21991	-0.23044	-0.11533	-0.66734
Kurtosis	6.45394	6.49041	6.03784	4.79005	6.66166	8.03972	6.78240	5.04472	6.18174	6.39633	9.96161
Jarque-Bera	744.45079	719.39733	544.60981	191.39299	790.30896	1552.43422	858.25169	256.99029	607.23296	680.80834	2951.91390
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410

Figure 3.5. *Box plots. Database of daily returns.*

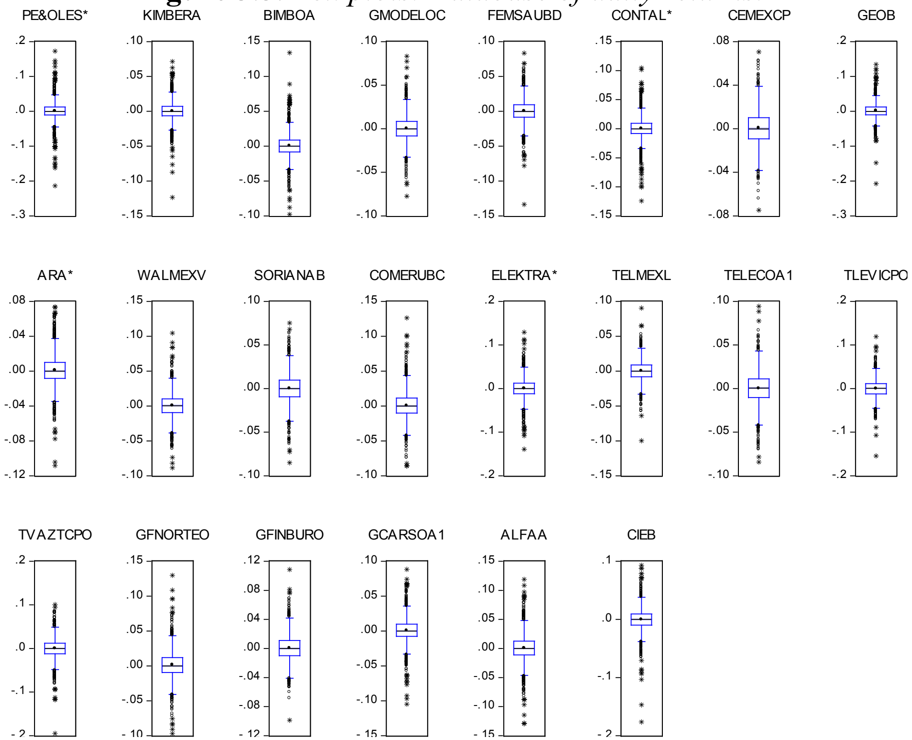
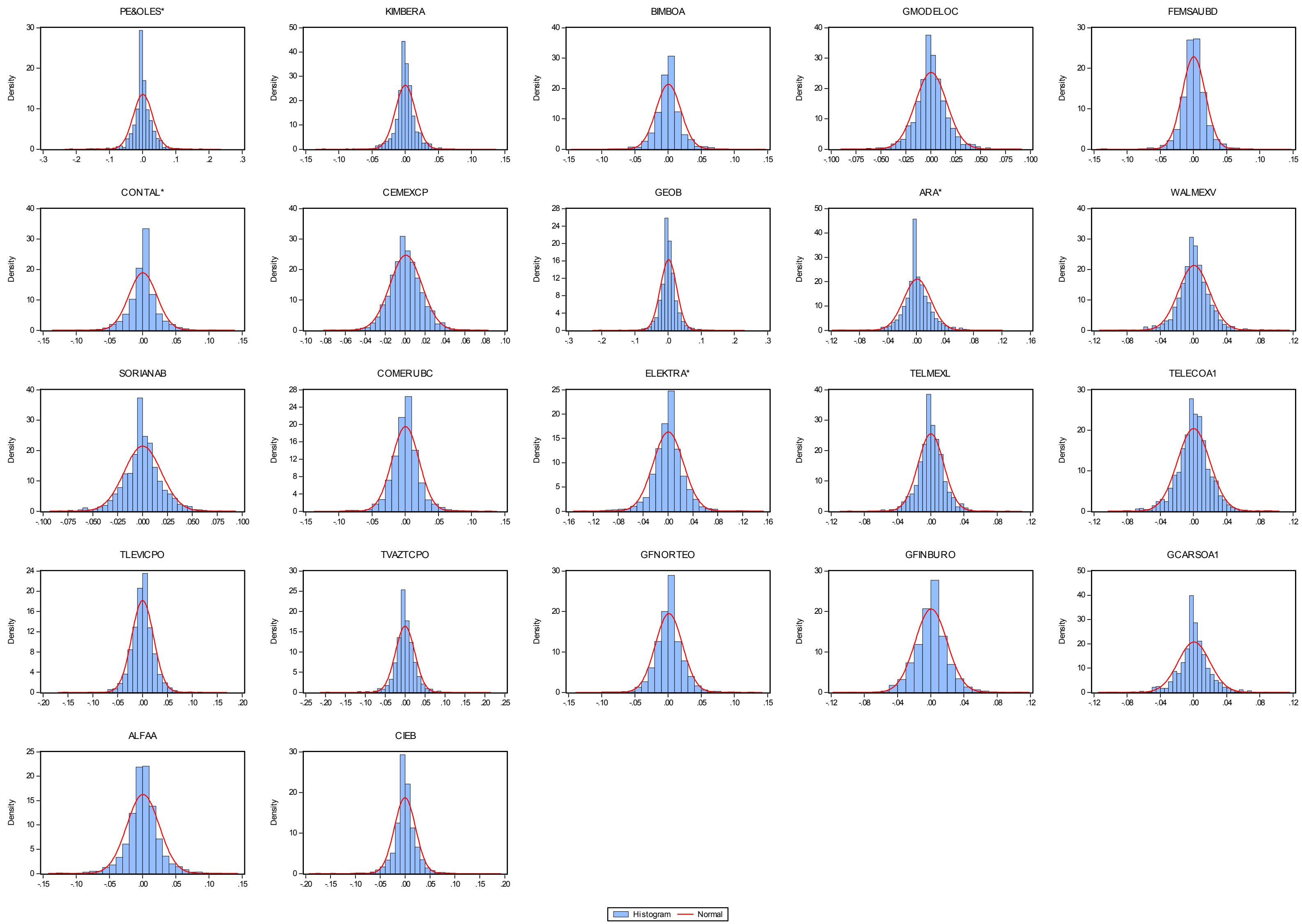


Figure 3.6. *Histograms. Database of daily returns.*



3.3. Methodology for the econometric contrast of the Arbitrage Pricing Theory.

As a complement to the extraction of latent systematic risk factors by way of the four techniques used in this Thesis, we carried out an econometric contrast of the Arbitrage Pricing Theory (APT) using the underlying systematic risk factors extracted via Principal Component Analysis (PCA), Factor Analysis (FA), Independent Component Analysis (ICA) and Neural Networks Principal Component Analysis (NNPCA), in order to test its validity as a suitable pricing model for the sample and periods considered. The methodology for the contrast used to test the presence of relevant risk premiums represents only a first approach to the different existent econometric methodologies of validation of the APT, so the results should be viewed in that light[80].

3.3.1. The Arbitrage Pricing Theory model.

The APT has been proposed as an alternative to the Capital Asset Pricing Model (CAPM), but it does not provide a complete solution. The APT has some advantages over the CAPM since it represents a more generalized model; it considers risk factors other than the market, it does not need restrictive assumptions such as normality in the distributions of returns and the investors' utility functions, and the market portfolio does not play any role; however, it shares some of the CAPM's weaknesses, like the linearity of its specification and the requirement of using historical data. The APT is supported in two main fundaments or pillars: a) a generative multifactor model of returns and b) an arbitrage argument. Thus, whereas the CAPM begins with the market model, the APT starts with a generative multifactor model of returns defined by the following expression:

[80] The methodologies of contrast of the APT have presented many variations and version since the seminal empirical paper of Roll & Ross (1980). Interested reader can consult alernative methodologies of contrast in Campbell *et al.* (1997), Cochrane (2000), Nieto (2001a, 2001b), Marin & Rubio (2001), Leyva (2010, 2014).

$$R_{it} = E(R_i) + \beta_{1i} \cdot F_{1t} + \beta_{2i} \cdot F_{2t} + \ldots + \beta_{ji} \cdot F_{jt} + \varepsilon_{it}, \tag{3.2}$$

where, β_{jig} represents the sensitivity of equity i to factor j, F_{jt} the value of the systematic risk factor j in time t common for all the stocks, and ε_i the idiosyncratic risk affecting only equity i.

The statistical approach to the APT assumes that the return on equity depends on a set of unobservable factors common to all stocks (F_s) and on one specific component (ε). It is assumed that the factors are uncorrelated with each other, as are the model's residual terms, both with each other and with the factors. The problem here is that the values of the factors are unobservable, and so the betas cannot be estimated through a regression model, as is done in the market model. Subsequently, we need to use extraction techniques, such as the ones posed in this research, to estimate the former equation for all the assets simultaneously, and to be able to extract the value of the factors (F_s) and calculate their loadings or betas (β_s).

The arbitrage argument or principle of arbitrage absence is based on the following reasoning. Taking into account the "single price law", in the same market two identical assets should have the same price; otherwise it would be possible to carry out an arbitrage transaction and obtain a differential profit. At the heart of APT and its pricing model lies arbitrage opportunities analysis, since only in its absence can we define a linear relation between the expected returns and the systematic risks. In order to avoid arbitrage possibilities, the return on equity must be equal to the expected return on the portfolio that combines the factor portfolios and the riskless asset. An arbitrage portfolio is any portfolio constructed with no capital invested and no risk taken that yields a null return on average.

By applying the arbitrage argument to the multifactor generative model, we arrive at the fundamental APT pricing equation[81]:

$$E(R_i) = \lambda_0 + \lambda_1 \cdot \beta_{1i} + \lambda_2 \cdot \beta_{2i} + \ldots + \lambda_k \cdot \beta_{ki}, \tag{3.3}$$

where, λ_0 represents the riskless interest rate, λ_k the risk premium for each kind of systematic risk factor, and β_k the sensitivities or exposures to each type of systematic risk.

3.3.2. Statistical risk factors.

Our investigation is based upon the statistical approach of multivariate asset-pricing models; subsequently, we assume that the values of systematic risk factors are unobservable and that they must be extracted by means of statistical techniques. This approach presents certain advantages over others: gathering the required information is less expensive and more accessible than in macroeconomic or fundamental models; it is less subjectively biased because it does not predefine either the number or the nature of factors, so it is less exposed to an econometric specification error; and finally, the factors extracted are directly supported by a strong asset-pricing theory: the Ross (1976) APT.

In addition, it involves two differentiated processes namely, risk extraction and risk attribution, which make it more objective. Conversely, statistical factors do not have a direct economic or financial interpretation, although in a second phase they can be correlated or decomposed with the help of explicit variables[82]. In other words, from this standpoint, risk measurement and risk attribution are different steps of the process, while the rest of the approaches, such as the market, macroeconomic, fundamental and technical, usually mix these two differentiated processes in one step.

[81] A mathematical demonstration for obtaining the fundamental pricing equation from the generative multifactor model of returns by the application of the arbitrage argument can be found in Amenc *et al.* (2003).

[82] See Amenc *et al.* (2003) and SUNGARD (2010).

3.3.3. Methodology for the Econometric contrast.

The APT's pricing equation in expression 3.2 can be tested by way of an average cross-section methodology estimating the Ordinary Least Squares (OLS) coefficients of the following regression model:

$$\overline{R_i} = \lambda_0 + \lambda_1 \cdot \beta_{1i} + \lambda_2 \cdot \beta_{2i} + \ldots + \lambda_k \cdot \beta_{ki} + \overline{\varepsilon_i}\ , \qquad (3.4)$$

Since both factors and sensitivities are computed simultaneously by the multivariate techniques usually employed, such as PCA and FA (Amenc & Le Sourd, 2003), the straight methodology for contrasting the APT under the statistical approach, use directly the loadings estimated in expression 3.1 as the betas in the former regression model (Gómez-Bezares *et al.* 1994). Nevertheless, as Marin & Rubio (2001) and Nieto (2001a) remark, this methodology could present some econometric problems such as heteroscedasticity and autocorrelation in the residuals in addition to error in variables, which would yield inefficient OLS estimators with biased variances. One possible solution, not absent of problems but beneficial because of its simplicity, to the foregoing problems is to employ a two-stage methodology widely used in the fundamental and macroeconomic approach to the APT, where in a first stage we estimate the betas to use in expression 3.3 from the scores of the extracted factors, then in a second stage we estimate the lambdas.

Following Bruno *et al* (2002)[83], in the first stage we estimated the betas or sensitive to the underlying risk factors to use in expression 3.3, by regressing the factor scores obtained by PCA, FA, ICA and NNPCA as a cross-section on the returns and excesses. In order to improve the efficiency of the parameter estimates and to eliminate autocorrelation in the error terms of the regressions, we used Weighted Least Squares (WLS)[84] for PCA, FA and ICA, and Seemingly Unrelated Regression (SUR) for NNPCA to estimate the entire system of equations at the same time.

[83] In their work, the authors use principal component analysis to extract the underlying risk factors from a set of macroeconomic variables in the Spanish market.

[84] According to this methodology, as stated in the Eviews 7® User´s Guide II (Quantitative Micro Software, 2010): "The equation weights are the inverses of the estimated equation variances, and are derived from unweighted estimation of the parameters of the system".

We had to use two different methodologies for running this stage concerning the simultaneous computation of the betas, due to the nature of our data and the mathematic algorithms utilized in each technique. For PCA, FA and ICA, we used the Weighted Least Squares methodology; and for NNPCA, we used the Seemingly Unrelated Regression (SUR)[85].

The Weighted Least Squares methodology or cross-equation weighing accounts for cross-equation heteroscedasticity by minimizing the weighted sum-of-squared residuals. The equation weights are the inverses of the estimated equation variances, and are derived from the unweighted estimation of the parameters of the system. This method yields identical results to unweighted single-equation least squares if there are no cross-equation restrictions[86].

The Seemingly Unrelated Regression also known as the multivariate regression, or Zellner's method, estimates the parameters of the system, thus accounting for heteroscedasticity, and the contemporaneous correlation in the errors across equations. The estimates of the cross-equation covariance matrix are based upon parameter estimates of the unweighted system[87].

The SUR methodology supplies better estimators than WLS in the system of equation computing of parameters, free of the autocorrelation and heteroscedasticity in the residuals of the model, which makes the estimation of the betas more reliable.

[85] Our first attempt to estimate all the betas in the system of equation for all the techniques was a Seemingly Unrelated Regression (SUR), however, the estimation was not possible since the SUR methodology requires computing the inverse of the residual matrix, and our data produce a residual matrix near a singular one; subsequently, it was not feasible to compute its inverse. Evidently, we are aware of this situation could have conditioned our results in the econometric contrast.

[86] For details see Greene (2008).

[87] For details see and Greene (2008) and Zellner (1962).

Later, in accordance with Jordan & García (2003)[88], in the second stage we estimated the lambdas or risk premiums in expression 3.3 by regressing the betas obtained in the first stage as a cross-section on the average returns and excesses, using Ordinary Least Squares. In order to avoid the econometric problems of heteroscedasticity and autocorrelation in the residuals of the model estimated through OLS, we used Ordinary Least Squared corrected by heteroscedasticity and autocorrelation by means of the Newey-West heteroscedasticity and autocorrelation consistent covariance estimates (HEC). Additionally, we verified the normality in the residuals by carrying out the Jarque-Bera test of normality.

In order to accept the APT pricing model, we require the statistical significance of at least one parameter lambda different from λ_0[89], and the equality of the independent term to its theoretic value, i.e., the average returns, in the models expressed in returns:

$$\lambda_0 = \overline{R_0}\,, \tag{3.5}$$

and zero, in the models expressed in excesses of the riskless interest rate:

$$\lambda_0 = 0 \tag{3.6}$$

We used Wald's test to confirm these equalities.

In addition, although other studies related to the APT have taken a weaker criterion for accepting the models, we were very demanding in this respect; i.e., we only accepted the models completely when not only the two previous requirements were fulfilled, but also when the results of the regression warranted a high adjusted R^2, a global statistical significance of the model given by the F statistic, and also fulfilled normality in the residuals of the estimation measured by the Jarque-Bera test.

[88] In their study the authors use factor analysis to extract the underlying risk factors from a set of returns on mutual funds in the Spanish market.

[89] The ideal situation is that more than one parameter different from λ_0 be statistically significant, since the APT assumes that there are multiple underlying risk factors in the economy affecting the returns on equities, not only one.

Chapter 4

Principal Component Analysis and Factor Analysis: Estimation of the generative multifactor model of returns*.

* The research related to this chapter has generate the following academic products:

1. REFEREED PUBLICATIONS:
    - 1.1. **Ladrón de Guevara, R., & Torra, S. (2014). 'Estimation of the underlying structure of systematic risk using principal component analysis and factor analysis'. *Contaduría y Administración* 59 (3), julio-septiembre: 197-234. UNAM. ISSN: 0186-1042. Revista indexada en el SCOPUS y el Índice de Revistas Mexicanas de Investigación Científica y Tecnológica del Consejo Nacional de Ciencia y Tecnología (CONACYT). DOI:10.1016/S0186-1042(14)71270-7**
    - 1.2. Ladrón de Guevara, R., & Torra, S. (2010). 'Statistical approach to the Arbitrage Pricing Theory. Latent Variables Analysis Techniques for extracting pervasive systematic risk factors'. In: A. Kutan (Ed.) Proceedings of The Society for the Study of Emerging Markets EuroConference 2010: Challenges and Opportunities in Emerging Markets. Milas: SSEM.
    - 1.3. Ladrón de Guevara, R., & Torra, S. (2010). 'Multivariate analysis techniques for extracting pervasive systematic risk factors. Empirical contrast of the Arbitrage Pricing Theory on the Mexican Stock Exchange' *Memorias en extenso del XIV Congreso Internacional de Investigación en Ciencias Administrativas. Academia de Ciencias Administrativa*. Monterrey, México: ITESM. ISBN: 978-607-501-009-0.
    - 1.4. Ladrón de Guevara, R., & Torra, S. (2008). 'Asset-Pricing Model APT (Arbitrage Pricing Theory) on the Mexican Stock Exchange: extraction methods of pervasive systematic risk factors.' In: P. Koveos (Ed.), *Investment in a Global Economy: its Environment, Finance, and Economics,* 85-96. Athens, Greece: ATINER. ISBN: 968-960-8872-36-1.

2. REFEREED CONFERENCES:
    - 2.1. Ladrón de Guevara, R., & Torra, S. 'Estimation of the underlying structure of systematic risk using principal component analysis and factor analysis'. *XV Congreso Internacional de Investigación en Ciencias Administrativas.* ACACIA – Universidad Veracruzana. Mayo 17-20, 2011. Boca del Rio, Ver.
    - 2.2. Ladrón de Guevara, R., & Torra, S. 'Statistical approach to the Arbitrage Pricing Theory. Latent Variables Analysis Techniques for extracting pervasive systematic risk factors.' The Society for the Study of Emerging Markets' EuroConference 2010: Challenges and Opportunities in Emerging Markets. SSEM. July 16-18, 2010, Milas, Turkey.
    - 2.3. Ladrón de Guevara, R., & Torra, S. 'Multivariate analysis techniques for extracting pervasive systematic risk factors. Empirical contrast of the Arbitrage Pricing Theory on the Mexican Stock Exchange.' *XIV Congreso Internacional de Investigación en Ciencias Administrativas.* ACACIA - ITESM. Abril 27 – 30, 2010. Monterrey, México.
    - 2.4. Ladrón de Guevara, R., & Torra, S. 'Asset-Pricing Model APT (Arbitrage Pricing Theory) on the Mexican Stock Exchange: extraction methods of pervasive systematic risk factors'. *5th International Conference on Finance.* Athens Institute for Education and Research (ATINER). July 2 – 4, 2007, Athens, Greece.

3. CONFERENCES BY INVITATION:
    - 3.1. Ladrón de Guevara, R., & Torra, S. 'Classic Multivariate Analysis Techniques for extracting systematic risk factors'. *Actuarial Risk*. Centro de Investigaciones en Matemáticas (CIMAT). Guanajuato, Guanajuato. Septiembre 22-30, 2010.

4.1. Introduction and Review of Literature.

Following a generative multifactor model of returns and an arbitrage argument, the Arbitrage Pricing Theory (APT) prices an equity by considering a set of common systematic risk factors assumed to influence the return produced. Empirical studies, mainly of developed markets such as the New York (NYSE), American (AMEX), London (LSE) and Tokyo (TSE) Stock Exchanges, have proposed different approaches to identify the types of systematic risk factors considered by multifactor models. Zangari (2003) presents a classification of risk factors based on whether their value is observable or not, dividing them into market, macroeconomic, fundamental, sector, technical and statistical factors. In general, the empirical evidence provided is contradictory, both supporting and rejecting the APT, especially when statistical factors are used. The market factor approach is practically an interpretation of the Capital Asset Pricing Model (CAPM), where there is only one common factor and it is observable. Both macroeconomic and fundamental models have been widely discussed in the literature; in many empirical papers sets of predefined variables, procedures and methodologies, for different countries, are examined[90]. Overall, findings have been favorable for both approaches, although there is no generalized consensus about the nature of factors. The macroeconomic approach seeks to identify, *a priori,* a set of observable macroeconomic time series as proxies of the value of the systematic risk factors. According to Yip & Xu (2000), the macroeconomic variables can be classified into four categories: inflation, industrial production, investor confidence and interest rates. On the other hand, in the fundamental approach, the systematic risk factors are approximated by means of predefined financial and accounting variables that reflect the exposure to unobservable factors, such as size, leverage, cash flow, price-earnings ratio (PER) and book-to-market ratio. As in the macroeconomic models, there is no general agreement among the different studies on the nature of factors. The main difference between the macroeconomic and the fundamental standpoints is the elements they consider as given in a multifactor model. The former consider the value of the systematic risk factors as given and estimate, generally by way of a two stage

[90] A revision of empirical studies using approaches other than the statistical one is beyond the scope of this research; however, interested readers can easily find many references in the financial literature.

methodology, first the exposures or sensitivities to each kind of systematic risk, and then, their related risk premiums. The latter considers as given the exposures or sensitivities to each kind of systematic risk, since it assumes that the values of the systematic risk are unobservable, and estimate the risk premiums for each one of them. The other two security-specific approaches use technical and sector variables as proxies of the effects of unobserved factors, although very little empirical investigation has been carried out exclusively under these perspectives. The statistical approach focuses mainly on uncovering a suitable number of pervasive factors, regardless of their nature[91], through latent variables analysis techniques such as Principal Component Analysis (PCA) and Factor Analysis (FA). In this case, both the risk premiums and the exposure to them are usually estimated simultaneously. Roll & Ross (1980), Brown & Weinstein (1983), Chen (1983), Bower *et al.* (1984), Cho *et al.* (1984) Connor & Korajczyk (1988), Lehmann & Modest (1988) and Hasbrouck & Seppi (2001) obtained favorable results, revealing between three and five priced factors in the American stock market; Beenstock *et al.* (1988) identified twenty priced factors in the UK stock exchange and Elton & Gruber (1988) found four factors in the Japanese market. Nevertheless, Reinganum (1981) rejected statistical APT as a means of explaining stock price variations for the NYSE and AMEX, as did Gómez-Bezares *et al.* (1994), Nieto (2001a), and Carbonell & Torra (2003) for the Spanish Stock Exchange (SSE). Moreover, Abeysekera & Mahajan (1987) obtained mixed results for the London Stock Exchange, as did Jordán & García (2003) for the Spanish Mutual Funds Market.

There is no clear supremacy of one approach over the others. Among the theoretical and empirical comparative studies made, Maringer (2004) presents a good summary of the advantages, disadvantages and recommended uses of macroeconomic, fundamental and statistical models; Connor (1995) shows that statistical and fundamental models outperform macroeconomic models in terms of explanatory power, and that fundamental models slightly outperform statistical ones for the USA market; Chan *et al.* (1998) found evidence that fundamental factors perform better than macroeconomic, technical, statistical and market factors in the UK and Japanese markets; on the other hand, Teker & Varela (1998) showed that the statistical model outperforms the macroeconomic one for the US market; and Cauchie *et al.* (2004)

[91] In a second stage, it is possible to identify the pervasive factors with some financial or macroeconomic variables by means of correlation procedures or other kind of methodologies.

demonstrated that statistical factors yield a better representation of the determinants of the Swiss market stock returns than the macroeconomic ones. In addition, Miller (2006a) makes a new comparison, complementing that of Connor's classic study. Consequently, three well-known risk analysis and portfolio management firms, MSCI[92], FTSE[93] and SUNGARD[94], have opted mostly for the fundamental, macroeconomic and statistical approaches, respectively, for constructing their worldwide multifactor risk models, portfolio analytics and risk reporting commercial products.

Other studies have attempted to combine the different approaches. Miller (2006b) proposed a hybrid version of a multifactor model, combining fundamental and statistical factors, in which the latter are used to explain the fundamental model's residual part, obtaining modest results on the Japanese market. Liu & Melas (2007) proposed that fundamental models can be used as an approach to extract the effect of the macroeconomic factors, by dividing the model's common fundamental factors into two sub-parts: one explained by macroeconomic factors and the other by non-macroeconomic factors.

Empirical investigation of multivariate asset-pricing models in emerging stock markets has been relatively scarce. Most studies have been based on a macroeconomic perspective, finding two or three priced factors. Results have been mixed concerning priced factors across the markets[95]. With respect to the present study, the following reviews have used the statistical definition of the APT: Ch'ng & Gupta (2001) on the Malaysia Stock Market, and Dhankar & Singh (2005) on the Indian Stock Exchange, revealing two and five priced factors, respectively; Iqbal & Heider (2005) on the Karachi Stock Exchange, and Mubben *et al.* (2015) on the Turkish stock market, finding two priced factors in both studies.

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[92] For a more extensive study of the MSCI models (before MSCI-BARRA) see Sheikh (1996), BARRA (1998), Amenc & Le Sourd (2003), and MSCI (2015).

[93] For more information about FTSE models (before FTSE-BIRR) see Burmeister *et al.* (2003) and FTSE (2015).

[94] For more details about Sungard model (before Sungard-APT) see Amenc & Le Sourd (2003) and Sungard (2010, 2015a, 2015b). Currently, Sungard will be bought by Fidelity National Information Services.

[95] Some references are: van Rensburg (2000) on Johannesburg; Ch'ng & Gupta (2001) on Malaysia; Aquino (2005) on the Philippines; Dhankar & Singh (2005) on India; Twerefou & Nimo (2005) on Ghana; Iqbal & Haider (2005) on Karachi; Shum & Tang (2005) on Hong Kong, Singapore, and Taiwan; and Fuentes *et al.* (2006) on Chile.

Little research has been carried out regarding the application of the APT for the Mexican Stock Exchange. To the best of our knowledge, the only references are de la Calle (1991), Navarro & Santillán (2001), López-Herrera & Vázquez. (2002 a and b), and Valdivieso (2004), all of whom used the macroeconomic approach. Although these authors found evidence of around four priced factors, there is a problem of low explanation power in some cases. In addition, Saldaña *et al.* (2007) used a macroeconomic and fundamental combined approach of the APT applied on the telecommunication sector of the Mexican Stock Exchange, finding favorable evidence of this asset pricing model. Conversely, Treviño (2011) presents a more robust econometric methodology for a longer period of time, finding little evidence in favor of a macroeconomic APT applied on the Mexican stock market. Additionally, López-Herrera & Ortiz (2011) carry on a multifactor beta model to explain the relationship between macroeconomic factors and asset pricing in Mexico, United States and Canada, in order to analyze the integration of each market with global macroeconomic variables.

Regarding studies focused on Latin America where APT has been used under different approaches we can mention the following. Arango *et al.* (2013) carry on the APT under the macroeconomic approach on the Colombian Stock Exchange, using principal component analysis to summarize the set of macroeconomic factors and financial variables utilized in the study. They find that risk perception is the most important variable to explain stock's returns. Kristjanpoller & Morales (2011) apply the APT to the Chilean stock market under the macroeconomic approach as well; they find some evidence regarding the impact of some macroeconomic variables on the returns on equities. Londoño *et al*. (2010) test the APT on the Colombian market, under two approaches: a) a macroeconomic and b) a macroeconomic plus international stock markets indicators. Furthermore, they use a multilayer neural network to relate the main index from the Colombian Stock Exchange to the factors considered. Their findings show that the neural network approach is more effective than a traditional statistical one[96]. da Costa & Soares (2009) utilize a fundamental version of the APT applied to the Brazilian banking sector, finding weak evidence supporting this model. Oliveira (2011)

[96] The better results may be explained by the non-linear specification of the APT, which is out of the scope of this study but represents a future line of research of the authors as a continuation of the present work.

presents a comparative study using both the macroeconomic and the statistical approach of the APT, applied on three groups of countries composed by developed and emerging markets, where some Latin American countries such as: Argentina, Chile and Mexico, are included. In this case the statistical factors are extracted by means of principal component analysis. Finally, Tabak & Staub (2007) use the APT to infer the probability of financial institution failure for banks in Brazil.

As stated before, the aim of the present study is to fill a gap in the financial literature by testing a statistical definition of the APT on an important emerging financial market, the Mexican Stock Exchange. In this chapter we shall extract the pervasive systematic risk factors by means of the two classic techniques used for extraction of latent factors: Principal Component Analysis, and Factor Analysis through Maximum Likelihood. The structure of the present chapter is as follows: sections 4.2 presents the fundamentals of PCA and FA, section 4.3 describes the empirical study, and finally some conclusions are drawn in section 4.4.

4.2. Classical statistical risk extraction factors techniques.

The two most commonly used multivariate analysis techniques for extracting risk factors are Principal Component Analysis and Factor Analysis, but there is still no firm view as to which one is the ideal technique. Classical studies have utilized both; for example: Roll & Ross (1980), in their seminal empirical work, carried out Factor Analysis through Maximum Likelihood (MLFA), suggesting that returns on equities are determined by the factor loadings or betas; however, Chamberlain & Rothschild (1983) and Connor & Korajczyk (1988) claimed that eigenvectors obtained by PCA could also be used as factor loadings. In opposition to these views, Shukla *et al.* (1990) asserted that PCA is only equivalent to FA when the idiosyncratic risk for every asset is the same, since PCA does not consider the specific risks. We could say that FA is closer to the underlying spirit of APT than is PCA; nevertheless, the latter presents some advantages such as: offering a unique mathematical solution, making less strong explicit assumptions about the data, and the possibility to estimate as many factors as there are variables.

4.2.1. Principal Component Analysis (PCA).

Strictly speaking, PCA is not a model, as it merely represents a geometric transformation and projection of data in order to facilitate their interpretation. PCA seeks to obtain a smaller number of artificial variables, the principal components, via a linear combination of the original ones, assuming two basic restrictions: the principal components must be orthogonal to each other, and they must have decreasing variances. Each original variable contributes with a different weight to the principal component formation. In other words, we want to project the original data onto a smaller dimension where the components will be mutually uncorrelated and at the same time retain the maximal possible variance, i.e. the risk. The mathematical expression of the idea behind PCA is as follows:

$$
\begin{array}{ccccccccccccc}
y_1 & = & a_{11}x_1 & + & a_{12}x_2 & + & \cdots & + & a_{ij}x_j & + & \cdots & + & a_{1p}x_p \\
y_2 & = & a_{21}x_1 & + & a_{22}x_2 & + & \cdots & + & a_{2j}x_j & + & \cdots & + & a_{2p}x_p \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
y_h & = & a_{h1}x_1 & + & a_{h2}x_2 & + & \cdots & + & a_{hj}x_j & + & \cdots & + & a_{hp}x_p \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
y_p & = & a_{p1}x_1 & + & a_{p2}x_2 & + & \cdots & + & a_{pj}x_j & + & \cdots & + & a_{pp}x_p
\end{array} \tag{4.1}
$$

Where: y denotes the principal components; a, the coefficients or loadings for each variable in each component construction, and x, the original variables. Generalizing in abbreviated matrix notation for the generic principal component h we have:

$$\mathbf{y}_h = \mathbf{X}\mathbf{a}_h \tag{4.2}$$

And considering all the equations together for all the observations:

$$\mathbf{Y} = \mathbf{X}\mathbf{A} \tag{4.3}$$

In order to estimate the vector $\mathbf{a}_h$ we have to decompose the covariance matrix by way of the linear algebra concept of eigenvalue decomposition (EVD)[97], where $\mathbf{a}_h$ will be the eigenvector associated with the h-esim eigenvalue (λ_h) of the covariance or correlation matrix, after been ranked from higher to lower. In the classic version for the econometric contrast of the APT, loadings a will represent the exposures to the pervasive systematic risk factors, the betas of the APT model that will be regressed on the asset returns to obtain the factor returns or factor risk premiums (lambdas in the APT pricing equation)[98]. These betas or factor loadings, which together form the factor matrix, are the correlation between each variable and the principal components. According to Uriel & Aldas (2005) we can compute them by using the correlation coefficient r_{hj} between the h-esim component and the j-esim variable, as well. Expression 4.4 corresponds to the case when we use original values of data and expression 4.5 when we use standardized variables.

$$r_{hj} = \frac{\lambda_h \mathbf{u}_{hj}}{\sqrt{\mathrm{var}(\mathbf{x}_j)}\sqrt{\lambda_h}} \tag{4.4}$$

$$r_{hj} = a_{hj}\sqrt{\lambda_h} \tag{4.5}$$

Finally in PCA, we can obtain as many principal components as there are variables, because the covariance matrix (**S**) to be decomposed will contain in its main diagonal the total amount of variance represented, in the case of using the correlation matrix, by the value of one. In other words, we will try to explain the total amount of variance of the observed variables.

[97] The eigenvalue decomposition implies: **S**=**ULU**'; where **S** is the covariance matrix; **U**, the eigenvector matrix; **L**, the eigenvalue matrix, and **U**' the matrix **U** transposed. When we use normalized data the matrix **S** is equal to the correlation matrix **R**.

[98] In this study we carry on a two-stage version for the econometric contrast explained in Chapter 3.

4.2.2. Factor Analysis (FA).

Factor Analysis represents an explicit model with its own hypothesis, assuming that the original variables are a linear combination of the underlying factors. Although FA seeks to obtain a smaller number of factors, like PCA, its philosophy is completely different. In FA, we construct the *p* variables[99] through a linear combination of their *m* pervasive common factors[100] (with $m<p$), their particular weights or exposures (betas), and a specific error term. In order to construct those factors, it is necessary to estimate the *commonality* or proportion of the variance explained by the common factors. Then, we have to split the variance and covariance matrix into two parts, one explained by common factors and the other by the error term. The fundamental idea of FA can be expressed in formal terms as follows:

$$\begin{array}{ccccccccccccccc}
x_1 & = & \mu_1+\lambda_{11}f_1 & + & \lambda_{12}f_2 & + & \cdots & + & \lambda_{1h}f_h & + & \cdots & + & \lambda_{1m}f_m & + & u_1 \\
x_2 & = & \mu_2+\lambda_{21}f_1 & + & \lambda_{22}f_2 & + & \cdots & + & \lambda_{2h}f_h & + & \cdots & + & \lambda_{2m}f_m & + & u_2 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
x_j & = & \mu_j+\lambda_{j1}f_1 & + & \lambda_{j2}f_2 & + & \cdots & + & \lambda_{jh}f_h & + & \cdots & + & \lambda_{jm}f_m & + & u_j \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
x_p & = & \mu_p+\lambda_{p1}f_1 & + & \lambda_{p2}f_2 & + & \cdots & + & \lambda_{ph}f_h & + & \cdots & + & \lambda_{pm}f_m & + & u_p
\end{array} \tag{4.6}$$

where $\mu_1, \mu_2, ..., \mu_j, ... \mu_p$ denote the vector of means of the variable; $x_1, x_2, ..., x_j, ... x_p$; the observable variables; $f_1, f_2, ..., f_h, ..., f_m$, the common factors; λ_{jh}, the factor loading *h* in variable *j;* and $u_1, u_2, ..., u_p$, are the specific factors. Generalizing for the generic variable *j*, we can express the value of a row of the former equations in condensed vector notation as follows:

$$\mathbf{x_j} = \mu_j + \boldsymbol{\lambda}_\mathbf{j}'\mathbf{f} + u_j \tag{4.7}$$

And gathering all the equations for all the observations:

$$\mathbf{X} = \mathbf{1}\boldsymbol{\mu} + \mathbf{F}\boldsymbol{\Lambda}' + \mathbf{U} \tag{4.8}$$

[99] In our case, returns on equities.
[100] In our context, systematic risk factors.

In FA the elements of matrix $\mathbf{\Lambda}$ (the λ coefficients) are the factor loadings applied to the common factors. They constitute the elements of the factor matrix and can be computed by the correlation coefficient r_{hj} in expressions 4.4 and 4.5 as well. There are many techniques to estimate the parameters of the factor model. We can divide them into two approaches: a) based on the eigenvalue decomposition and b) based on the estimation of equations to reconstruct the correlation matrix. In FA, the number of factors (*m)* is smaller than the number of variables (*p*) because the correlation matrix of returns to be decomposed contains in its main diagonal an estimation of the initial commonality[101], depending on the estimation technique utilized. In other words we will explain only the amount of variance explained by common factors, i.e., the covariance or correlations among the variables.

To summarize, the main difference between these techniques is that in PCA the components are constructed as a linear combination of the observable variables, whereas in FA, the observable variables are explained by the common factors. Thus, although in PCA we can express the variables in terms of the principal components by way of an algebraic transformation, both methods will not be equivalent unless the error term in FA tends to zero, since in FA we assume that the specific factors are uncorrelated with each other and with the common factors.

4.3. Empirical Study. Methodology and results.

According to the stated in Chapter 3 we take the Arbitrage Pricing Theory as our theoretical framework which poses on one hand, a generative multifactor model of returns, and on the another hand, an arbitrage absence principle, that together, produce an asset pricing model. Nevertheless, the scope and limitations of our research are given precisely for the statistical approach to the APT. Our study is focused in the risk extraction process whose main objective is to uncover the underlying multifactor structure of systematic risk driving the returns on equities, independently of the number

[101] A number always less than one.

and nature of the factors. The risk attribution process is basically out of the scope of the present study, however, in this section we will attempt to provide a first approach to the meaning of the extracted systematic risk factors in order to be able to identify them. Likewise, the test of the arbitrage principle is out of the scope of the current study[102].

In other words, the main objective of our empirical study is to uncover the underlying generative multifactor structure of returns of our sample, by way of the use of classic dimension reduction or feature extraction techniques such as PCA and FA. The results will show that the generative multifactor model of returns performs very well; however the systematic risk factors extracted and the betas estimated must be tested in order to verify whether or not they are priced according to the APT pricing model. In a second stage of our methodology, we run an econometric contrast in order to determine which of them are statistically significant and consequently determine whether or not the APT is accepted as an asset pricing model in the context of our study.

4.3.1. Preliminary tests.

First of all, the following tests were carried out to establish the adequacy of the sample to be treated with the statistical techniques used in this study.

Strictly speaking, the first preliminary test consisted in verifying the univariate normal distribution of the returns on equities. We used the Jarque-Bera test on the four databases, finding that in most cases the stocks of our sample did not follow a univariate normal distribution as stated in Chapter 3[103].

The number of observations in all the databases was suitable. There were 291 observations in two databases and 1,410 in the other two. Luque (2000) recommends having at least 100 cases and no fewer than 50. Hair *et al.* (1999) considered it necessary to have five times more observations than variables. In our case, those figures would represent 100 and 110, respectively.

[102] Forthcoming researches will center on the risk attribution process of the statistical approach as well as on the test of the arbitrage principle of the APT.

[103] Although, the effects of this condition on our results are beyond the scope of this chapter, they will be treated in the following chapters.

The correlation matrix structure ensured the existence of a sufficient correlation level among the variables, according to the results of the following tests. Visual inspection of the correlation matrix revealed that a large number of correlation coefficients exceeded the generally accepted parameters and the context of rates of returns on equities[104].

Bartlett's sphericity test verified that the correlation matrix was significantly different from the identity matrix. In the four databases we obtained high values in this respect, fluctuating around 2,162.23 and 2,176.19 in the weekly databases, and around 9,707.33 and 9,723.98 in the daily databases, with a significance level of zero in all four cases; we reject the null hypothesis that the correlation matrix was an identity matrix, and conclude that the variables were mutually correlated. The higher the value of the statistic and the smaller the significance level, the less probability that the correlation matrix is an identity matrix[105]. The Kaiser-Meyer-Olkin index, in all four databases, was also very good. The results for this statistic in all four databases reached levels higher than 0.90. Its feasible values range from 0 to 1, values over 0.80 are considered to be good to excellent. The objective of this test is to compare the magnitudes of the observed correlation and the partial correlation coefficients among variables[106]. Tables 4.1 to 4.4 shows these previous tests results for the four databases.

Table 4.1. *Bartlett's spherecity test and Kaiser-Meyer-Olkin index. Database of weekly returns.*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,926
Bartlett's Test of Sphericity	Approx. Chi-Square	2162,227
	df	190
	Sig.	,000

[104] While some authors believe that a suitable correlation level must be higher than 0.3, many others think it must be at least 0.5. See Chapter 3 for consulting the correlation matrices of the four databases.
[105] For more details about Bartlett's sphericity test, see Luque (2000).
[106] For details, see Visauta & Martori (2003).

Table 4.2. *Bartlett's spherecity test and Kaiser-Meyer-Olkin index. Database of weekly excesses.*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,926
Bartlett's Test of Sphericity	Approx. Chi-Square	2176,187
	df	190
	Sig.	,000

Table 4.3. *Bartlett's spherecity test and Kaiser-Meyer-Olkin index. Database of daily returns.*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,955
Bartlett's Test of Sphericity	Approx. Chi-Square	9707,329
	df	231
	Sig.	,000

Table 4.4. *Bartlett's spherecity test and Kaiser-Meyer-Olkin index. Database of daily excesses.*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,955
Bartlett's Test of Sphericity	Approx. Chi-Square	9723,978
	df	231
	Sig.	,000

Finally, the anti-image correlation matrix and the Measures of Sampling Adequacy (MSA) also produced excellent results. The anti-image matrix is formed with the negatives of the partial correlation coefficient for each pair of variables, neutralizing the effect of the others. This measure requires small values for the coefficients. The levels obtained were over 0.90 in almost all cases. We found the MSA in the main diagonal of the anti-image correlation matrix. They would be the KMO, but for each variable individually, so their parameters and interpretation are the same as for the KMO[107]. Tables 4.5 to 4.8 display the results of these measures. Consequently, on the basis of the evidence produced, we were able to proceed with confidence to extract the risk factors using PCA and FA.

[107] See Visauta & Martori (2003).

Table 4.5. *Anti-image correlation matrix and Measures of Sampling Adequacy (MSA). Database of weekly returns.*

	PE&OLES *	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	GEOB	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B
PE&OLES*	.795[a]	-.006	-.033	.013	-.100	-.171	-.072	.039	.039	-.069	-.057	-.014	-.034	-.008	.023	.052	.006	.067	.025	-.030
BIMBOA	-.006	.875[a]	.144	-.117	-.053	.037	-.002	.014	.044	-.107	-.002	.035	-.162	-.042	-.052	.088	-.004	.063	-.037	-.124
GMODELOC	-.033	.144	.921[a]	-.104	-.013	.061	.043	.033	-.097	.000	-.024	-.044	-.058	-.047	-.104	-.012	.119	-.036	-.073	-.054
FEMSAUBD	.013	-.117	-.104	.941[a]	-.041	-.043	-.002	-.170	-.048	.024	-.129	-.075	.067	-.197	.116	-.008	-.077	-.070	-.033	-.133
CONTAL*	-.100	-.053	-.013	-.041	.909[a]	-.044	-.050	-.018	.095	-.080	-.016	.052	-.005	-.039	-.017	.046	.070	-.086	-.111	-.139
GEOB	-.171	.037	.061	-.043	-.044	.912[a]	-.190	-.028	-.089	.053	-.092	.056	-.001	-.052	-.132	-.144	-.130	.079	-.066	.020
ARA*	-.072	-.002	.043	-.002	-.050	-.190	.927[a]	.048	.019	-.112	-.081	-.099	.006	-.045	.105	.002	-.054	-.054	-.114	-.034
WALMEXV	.039	.014	.033	-.170	-.018	-.028	.048	.946[a]	-.129	-.005	.039	-.053	-.025	-.242	-.074	-.100	.053	-.056	-.076	.034
SORIANAB	.039	.044	-.097	-.048	.095	-.089	.019	-.129	.945[a]	-.184	.052	.048	-.067	-.043	-.140	-.035	-.051	-.096	-.029	-.194
COMERUBC	-.069	-.107	.000	.024	-.080	.053	-.112	-.005	-.184	.950[a]	-.074	-.024	.043	-.031	-.052	-.131	-.016	-.048	-.059	-.108
ELEKTRA*	-.057	-.002	-.024	-.129	-.016	-.092	-.081	.039	.052	-.074	.923[a]	.065	-.102	.013	-.347	-.062	-.001	-.056	-.148	.049
TELMEXL	-.014	.035	-.044	-.075	.052	.056	-.099	-.053	.048	-.024	.065	.877[a]	-.603	-.127	-.136	-.056	.037	-.037	.031	-.029
TELECOA1	-.034	-.162	-.058	.067	-.005	-.001	.006	-.025	-.067	.043	-.102	-.603	.864[a]	-.098	.119	.005	-.129	-.224	-.061	.051
TLEVICPO	-.008	-.042	-.047	-.197	-.039	-.052	-.045	-.242	-.043	-.031	.013	-.127	-.098	.950[a]	-.218	-.012	-.054	.023	-.002	-.018
TVAZTCPO	.023	-.052	-.104	.116	-.017	-.132	.105	-.074	-.140	-.052	-.347	-.136	.119	-.218	.908[a]	-.024	.077	-.084	-.067	-.107
GFNORTEO	.052	.088	-.012	-.008	.046	-.144	.002	-.100	-.035	-.131	-.062	-.056	.005	-.012	-.024	.959[a]	-.056	-.101	-.062	-.072
GFINBURO	.006	-.004	.119	-.077	.070	-.130	-.054	.053	-.051	-.016	-.001	.037	-.129	-.054	.077	-.056	.926[a]	-.156	-.056	-.235
GCARSOA1	.067	.063	-.036	-.070	-.086	.079	-.054	-.056	-.096	-.048	-.056	-.037	-.224	.023	-.084	-.101	-.156	.955[a]	-.029	-.064
ALFAA	.025	-.037	-.073	-.033	-.111	-.066	-.114	-.076	-.029	-.059	-.148	.031	-.061	-.002	-.067	-.062	-.056	-.029	.965[a]	-.004
CIEB	-.030	-.124	-.054	-.133	-.139	.020	-.034	.034	-.194	-.108	.049	-.029	.051	-.018	-.107	-.072	-.235	-.064	-.004	.936[a]

Notes: a. Measures of Sampling Adequacy(MSA)

Table 4.6. *Anti-image correlation matrix and Measures of Sampling Adequacy (MSA). Database of weekly excesses.*

	PE&OLES *	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B
PE&OLES*	.800[a]	-0.01	-0.03	0.01	-0.10	-0.17	-0.07	0.04	0.04	-0.07	-0.06	-0.01	-0.03	-0.01	0.02	0.05	0.01	0.07	0.03	-0.03
BIMBOA	-0.01	.876[a]	0.14	-0.12	-0.05	0.04	0.00	0.02	0.04	-0.11	0.00	0.04	-0.16	-0.04	-0.05	0.09	0.00	0.06	-0.04	-0.12
GMODELOC	-0.03	0.14	.921[a]	-0.10	-0.01	0.06	0.04	0.03	-0.10	0.00	-0.02	-0.04	-0.06	-0.05	-0.10	-0.01	0.12	-0.04	-0.07	-0.05
FEMSAUBD	0.01	-0.12	-0.10	.941[a]	-0.04	-0.04	0.00	-0.17	-0.05	0.02	-0.13	-0.08	0.07	-0.20	0.12	-0.01	-0.08	-0.07	-0.03	-0.13
CONTAL*	-0.10	-0.05	-0.01	-0.04	.910[a]	-0.05	-0.05	-0.02	0.09	-0.08	-0.02	0.05	-0.01	-0.04	-0.02	0.05	0.07	-0.09	-0.11	-0.14
GEOB	-0.17	0.04	0.06	-0.04	-0.05	.913[a]	-0.19	-0.03	-0.09	0.05	-0.09	0.05	0.00	-0.05	-0.13	-0.14	-0.13	0.08	-0.07	0.02
ARA*	-0.07	0.00	0.04	0.00	-0.05	-0.19	.928[a]	0.05	0.02	-0.11	-0.08	-0.10	0.01	-0.05	0.10	0.00	-0.05	-0.05	-0.11	-0.03
WALMEXV	0.04	0.02	0.03	-0.17	-0.02	-0.03	0.05	.946[a]	-0.13	-0.01	0.04	-0.05	-0.03	-0.24	-0.07	-0.10	0.05	-0.06	-0.08	0.03
SORIANAB	0.04	0.04	-0.10	-0.05	0.09	-0.09	0.02	-0.13	.945[a]	-0.18	0.05	0.05	-0.07	-0.04	-0.14	-0.03	-0.05	-0.10	-0.03	-0.19
COMERUBC	-0.07	-0.11	0.00	0.02	-0.08	0.05	-0.11	-0.01	-0.18	.951[a]	-0.07	-0.02	0.04	-0.03	-0.05	-0.13	-0.02	-0.05	-0.06	-0.11
ELEKTRA*	-0.06	0.00	-0.02	-0.13	-0.02	-0.09	-0.08	0.04	0.05	-0.07	.924[a]	0.06	-0.10	0.01	-0.35	-0.06	0.00	-0.06	-0.15	0.05
TELMEXL	-0.01	0.04	-0.04	-0.08	0.05	0.05	-0.10	-0.05	0.05	-0.02	0.06	.878[a]	-0.60	-0.13	-0.14	-0.05	0.04	-0.04	0.03	-0.03
TELECOA1	-0.03	-0.16	-0.06	0.07	-0.01	0.00	0.01	-0.03	-0.07	0.04	-0.10	-0.60	.865[a]	-0.10	0.12	0.00	-0.13	-0.22	-0.06	0.05
TLEVICPO	-0.01	-0.04	-0.05	-0.20	-0.04	-0.05	-0.05	-0.24	-0.04	-0.03	0.01	-0.13	-0.10	.950[a]	-0.22	-0.01	-0.06	0.02	0.00	-0.02
TVAZTCPO	0.02	-0.05	-0.10	0.12	-0.02	-0.13	0.10	-0.07	-0.14	-0.05	-0.35	-0.14	0.12	-0.22	.909[a]	-0.02	0.08	-0.08	-0.07	-0.11
GFNORTEO	0.05	0.09	-0.01	-0.01	0.05	-0.14	0.00	-0.10	-0.03	-0.13	-0.06	-0.05	0.00	-0.01	-0.02	.959[a]	-0.06	-0.10	-0.06	-0.07
GFINBURO	0.01	0.00	0.12	-0.08	0.07	-0.13	-0.05	0.05	-0.05	-0.02	0.00	0.04	-0.13	-0.06	0.08	-0.06	.926[a]	-0.16	-0.06	-0.23
GCARSOA1	0.07	0.06	-0.04	-0.07	-0.09	0.08	-0.05	-0.06	-0.10	-0.05	-0.06	-0.04	-0.22	0.02	-0.08	-0.10	-0.16	.955[a]	-0.03	-0.06
ALFAA	0.03	-0.04	-0.07	-0.03	-0.11	-0.07	-0.11	-0.08	-0.03	-0.06	-0.15	0.03	-0.06	0.00	-0.07	-0.06	-0.06	-0.03	.965[a]	0.00
CIEB	-0.03	-0.12	-0.05	-0.13	-0.14	0.02	-0.03	0.03	-0.19	-0.11	0.05	-0.03	0.05	-0.02	-0.11	-0.07	-0.23	-0.06	0.00	.936[a]

Notes: a. Measures of Sampling Adequacy(MSA)

Table 4.7. *Anti-image correlation matrix and Measures of Sampling Adequacy (MSA). Database of daily returns.*

	PE&OLES *	KIMBER A	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	CEMEX CP	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B
PE&OLES*	.898[a]	-.013	-.046	-.040	.023	-.090	-.013	-.064	-.027	-.018	-.029	-.029	-.033	-.002	-.015	.033	.002	.031	.036	-.006	.004	-.021
KIMBERA	-.013	.956[a]	-.066	-.092	-.009	-.053	-.045	-.003	-.014	-.050	-.029	-.015	.022	-.050	.008	-.020	.029	-.064	.023	-.067	-.007	-.160
BIMBOA	-.046	-.066	.964[a]	.028	-.033	-.096	-.040	-.024	-.043	-.027	-.036	-.021	-.055	-.025	-.042	.026	.007	.022	-.057	-.007	-.059	-.092
GMODELOC	-.040	-.092	.028	.962[a]	-.062	-.086	-.001	.042	.023	-.134	-.050	-.033	-.035	-.041	-.030	-.013	-.012	-.057	.019	-.022	-.049	-.006
FEMSAUBD	.023	-.009	-.033	-.062	.968[a]	.027	-.177	-.025	-.018	-.053	-.101	-.034	-.038	-.091	-.003	-.115	-.022	-.009	.015	-.063	-.017	-.078
CONTAL*	-.090	-.053	-.096	-.086	.027	.942[a]	-.067	-.027	-.022	-.015	-.011	-.049	-.017	-.001	.011	-.020	-.025	.053	-.027	-.026	.010	-.045
CEMEXCP	-.013	-.045	-.040	-.001	-.177	-.067	.964[a]	-.023	-.051	-.047	-.030	-.062	-.063	-.127	.035	-.104	-.018	-.083	-.058	.033	-.058	-.007
GEOB	-.064	-.003	-.024	.042	-.025	-.027	-.023	.962[a]	-.128	-.039	-.066	-.041	-.069	.000	-.013	-.055	.009	-.089	-.008	.026	-.063	-.045
ARA*	-.027	-.014	-.043	.023	-.018	-.022	-.051	-.128	.965[a]	-.009	.014	-.025	-.022	-.004	-.021	-.092	.006	-.074	-.077	-.001	-.036	-.072
WALMEXV	-.018	-.050	-.027	-.134	-.053	-.015	-.047	-.039	-.009	.970[a]	-.117	-.007	-.012	-.014	-.083	-.133	-.044	-.057	-.026	-.117	-.043	.001
SORIANAB	-.029	-.029	-.036	-.050	-.101	-.011	-.030	-.066	.014	-.117	.969[a]	-.100	-.003	.024	-.068	-.034	-.107	-.050	-.034	-.114	-.014	-.086
COMERUBC	-.029	-.015	-.021	-.033	-.034	-.049	-.062	-.041	-.025	-.007	-.100	.973[a]	-.064	-.001	-.022	.010	-.016	-.104	-.017	-.036	-.075	-.042
ELEKTRA*	-.033	.022	-.055	-.035	-.038	-.017	-.063	-.069	-.022	-.012	-.003	-.064	.957[a]	.039	-.011	-.065	-.243	-.083	-.040	-.069	-.090	-.034
TELMEXL	-.002	-.050	-.025	-.041	-.091	-.001	-.127	.000	-.004	-.014	.024	-.001	.039	.912[a]	-.485	-.190	-.059	-.010	.005	-.029	.000	.033
TELECOA1	-.015	.008	-.042	-.030	-.003	.011	.035	-.013	-.021	-.083	-.068	-.022	-.011	-.485	.921[a]	-.025	-.034	-.061	-.087	-.127	-.091	-.054
TLEVICPO	.033	-.020	.026	-.013	-.115	-.020	-.104	-.055	-.092	-.133	-.034	.010	-.065	-.190	-.025	.952[a]	-.274	-.025	-.016	-.030	-.038	-.016
TVAZTCPO	.002	.029	.007	-.012	-.022	-.025	-.018	.009	.006	-.044	-.107	-.016	-.243	-.059	-.034	-.274	.946[a]	.001	.011	-.009	-.084	-.059
GFNORTEO	.031	-.064	.022	-.057	-.009	.053	-.083	-.089	-.074	-.057	-.050	-.104	-.083	-.010	-.061	-.025	.001	.968[a]	-.075	-.017	-.023	-.047
GFINBURO	.036	.023	-.057	.019	.015	-.027	-.058	-.008	-.077	-.026	-.034	-.017	-.040	.005	-.087	-.016	.011	-.075	.965[a]	-.128	-.036	-.098
GCARSOA1	-.006	-.067	-.007	-.022	-.063	-.026	.033	.026	-.001	-.117	-.114	-.036	-.069	-.029	-.127	-.030	-.009	-.017	-.128	.967[a]	-.075	-.078
ALFAA	.004	-.007	-.059	-.049	-.017	.010	-.058	-.063	-.036	-.043	-.014	-.075	-.090	.000	-.091	-.038	-.084	-.023	-.036	-.075	.975[a]	.009
CIEB	-.021	-.160	-.092	-.006	-.078	-.045	-.007	-.045	-.072	.001	-.086	-.042	-.034	.033	-.054	-.016	-.059	-.047	-.098	-.078	.009	.962[a]

Notes: a. Measures of Sampling Adequacy(MSA)

Table 4.8. *Anti-image correlation matrix and Measures of Sampling Adequacy (MSA). Database of daily excesses.*

	PE&OLES *	KIMBER A	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	CEMEX CP	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B
PE&OLES*	,.96[a]	-.015	-.044	-.039	.028	-.089	-.015	-.068	-.029	-.022	-.027	-.030	-.033	-.005	-.015	.034	.003	.033	.035	-.004	.004	-.019
KIMBERA	-.015	.956[a]	-.066	-.092	-.010	-.052	-.044	-.003	-.014	-.049	-.030	-.016	.023	-.049	.007	-.020	.029	-.065	.025	-.067	-.007	-.160
BIMBOA	-.044	-.066	.964[a]	.028	-.033	-.096	-.040	-.024	-.043	-.027	-.035	-.020	-.056	-.025	-.042	.026	.006	.022	-.058	-.007	-.060	-.091
GMODELOC	-.039	-.092	.028	.962[a]	-.061	-.086	-.001	.042	.023	-.134	-.050	-.033	-.035	-.041	-.030	-.013	-.012	-.057	.018	-.022	-.050	-.006
FEMSAUBD	.028	-.010	-.033	-.061	.968[a]	.026	-.179	-.026	-.019	-.055	-.098	-.032	-.040	-.093	-.001	-.116	-.021	-.007	.011	-.062	-.019	-.074
CONTAL*	-.089	-.052	-.096	-.086	.026	.943[a]	-.066	-.026	-.022	-.015	-.011	-.048	-.018	.000	.011	-.021	-.025	.053	-.027	-.026	.010	-.045
CEMEXCP	-.015	-.044	-.040	-.001	-.179	-.066	.964[a]	-.021	-.050	-.045	-.032	-.063	-.062	-.125	.034	-.104	-.018	-.084	-.056	.032	-.057	-.009
GEOB	-.068	-.003	-.024	.042	-.026	-.026	-.021	.961[a]	-.129	-.038	-.067	-.042	-.067	.001	-.015	-.054	.009	-.090	-.005	.026	-.061	-.046
ARA*	-.029	-.014	-.043	.023	-.019	-.022	-.050	-.129	.965[a]	-.009	.013	-.026	-.021	-.003	-.022	-.092	.006	-.075	-.075	-.001	-.035	-.073
WALMEXV	-.022	-.049	-.027	-.134	-.055	-.015	-.045	-.038	-.009	.970[a]	-.119	-.009	-.009	-.012	-.085	-.132	-.044	-.059	-.022	-.118	-.042	-.002
SORIANAB	-.027	-.030	-.035	-.050	-.098	-.011	-.032	-.067	.013	-.119	.970[a]	-.099	-.005	.021	-.067	-.034	-.106	-.048	-.036	-.113	-.015	-.084
COMERUBC	-.030	-.016	-.020	-.033	-.032	-.048	-.063	-.042	-.026	-.009	-.099	.973[a]	-.064	-.002	-.022	.010	-.015	-.104	-.017	-.035	-.075	-.042
ELEKTRA*	-.033	.023	-.056	-.035	-.040	-.018	-.062	-.067	-.021	-.009	-.005	-.064	.957[a]	.041	-.012	-.065	-.244	-.084	-.040	-.070	-.090	-.035
TELMEXL	-.005	-.049	-.025	-.041	-.093	.000	-.125	.001	-.003	-.012	.021	-.002	.041	.912[a]	-.486	-.190	-.059	-.012	.008	-.030	.001	.031
TELECOA1	-.015	.007	-.042	-.030	-.001	.011	.034	-.015	-.022	-.085	-.067	-.022	-.012	-.486	.921[a]	-.025	-.033	-.060	-.088	-.126	-.091	-.054
TLEVICPO	.034	-.020	.026	-.013	-.116	-.021	-.104	-.054	-.092	-.132	-.034	.010	-.065	-.190	-.025	.952[a]	-.275	-.025	-.016	-.031	-.038	-.016
TVAZTCPO	.003	.029	.006	-.012	-.021	-.025	-.018	.009	.006	-.044	-.106	-.015	-.244	-.059	-.033	-.275	.946[a]	.002	.010	-.009	-.085	-.059
GFNORTEO	.033	-.065	.022	-.057	-.007	.053	-.084	-.090	-.075	-.059	-.048	-.104	-.084	-.012	-.060	-.025	.002	.968[a]	-.077	-.016	-.024	-.045
GFINBURO	.035	.025	-.058	.018	.011	-.027	-.056	-.005	-.075	-.022	-.036	-.017	-.040	.008	-.088	-.016	.010	-.077	.964[a]	-.130	-.035	-.100
GCARSOA1	-.004	-.067	-.007	-.022	-.062	-.026	.032	.026	-.001	-.118	-.113	-.035	-.070	-.030	-.126	-.031	-.009	-.016	-.130	.967[a]	-.076	-.077
ALFAA	.004	-.007	-.060	-.050	-.019	.010	-.057	-.061	-.035	-.042	-.015	-.075	-.090	.001	-.091	-.038	-.085	-.024	-.035	-.076	.975[a]	.008
CIEB	-.019	-.160	-.091	-.006	-.074	-.045	-.009	-.046	-.073	-.002	-.084	-.042	-.035	.031	-.054	-.016	-.059	-.045	-.100	-.077	.008	.962[a]

Notes: a. Measures of Sampling Adequacy(MSA)

4.3.2. Extraction of underlying systematic risk factors via PCA and MLFA.

In this study, we first obtained the generative multifactor model of returns in expression 3.1, using the classic multivariate techniques to extract the underlying factors Principal Component Analysis (PCA) and Maximum Likelihood Factor Analysis (MLFA)[108].

Since there is not a definite widespread criterion to define the best number of components to extract in PCA and in FA, we have used nine different criteria usually accepted in PCA and FA literature. These criteria have been: the arithmetic mean of the eigenvalues, the percentage of explained variance, the exclusion of the components or factors explaining a small amount of variance, the scree plot, the unretained eigenvalue contrast (Q statistic), the likelihood ratio contrast, Akaike's information criterion (AIC), the Bayesian information criterion (BIC), and the maximum number of components feasible to estimate in each technique. Considering that each criterion indicated a different number of factors to extract in each database, for the sake of comparison among techniques and pursuing the main objective of extracting a smaller number of risk factors than the number of stocks, we chose a window test for all the databases ranging from two to nine factors according to the results presented in Table 4.9.

[108] Using a Matlab® code programmed to perform the PCA and MLFA on our four databases, we obtained the scores of the principal components (**Y**) and the common factors (**F**) hierarchically ordered, as well as the matrices of weights for PCA and FA (**A** and **Λ**, respectively).

Table 4.9. *Number of Components or Factors to retain.*

	DATABASE OF WEEKLY RETURNS		**DATABASE OF WEEKLY EXCESSES**		**DATABASE OF DAILY RETURNS**		**DATABASE OF DAILY EXCESSES**	
CRITERIA	**PCA**	**MLFA**	**PCA**	**MLFA**	**PCA**	**MLFA**	**PCA**	**MLFA**
Arithmetic mean of the eigenvalues.	4	3	4	5	4	2	4	2
Percentage of explained variance (90%).	14	9	14	9	18	9	18	9
Exclusion of the components/factors explaining a small amount of variance (<1%).	19	13-14	19	14	21	13	21	13
Scree plot.	3-4	4	3-4	5	3-4	4	3-4	3-4
Unretained eigenvalues contrast (Q statistic).	19	12	19	11	21	14	21	14
Likelihood ratio contrast.	4	4	4	4	9	8	10	8
Akaike's information criterion (AIC).	4	5	4	5	9	9	10	9
Bayesian information criterion (BIC).	4	2	4	2	9	3	10	3
Maximum number of components / factors feasible to estimate.	20	14	20	14	22	15	22	15
Number of components / factors to be tested.	3, 4, 14, 19, 20	2, 3, 4, 5, 9 12, 13, 14	3, 4, 14, 19, 20	2, 4, 5, 9, 11, 14	3, 4, 9, 18, 21, 22	2, 3, 4, 8, 9, 13, 14, 15	3, 4, 10, 18, 21	2, 3, 4, 8, 9, 13, 14, 15
Comparable number of components / factors to be tested in each database.	2, 3, 4, 5, 9, 12, 13, 14		2, 3, 4, 5, 9, 11, 14		2, 3, 4, 7, 8, 9, 13, 14, 15		2, 3, 4, 7, 8, 9, 10, 13, 14, 15	
Comparable range of components / factors to be tested for all databases looking for a reduction in the dimensionality.	**2-9**		**2-9**		**2-9**		**2-9**	

Subsequently, we estimated eight different multifactor models to extract from 2 to 9 principal components and common factors for each one of our four databases[109]. Then, we proceeded to reconstruct the original variables according to the generation process of each technique by computing the following expression in PCA[110]:

$$\mathbf{X} = \mathbf{Y}\mathbf{A}' \qquad (4.9)$$

And the following expression in FA[111]:

$$\mathbf{X} = \mathbf{1}\boldsymbol{\mu} + \mathbf{F}\boldsymbol{\Lambda}' \qquad (4.10)$$

[109] The total number of estimated multifactor models was 32 for PCA and 32 for MLFA.
[110] This expression represents an algebraic transformation of the expression 4.3 taken from Peña (2002).
[111] This expression is the same expression that expression 4.8 but without including the matrix of specific factors **U**, because this matrix represents the error in reproduction of the original variables, which will be known after the reconstruction process and is computed by: $\mathbf{U}=\mathbf{X}-\mathbf{X}_r$, where $\mathbf{X}_r$ is the matrix **X** reconstructed.

We use a graphic methodology in order to detect the suitability of the reproduction of the observed returns by way of our generative multifactor model estimated, from a visual standpoint. In order to observe the behavior of the complete series, we present the line plots including all the observations of the sample. For reasons of saving space, in this section we only present in this chapter the lines plots of the observed and reproduced returns of the first five stocks of the database of weekly returns, which belong to the experiment where we extracted nine underlying factors[112]. Nevertheless, the rest of the estimations when eight, seven, six, five, four, three and two components or factors where extracted present similar behavior[113]. Figure 4.1 show the results of PCA and Figures 4.2 those of FA. We can easily observe that the reconstruction of the observed returns or excesses was outstanding for almost all the stocks in the four databases, which imply that the estimation of the generative multifactor model of returns performed by both PCA and FA was successful. Nevertheless, the highest and lowest peaks in some stocks were not very well reconstructed.

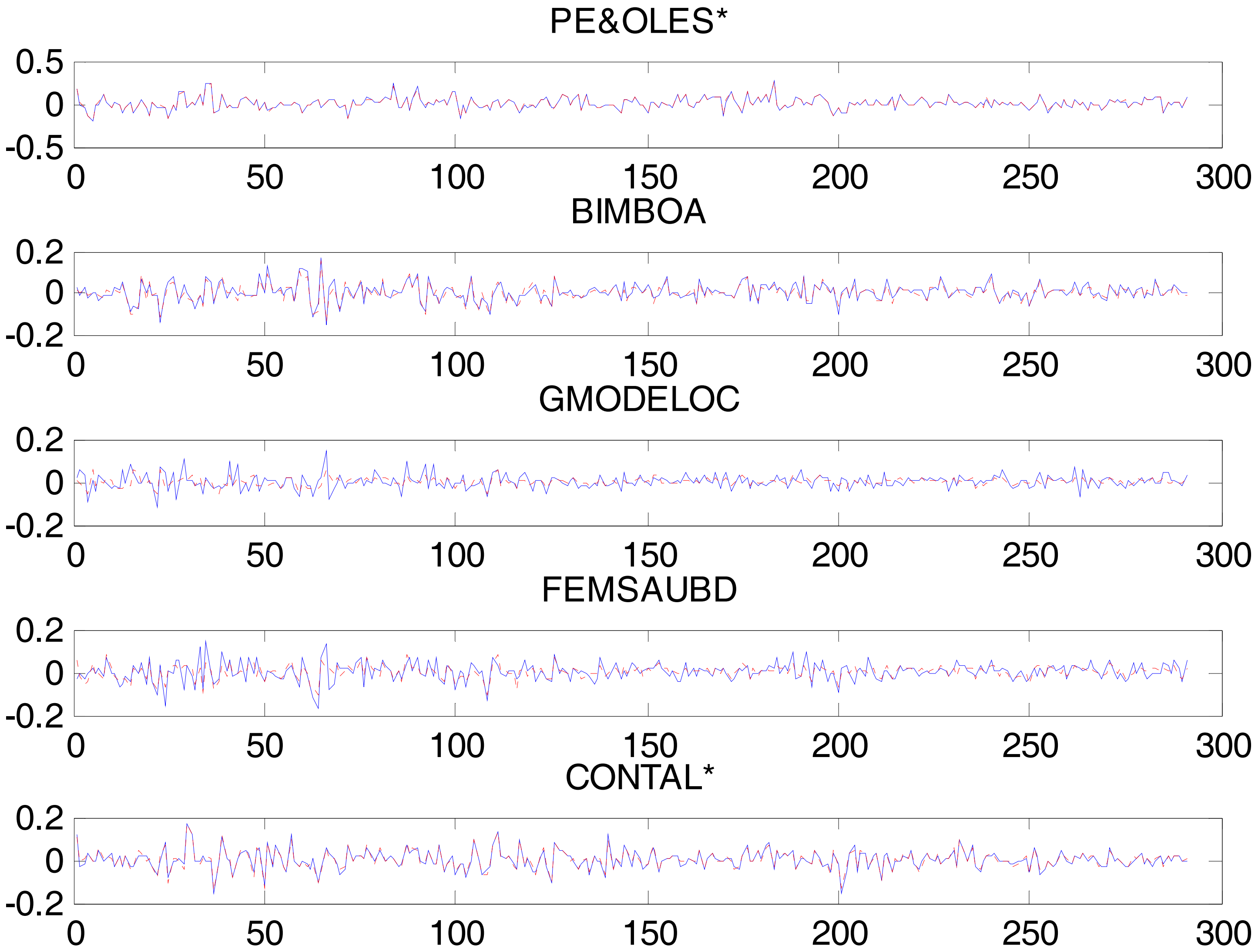
4.3.3. Explanation of the variability by the extracted components or factors.

The amount of variance explained by the extracted components or factors, as well as the accumulated one, is presented in Table 4.10. We can observe that in all cases the three first components and factors explain between the 66% and the 84% of variability, which give some evidence about the importance of those components or factors. Factor analysis overcomes principal component analysis in this aspect, since in the four databases produce higher percentage of accumulated explanation. Moreover, in almost all cases the factors extracted by FA explain higher amounts of variance than those estimated by PCA.

112 All the empirical results presented in this document will be related to the experiment when nine factors were extracted, since this dimension was the one that produced the best level of reconstruction of the observed returns by way of the generative multifactor models of returns estimated by way of the four techniques in the four databases studied.

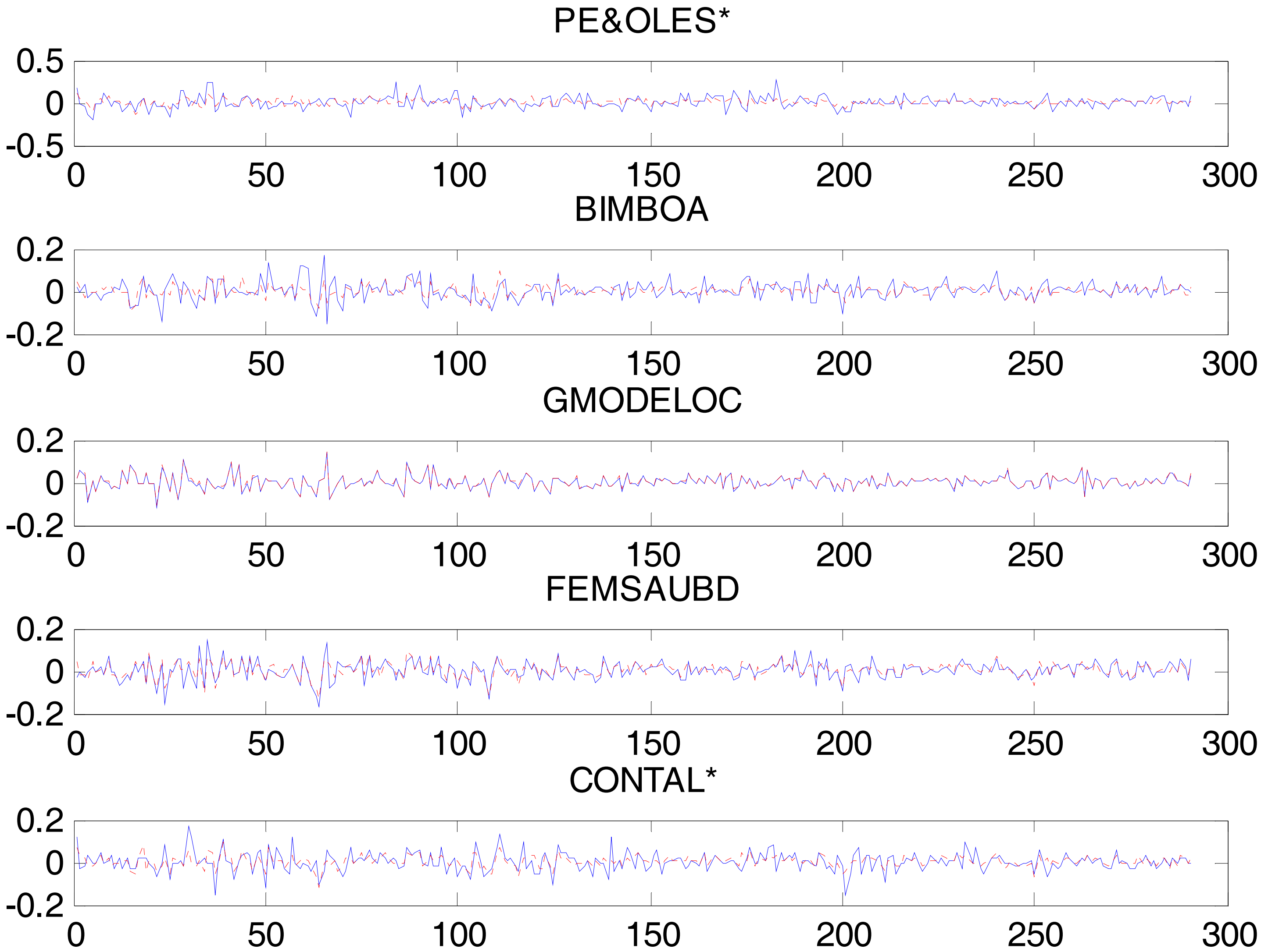
113 The plots regarding the rest of the stocks in the four databases for PCA and FA are included in Appendix_2 from Figures 1 to 6 and Figures 7 to 12 of Chapter 4, respectively. For the sake of saving space, in all the empirical chapters of this dissertation we only present the results regarding the experiment when nine factors were extracted because, in general, it represents the best performance in the reconstruction of the observed returns. The results corresponding the rest of the experiments when eight, seven, six, five, four, three and two factors were extracted are not included in this dissertation since they represent an excessive amount of information to be included in the document. Nevertheless, the results of those experiments are considered in the analysis reported in this work. In addition, all that information will serve to analyze more deeply the sensitivity level of the results in a dynamic perspective in future researches.

Figure 4.1. *Principal Component Analysis. Observed and reproduced variables. Line plots. Database of weekly returns. Nine components extracted.*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 4.2. *Factor Analysis. Observed and reproduced variables. Line plots. Database of weekly returns. Nine components extracted.*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Table 4.10. *Variance explained and accumulated. Principal Component Analysis and Factor Analysis. Explained Variance.*

	Principal Component Analysis			Factor Analysis		
	Principal Component	Explained Variance (%)	Accumulated Explained Variance (%)	Factor	Explained Variance (%)	Accumulated Explained Variance (%)
Database of weekly returns	1	46.63	46.63	1	45.46	45.46
	2	13.08	59.70	2	15.67	61.13
	3	8.08	67.78	3	10.27	71.41
	4	6.90	74.68	4	5.82	77.23
	5	6.18	80.86	5	6.44	83.67
	6	5.33	86.19	6	6.91	90.58
	7	4.94	91.13	7	3.20	93.78
	8	4.61	95.74	8	3.36	97.15
	9	4.26	100.00	9	2.85	100.00
Database of weekly excesses	1	46.82	46.82	1	45.68	45.68
	2	13.04	59.86	2	15.68	61.36
	3	8.04	67.90	3	10.22	71.58
	4	6.88	74.78	4	5.80	77.38
	5	6.15	80.93	5	6.41	83.79
	6	5.32	86.25	6	6.85	90.64
	7	4.92	91.17	7	3.17	93.81
	8	4.59	95.76	8	3.35	97.16
	9	4.24	100.00	9	2.84	100.00
Database of daily returns	1	46.62	46.62	1	70.63	70.63
	2	12.81	59.43	2	7.73	78.36
	3	7.34	66.77	3	6.31	84.68
	4	6.62	73.39	4	3.32	88.00
	5	6.04	79.43	5	3.00	91.00
	6	5.87	85.30	6	2.54	93.54
	7	5.34	90.64	7	2.49	96.04
	8	4.89	95.53	8	2.49	98.53
	9	4.47	100.00	9	1.47	100.00
Database of daily excesses	1	46.64	46.64	1	71.03	71.03
	2	12.83	59.47	2	6.95	77.98
	3	7.35	66.82	3	6.31	84.28
	4	6.60	73.42	4	3.32	87.60
	5	6.04	79.46	5	2.83	90.43
	6	5.86	85.33	6	2.76	93.19
	7	5.33	90.66	7	3.19	96.38
	8	4.89	95.55	8	1.95	98.33
	9	4.45	100.00	9	1.67	100.00

4.3.4. Interpretation of the extracted factors.

Although the second process of the statistical approach to the APT, i.e., the risk attribution stage, is out of the scope of this study, in this section we will make a first attempt to propose an interpretation of the meaning or nature of the systematic risk factors extracted, following a classic approach which has been widely used when PCA and FA are used to reduce dimensionality or to extract features from a multifactor dataset. This approach is based on using the factor loading matrix estimated in the extraction process to identify the loading of each variable in each component or factor; high factor loadings in absolute terms indicate a strong relation between the variables and the factor. In our context, the factors will be saturated with loadings of one stock or a group of stocks that may help us to identify those factors with some economic sectors, as a first approach of interpretation of each component or factor.

In line with the previously reported results, we only present the factor loading matrix plots of each database, which belong to the experiment where we extracted nine underlying factors; Figures 4.3 to 4.6 present the results of PCA and Figures 4.7 to 4.11 those for FA. In those figures we can distinguish visually the stocks with a major weight in the formation of each component[114].

In addition, we constructed some tables summarizing the results derived from the analysis of the factor loading matrices and plots, where we propose some economic sector that may be related to each factor. We group together the stocks with the highest loading in each factor according the economic sectors official classification used in the Mexican Stock Exchange. For each technique, first we present a table where we include: the name of the stocks with the major loadings in each component or factor, the description of the economic sector where they belong, and the sign of their corresponding loadings. Secondly, we propose a preliminary economic sector interpretation which is displayed separately also in a summary table. Tables 4.11 to 4.13 correspond to PCA and Tables 4.14 to 4.16 to FA.

[114] For the sake of saving space, the figures related to the experiments when eight, seven, six, five, four, three and two factors were extracted are not included in this document.

Figure 4.3. *Loadings matrices plots for interpretation of extracted factors.*
Principal Component Analysis*.*
Database of weekly returns.
Nine components extracted.

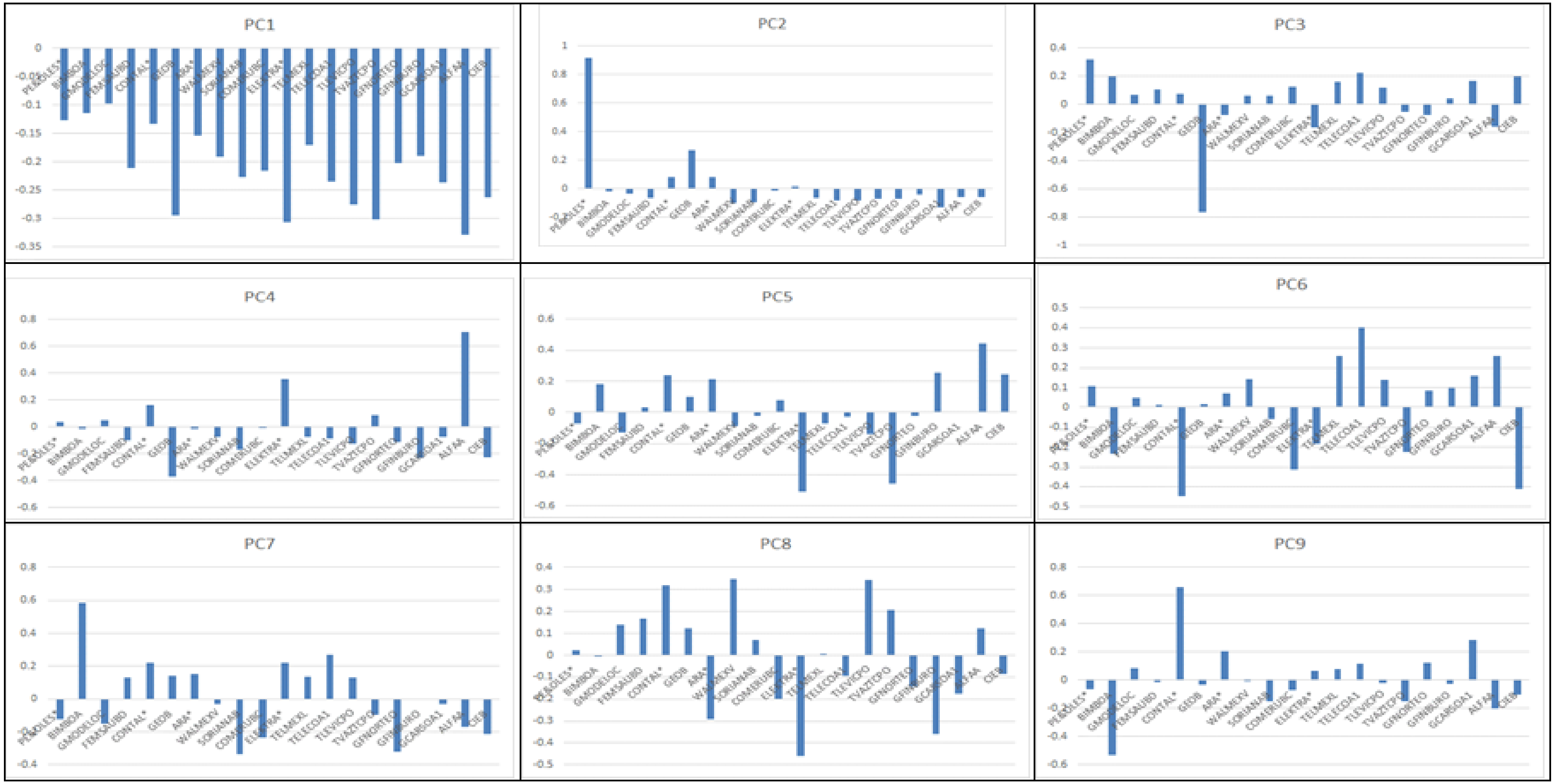


Figure 4.4. *Loadings matrices plots for interpretation of extracted factors.*
Principal Component Analysis*.*
Database of weekly excesses.
Nine components extracted.

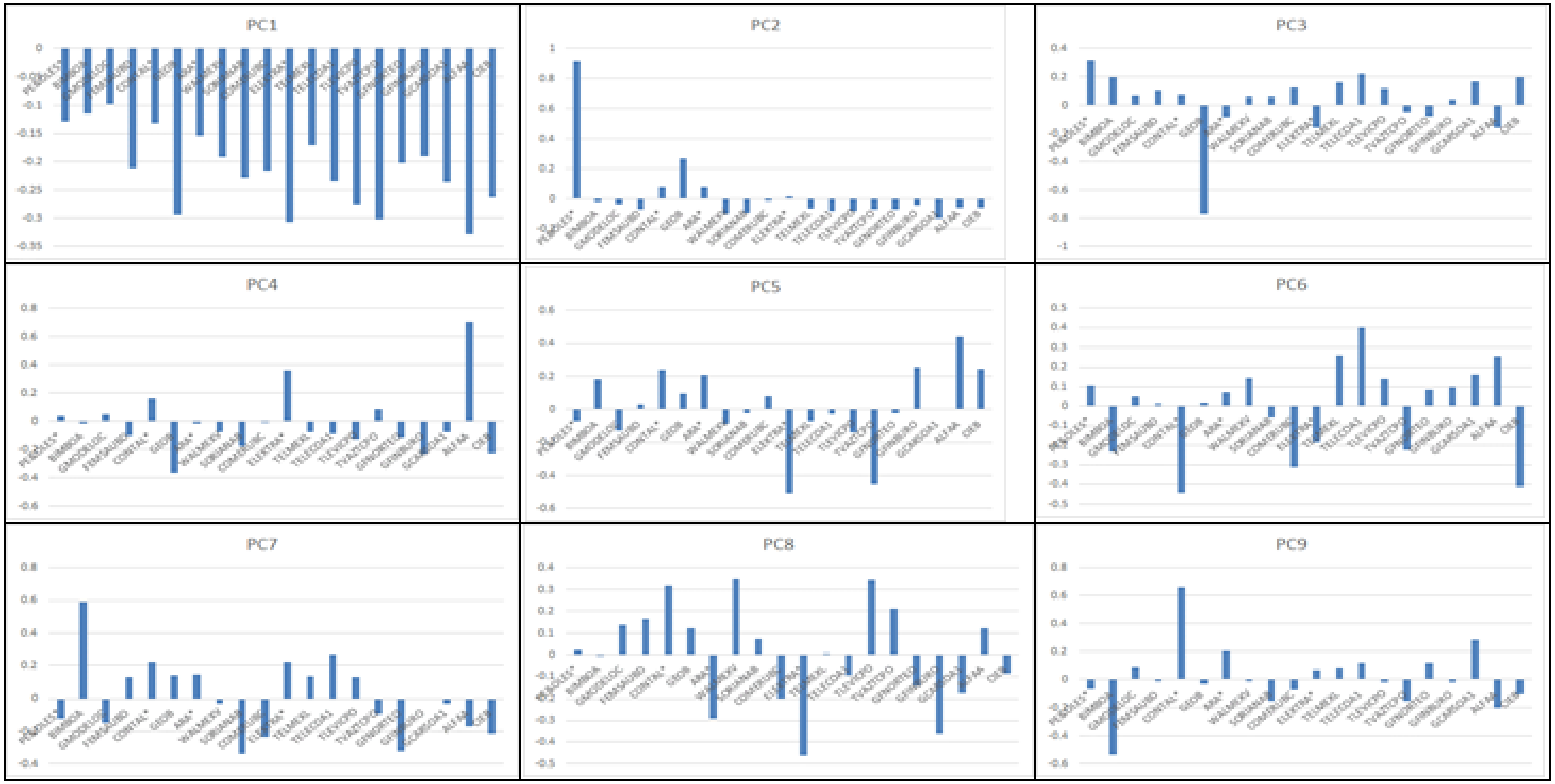


Figure 4.5. *Loadings matrices plots for interpretation of extracted factors.*
Principal Component Analysis.
Database of daily returns.
Nine components extracted.

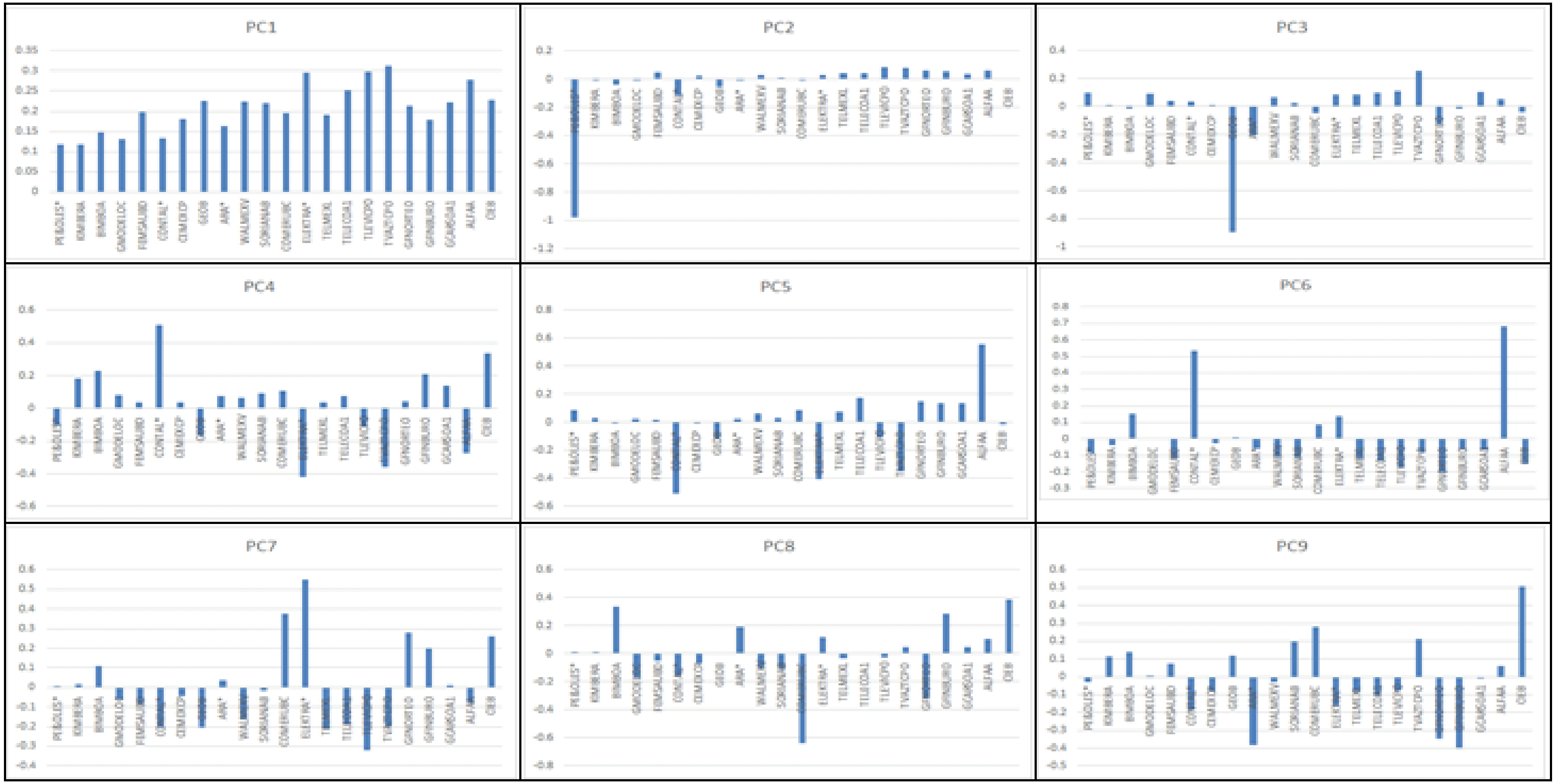


Figure 4.6. *Loadings matrices plots for interpretation of extracted factors.*
Principal Component Analysis.
Database of daily excesses.
Nine components extracted.

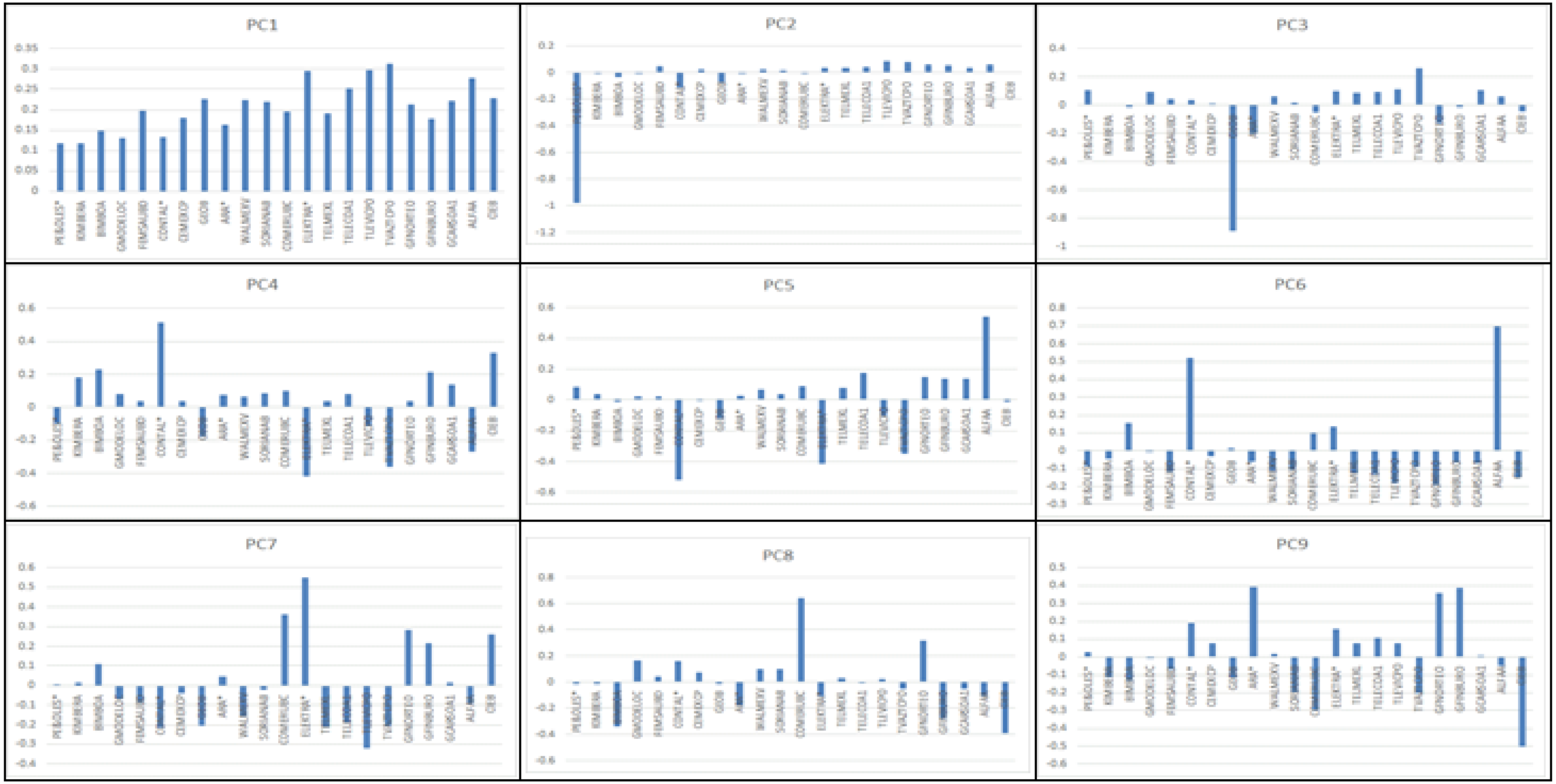


Figure 4.7. *Loadings matrices plots for interpretation of extracted factors.*
Factor Analysis*.*
Database of weekly returns.
Nine components extracted.

Figure 4.8. *Loadings matrices plots for interpretation of extracted factors.*
Factor Analysis.
Database of weekly excesses.
Nine components extracted.

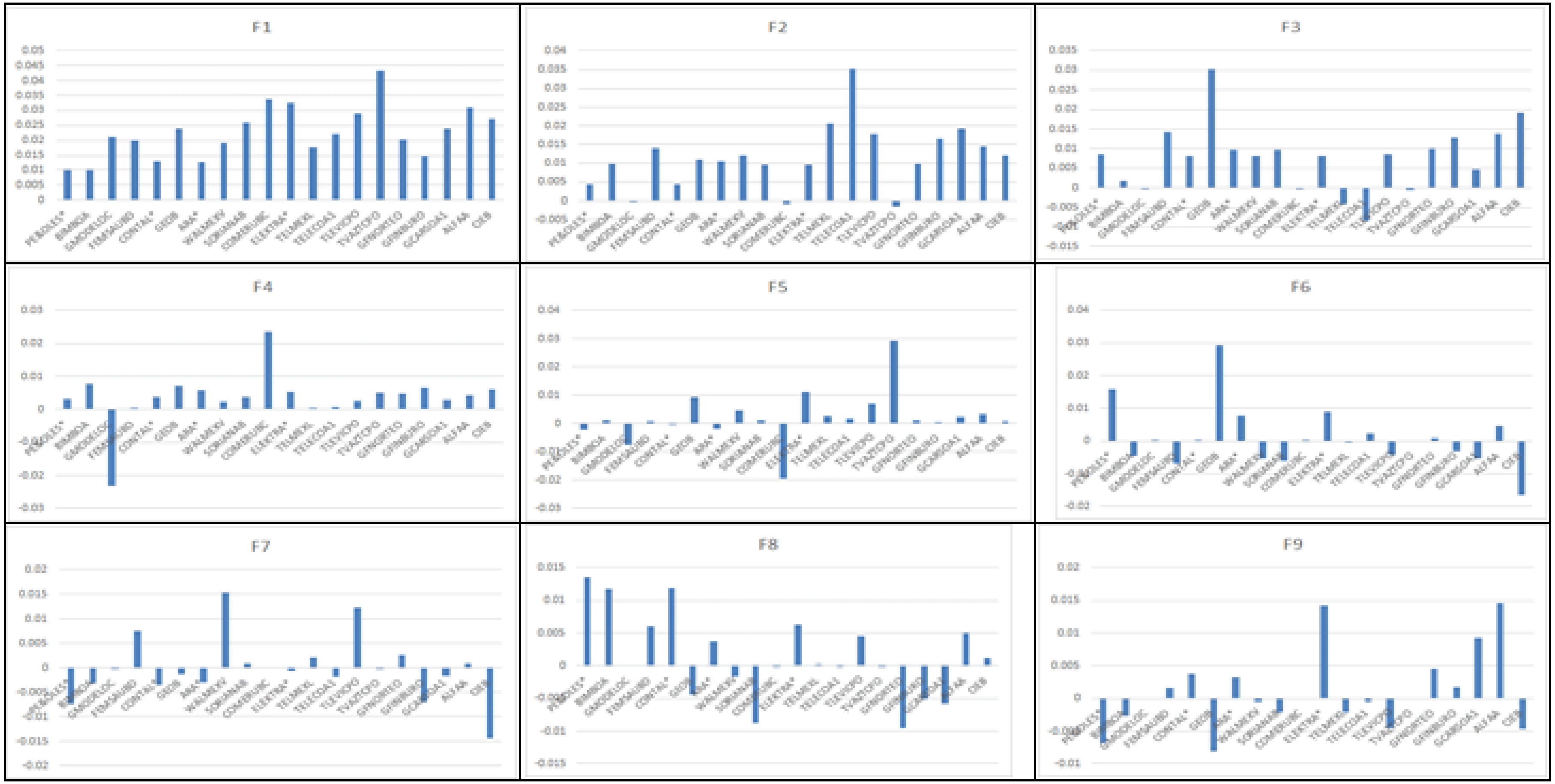


Figure 4.9. *Loadings matrices plots for interpretation of extracted factors.*
***Factor Analysis**.*
Database of daily returns.
Nine components extracted.

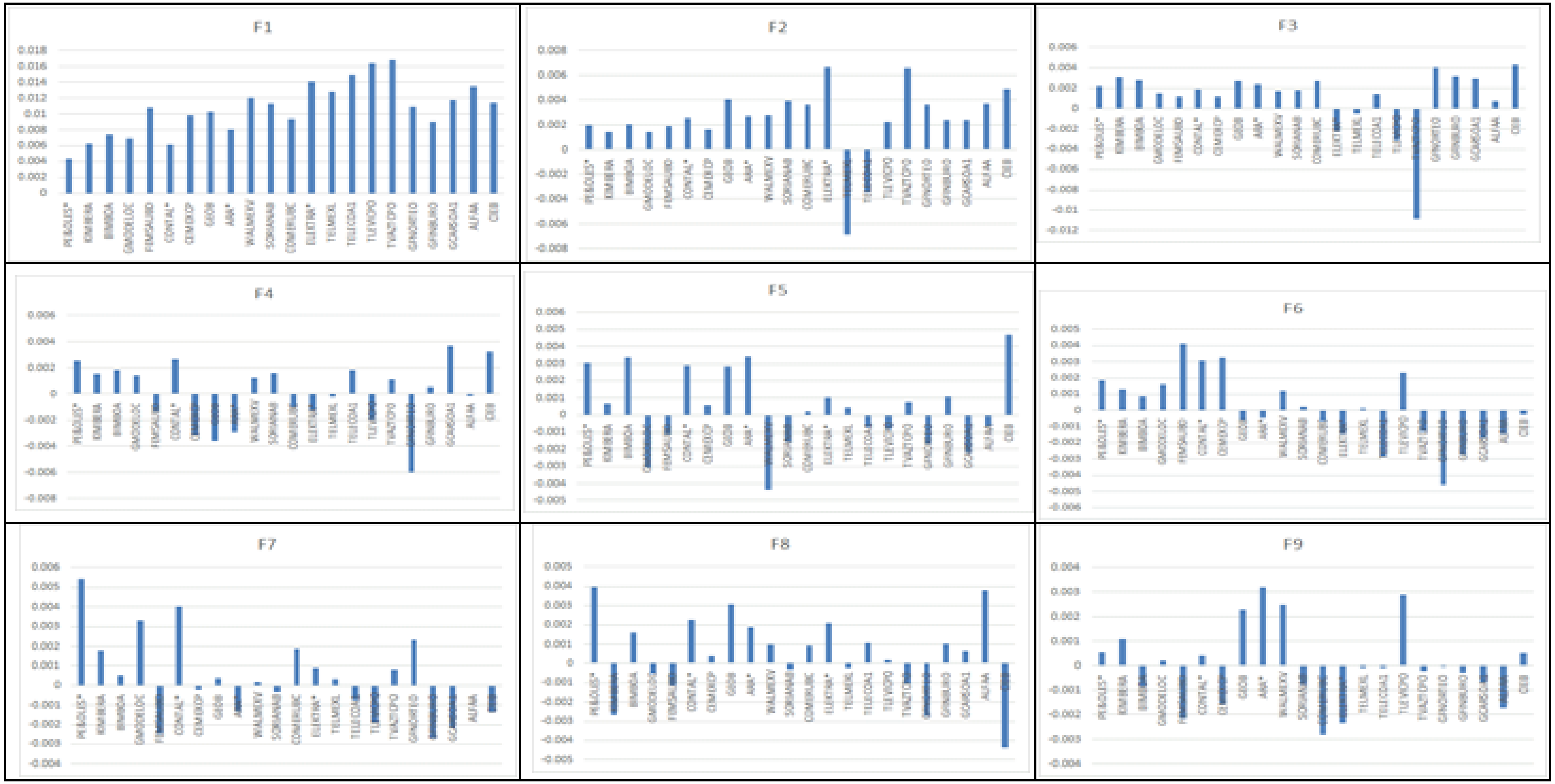


Figure 4.10. *Loadings matrices plots for interpretation of extracted factors.*
Factor Analysis*.*
Database of daily excesses.
Nine components extracted.

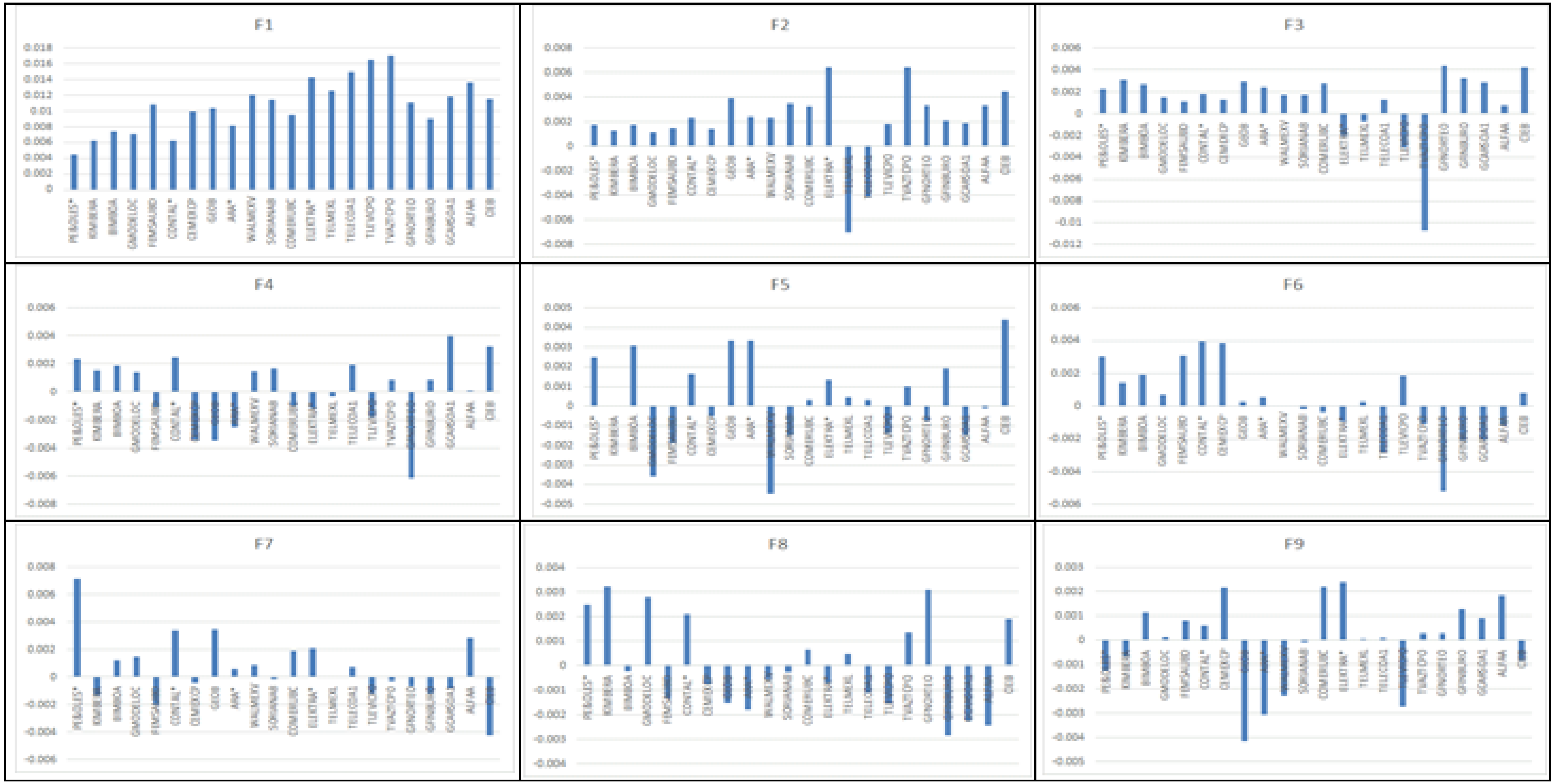


Table 4.11. *Details of results. Sector interpretation of components.*
Principal Component Analysis.
Nine components extracted.

PRINCIPAL COMPONENT ANALYSIS							
Database of Weekly Returns				Database of Weekly Excesses			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
PC1	IPC (-)	Market	Market factor	**PC1**	IPC (-)	Market	Market factor
PC2	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)	**PC2**	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)
PC3	GEOB (-)	Construction: House building	Construction sector factor	**PC3**	GEOB (-)	Construction: House building	Construction sector factor
	ALFAA (+)	Capital goods: Industrial Conglomerate / Holdings			ALFAA (+)	Capital goods: Industrial Conglomerate / Holdings	
PC4	ELEKTRA* (+)	Specialty retail: Home furnishing retail	Capital goods consume sector factor	**PC4**	ELEKTRA* (+)	Specialty retail: Home furnishing retail	Capital goods consume sector factor
	GEOB (-)	Construction: House building			GEOB (-)	Construction: House building	
	ELEKTRA* (-)	Specialty retail: Home furnishing retail			ELEKTRA* (-)	Specialty retail: Home furnishing retail	
PC5	TVAZTECPO (-)	Communication media: Radio & television services	Salinas Group sector factor	**PC5**	TVAZTECPO (-)	Communication media: Radio & television services	Salinas Group sector factor
	ALFAA (+)	Capital goods: Industrial Conglomerate / Holdings			ALFAA (+)	Capital goods: Industrial Conglomerate / Holdings	
	CONTAL* (-)	Beverages: Soft drinks			CONTAL* (-)	Beverages: Soft drinks	
PC6	CIEB (-)	Hotels, restaurants & leisure: Leisure facilities	Ordinary consume sector factor	**PC6**	CIEB (-)	Hotels, restaurants & leisure: Leisure facilities	Ordinary consume sector factor
	COMERUBC (-)	Consumer staples: Hypermarkets and supercenters			COMERUBC (-)	Consumer staples: Hypermarkets and supercenters	
	TELECOA1 (+)	Telecommunications services: Wireless telecommunications services			TELECOA1 (+)	Telecommunications services: Wireless telecommunications services	
PC7	BIMBOA (+)	Food products: Production and commercialization of food products	Food sector factor (Bimbo factor)	**PC7**	BIMBOA (+)	Food products: Production and commercialization of food products	Food sector factor (Bimbo factor)
	ELEKTRA* (-)	Specialty retail: Home furnishing retail			ELEKTRA* (-)	Specialty retail: Home furnishing retail	
	GFINBURO(-)	Financial services: Financial groups			GFINBURO(-)	Financial services: Financial groups	
PC8	WALMEXV (+)	Consumer staples: Hypermarkets and supercenters	Miscellaneous sectors factor	**PC8**	WALMEXV (+)	Consumer staples: Hypermarkets and supercenters	Miscellaneous sectors factor
	TELEVICPO (+)	Communication media: Radio & television services			TELEVICPO (+)	Communication media: Radio & television services	
	CONTAL* (+)	Beverages: Soft drinks			CONTAL* (+)	Beverages: Soft drinks	
	CONTAL* (+)	Beverages: Soft drinks			CONTAL* (+)	Beverages: Soft drinks	
	BIMBOA (-)	Food products: Production and commercialization of food products			BIMBOA (-)	Food products: Production and commercialization of food products	
PC9	GFINBURO (-)	Financial services: Financial groups	Beverages and food sector factor	**PC9**	GFINBURO (+)	Financial services: Financial groups	Beverages and food sector factor
	ARA* (-)	Construction: House building			GFNORTEO (+)	Financial services: Financial groups	
	GFNORTEO (-)	Financial services: Financial groups			ARA* (+)	Construction: House building	

Table 4.12. *Details of results. Sector interpretation of components. Principal Component Analysis. Nine components extracted. (Cont.)*

PRINCIPAL COMPONENT ANALYSIS

Database of Daily Returns				Database of Daily Excesses			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
PC1	IPC (+)	Market	Market factor	**PC1**	IPC (+)	Market	Market factor
PC2	PE&OLES* (-)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)	**PC2**	PE&OLES* (-)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)
PC3	GEOB (-)	Construction: House building	Construction sector factor	**PC3**	GEOB (-)	Construction: House building	Construction sector factor
PC4	CONTAL* (+) CIEB (+) ELEKTRA (-) TVAZTECPO (-)	Beverages: Soft drinks Hotels, restaurants & leisure: Leisure facilities Specialty retail: Home furnishing retail Communication media: Radio & television services	Entertainment consume sector factor.	**PC4**	CONTAL* (+) CIEB (+) ELEKTRA (-) TVAZTECPO (-)	Beverages: Soft drinks Hotels, restaurants & leisure: Leisure facilities Specialty retail: Home furnishing retail Communication media: Radio & television services	Entertainment consume sector factor.
PC5	ALFA (+) CONTAL* (-) ELEKTRA (-) TVAZTECPO (-)	Capital goods: Industrial Conglomerate / Holdings Beverages: Soft drinks Specialty retail: Home furnishing retail Communication media: Radio & television services	Holding / Beverage / Salinas group factor.	**PC5**	ALFA (+) CONTAL* (-) ELEKTRA (-) TVAZTECPO (-)	Capital goods: Industrial Conglomerate / Holdings Beverages: Soft drinks Specialty retail: Home furnishing retail Communication media: Radio & television services	Holding / Beverage / Salinas group factor.
PC6	ALFA (+) CONTAL* (+)	Capital goods: Industrial Conglomerate / Holdings Beverages: Soft drinks	Holding / Food and beverage sector factor	**PC6**	ALFA (+) CONTAL* (+)	Capital goods: Industrial Conglomerate / Holdings Beverages: Soft drinks	Holding / Food and beverage sector factor
PC7	ELEKTRA (+) COMERUBC (+) TELEVICPO (-)	Specialty retail: Home furnishing retail Consumer staples: Hypermarkets and supercenters Communication media: Radio & television services	Ordinary consume sector factor	**PC7**	ELEKTRA (+) COMERUBC (+) TELEVICPO (-)	Specialty retail: Home furnishing retail Consumer staples: Hypermarkets and supercenters Communication media: Radio & television services	Ordinary consume sector factor
PC8	COMERUBC (-) GFNORTEO (-) CIEB (+) BIMBOA (+)	Consumer staples: Hypermarkets and supercenters Financial services: Financial groups Hotels, restaurants & leisure: Leisure facilities Food products: Production and commercialization of food products	Miscellaneous sectors factor	**PC8**	COMERUBC (+) GFNORTEO (+) CIEB (-) BIMBOA (-)	Consumer staples: Hypermarkets and supercenters Financial services: Financial groups Hotels, restaurants & leisure: Leisure facilities Food products: Production and commercialization of food products	Miscellaneous sectors factor
PC9	CIEB (+) GFINBURO (-) ARA* (-) GFNORTEO (-)	Hotels, restaurants & leisure: Leisure facilities Financial services: Financial groups Construction: House building Financial services: Financial groups	Infrastructure / Financial sector factor	**PC9**	CIEB (-) GFINBURO (+) GFNORTEO (+) ARA* (+)	Hotels, restaurants & leisure: Leisure facilities Financial services: Financial groups Financial services: Financial groups Construction: House building	Infrastructure - Financial sectors factor

Table 4.13. *Summary of results.*
Sector interpretation of components.
Principal Component Analysis.
Nine components extracted.

PRINCIPAL COMPONENT ANALYSIS							
Database of Weekly Returns		Database of Weekly Excesses		Database of Daily Returns		Database of Daily Excesses	
PC1	Market factor	**PC1**	Market factor	**PC1**	Market factor	**PC1**	Market factor
PC2	Mining sector factor (Peñoles factor)	**PC2**	Mining sector factor (Peñoles factor)	**PC2**	Mining sector factor (Peñoles factor)	**PC2**	Mining sector factor (Peñoles factor)
PC3	Construction sector factor	**PC3**	Construction sector factor	**PC3**	Construction sector factor	**PC3**	Construction sector factor
PC4	Capital goods consume sector factor	**PC4**	Capital goods consume sector factor	**PC4**	Entertainment consume sector factor.	**PC4**	Entertainment consume sector factor.
PC5	Salinas Group sector factor	**PC5**	Salinas Group sector factor	**PC5**	Holding / Beverage / Salinas group factor.	**PC5**	Holding / Beverage / Salinas group factor.
PC6	Ordinary consume sector factor	**PC6**	Ordinary consume sector factor	**PC6**	Holding / Food and beverage sector factor	**PC6**	Holding / Food and beverage sector factor
PC7	Food sector factor (Bimbo factor)	**PC7**	Food sector factor (Bimbo factor)	**PC7**	Ordinary consume sector factor	**PC7**	Ordinary consume sector factor
PC8	Miscellaneous sectors factor	**PC8**	Miscellaneous sectors factor	**PC8**	Miscellaneous sectors factor	**PC8**	Miscellaneous sector factor
PC9	Beverages and food sector factor	**PC9**	Beverages and food sector factor	**PC9**	Infrastructure / Financial sector factor	**PC9**	Infrastructure - Financial sectors factor

Table 4.14. *Details of results.*
Sector interpretation of components.
Factor Analysis.
Nine factors extracted.

FACTOR ANALYSIS							
Database of Weekly Returns				**Database of Weekly Excesses**			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
F1	IPC (+)	Market	Market factor	**F1**	IPC (+)	Market	Market factor
F2	TELECOA1 (+)	Telecommunications services: Wireless telecommunications services	Slim Group factor	**F2**	TELECOA1 (+)	Telecommunications services: Wireless telecommunications services	Slim Group factor
	TELMEXL (+)	Telecommunications services: Wireless telecommunications services			TELMEXL (+)	Telecommunications services: Wireless telecommunications services	
	GCARSOA1 (+)	Capital goods: Industrial Conglomerate / Holdings			GCARSOA1 (+)	Capital goods: Industrial Conglomerate / Holdings	
	GFINBURO (+)	Financial services: Financial groups			GFINBURO (+)	Financial services: Financial groups	
F3	GEOB (+)	Construction: House building	Construction sector factor	**F3**	GEOB (+)	Construction: House building	Construction sector factor
F4	COMERUBC (+)	Consumer staples: Hypermarkets and supercenters	Ordinary consume sector factor	**F4**	COMERUBC (+)	Consumer staples: Hypermarkets and supercenters	Ordinary consume sector factor
	GMODELOC (-)	Beverages: Brewers			GMODELOC (-)	Beverages: Brewers	
F5	TVAZTECPO (+)	Communication media: Radio & television services	Communication / commercial sectors factor	**F5**	TVAZTECPO (+)	Communication media: Radio & television services	Communication / commercial sectors factor
	COMERUBC (-)	Consumer staples: Hypermarkets and supercenters			COMERUBC (-)	Consumer staples: Hypermarkets and supercenters	
F6	GEOB (+)	Construction: House building	Infrastructure / Mining sectors factor	**F6**	GEOB (+)	Construction: House building	Infrastructure / Mining sectors factor
	PE&OLES (+)	Metal and mining: Precious metals and minerals			PE&OLES (+)	Metal and mining: Precious metals and minerals	
	CIEB (-)	Hotels, restaurants & leisure: Leisure facilities			CIEB (-)	Hotels, restaurants & leisure: Leisure facilities	
F7	WALMEXV (+)	Consumer staples: Hypermarkets and supercenters	Ordinary consume / entertainment sectors factor	**F7**	WALMEXV (+)	Consumer staples: Hypermarkets and supercenters	Ordinary consume / entertainment sectors factor
	TELEVICPO (+)	Communication media: Radio & television services			TELEVICPO (+)	Communication media: Radio & television services	
	CIEB (-)	Hotels, restaurants & leisure: Leisure facilities			CIEB (-)	Hotels, restaurants & leisure: Leisure facilities	
F8	PE&OLES (+)	Metal and mining: Precious metals and minerals	Miscellaneous sectors factor	**F8**	PE&OLES (+)	Metal and mining: Precious metals and minerals	Miscellaneous sectors factor
	CONTAL* (+)	Beverages: Soft drinks			CONTAL* (+)	Beverages: Soft drinks	
	BIMBOA (+)	Food products: Production and commercialization of food products			BIMBOA (+)	Food products: Production and commercialization of food products	
	GFNORTEO (-)	Financial services: Financial groups			GFNORTEO (-)	Financial services: Financial groups	
	SORIANAB (-)	Consumer staples: Hypermarkets and supercenters			SORIANAB (-)	Consumer staples: Hypermarkets and supercenters	
F9	ALFAA (+)	Capital goods: Industrial Conglomerate / Holdings	Capital goods consume / holdings sector factor	**F9**	ALFAA (+)	Capital goods: Industrial Conglomerate / Holdings	Capital goods consume / holding sectors factor
	ELEKTRA* (+)	Specialty retail: Home furnishing retail			ELEKTRA* (+)	Specialty retail: Home furnishing retail	
	GCARSOA1 (+)	Capital goods: Industrial Conglomerate / Holdings			GCARSOA1 (+)	Capital goods: Industrial Conglomerate / Holdings	
	GEOB (-)	Construction: House building			GEOB (-)	Construction: House building	
	TELEVICPO (+)	Communication media: Radio & television services			ARA* (-)	Construction: Housing	
	COMERUBC (-)	Consumer staples: Hypermarkets and supercenters			TELEVICPO (+)	Communication media: Radio & television services	

Table 4.15. *Details of results.*
Sector interpretation of components.
Factor Analysis.
Nine factors extracted. (Cont.)

FACTOR ANALYSIS							
Database of Daily Returns				**Database of Daily Excesses**			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
F1	IPC (+)	Market	Market factor	**F1**	IPC (+)	Market	Market factor
F2	TELMEXL (-) TVAZTECPO (+) ELEKTRA* (+)	Telecommunications services: Wireless telecommunications services Communication media: Radio & television services Specialty retail: Home furnishing retail	Communication / commercial sector factor	**F2**	TELMEXL (-) TVAZTECPO (+) ELEKTRA* (+)	Telecommunications services: Wireless telecommunications services Communication media: Radio & television services Specialty retail: Home furnishing retail	Communication / commercial sectors factor
F3	TVAZTECPO (-)	Communication media: Radio & television services	Radio and television sector factor (Azteca factor)	**F3**	TVAZTECPO (-)	Communication media: Radio & television services	Radio and television sector factor (Azteca factor)
F4	GFNORTEO (-)	Financial services: Financial groups	Financial sector factor (GF Norte Factor)	**F4**	GFNORTEO (-)	Financial services: Financial groups	Financial sector factor (GF Norte Factor)
F5	CIEB (+) ARA* (+) BIMBOA (+) PE&OLES (+) WALMEXV (-) GMODELOC (-)	Hotels, restaurants & leisure: Leisure facilities Construction: House building Food products: Production and commercialization of food products Metal and mining: Precious metals and minerals Consumer staples: Hypermarkets and supercenters Beverages: Brewers	Miscellaneous sectors factor	**F5**	WALMEXV (-) GMODELOC (-) CIEB (+) ARA* (+) GEOB (+) BIMBOA (+)	Consumer staples: Hypermarkets and supercenters Beverages: Brewers Hotels, restaurants & leisure: Leisure facilities Construction: House building Construction: House building Food products: Production and commercialization of food products	Miscellaneous sectors factor
F6	GFNORTEO (-) FEMSAUBD (+) CEMEXCP (+) CONTAL* (+)	Financial services: Financial groups Beverages: Diversified beverages Materials: Construction materials Food and beverage processing	Beverage / construction / financial sectors factor	**F6**	GFNORTEO (-) CONTAL* (+) CEMEXCP (+) FEMSAUBD (+)	Financial services: Financial groups Food and beverage processing Materials: Construction materials Beverages: Diversified beverages	Beverage / construction / financial sectors factor
F7	PE&OLES (+) CONTAL* (+) GMODELOC (-)	Metal and mining: Precious metals and minerals Food and beverage processing Beverages: Brewers	Mining / beverage sectors factor	**F7**	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor).
F8	CIEB (-) PE&OLES (+) ALFAA (+) GEOB (+)	Hotels, restaurants & leisure: Leisure facilities Metal and mining: Precious metals and minerals Capital goods: Industrial Conglomerate / Holdings Construction: House building	Leisure / Mining – Holdings - Construction sectors factor	**F8**	KIMBERA (+) GFNORTEO (+) GMODELOC (+) GFINBURO (+)	Household products: Cellulose and paper Financial services Beverages: Brewers Financial services: Financial groups	Financial / brewers / cellulose sector factor
F9	ARA* (+) TELEVICPO (+) COMERUBC (-)	Construction: House building Communication media: Radio & television services Consumer staples: Hypermarkets and supercenters	Construction / communication / commercial sectors factor	**F9**	GEOB (-) ARA* (-) TELEVICPO (+)	Construction: House building Construction: Housing Communication media: Radio & television services	Construction sector factor

Table 4.16. *Summary of results.*
Sector interpretation of factors.
Factor Analysis.
Nine factors extracted.

FACTOR ANALYSIS							
Database of Weekly Returns		**Database of Weekly Excesses**		**Database of Daily Returns**		**Database of Daily Excesses**	
F1	Market factor	**F1**	Market factor	**F1**	Market factor	**F1**	Market factor
F2	Slim Group factor	**F2**	Slim Group factor	**F2**	Communication / commercial sector factor	**F2**	Communication / commercial sector factor
F3	Construction sector factor	**F3**	Construction sector factor	**F3**	Radio and television sector factor (Azteca factor)	**F3**	Radio and television sector factor (Azteca factor)
F4	Ordinary consume sector factor	**F4**	Ordinary consume sector factor	**F4**	Financial sector factor (GF Norte Factor)	**F4**	Financial sector factor (GF Norte Factor)
F5	Communication / commercial factor	**F5**	Communication / commercial factor	**F5**	Miscellaneous sectors factor	**F5**	Miscellaneous sectors factor
F6	Infrastructure / Mining sector factor	**F6**	Infrastructure / Mining sector factor	**F6**	Beverage / construction / financial sector factor	**F6**	Beverage / construction / financial sector factor
F7	Ordinary consume / entertainment sector factor	**F7**	Ordinary consume / entertainment sector factor	**F7**	Mining / beverage sector factor	**F7**	Mining sector factor (Peñoles factor).
F8	Miscellaneous sectors factor	**F8**	Miscellaneous sectors factor	**F8**	Leisure / Mining – Holdings - Construction sectors factor	**F8**	Financial / brewers / cellulose sector factor
F9	Capital goods consume / holding sector factor	**F9**	Capital goods consume / holding sector factor	**F9**	Construction / communication / commercial sector factor	**F9**	Construction sector factor

In general, as expected by theory, in both techniques for the four datasets, the first component or factor is clearly related to the market factor[115]. In addition, there is no difference, regarding the interpretation of factors, in the models expressed in returns and those specified in excesses, with the exception of the factor seven, eight and nine extracted via factor analysis in the daily databases[116]. Concerning PCA, we can detect certain stability in the factor attribution until the fourth retained component; however, we can make a distinction regarding the fact that the second and third components are identified with the mining and construction sector, respectively, in the four databases; while, the fourth presents a little different construction between weekly and daily databases. From the fifth to the ninth components we can detect more clear differences in the interpretation of components extracted from the weekly and the daily databases. Respecting FA, there is a marked difference between the interpretation of factors that affect the weekly and daily returns, as we can observe in the Table 4.16. These results lead us to think that in this case the frequency of data affects more the factors extraction and consequently the way in that the covariance matrix is factorized. Relating both techniques, in addition to the first factor, only the third factor might be identified as the same factor for almost all the datasets and expression of the model, which corresponds to the construction sector. We can remark that we can identify two factors related to two important business groups in Mexico, which we may explain as market movers in the Mexican Stock Exchange. These components or factors are the PC5 extracted by PCA from the weekly databases, that it may be understood as the Salinas Group factor; and the F2, extracted by FA, in the weekly datasets, that we may associate with the Slim Group.

[115] In PCA and FA the first component or factor, which is the one that explain the greatest amount of the variability, is usually formed by a combination of all the original variables. In our case, that conformation would be identified with the market factor since it would represent a combination of all the stocks considered in the study.

[116] We consider the same interpretation given that the loadings of the stocks in the construction of the components in these two databases were very similar; nevertheless, the signs of those loadings vary in some cases.

In addition, attending to the explained variance of each components or factors extracted (See Table 4.10), we could select the first three of them in each dataset as the main factors, which lead us to think that: the market factor (for all datasets and both techniques), mining factor (for PCA), the Slim Group and communication/commercial factors (for the weekly and daily datasets using FA, respectively), the construction sector (for PCA and weekly databases in FA), and the radio and television sector factor (for daily databases en FA), could be the most important factors explaining the returns on equities in the Mexican Stock Exchange. These results match approximately with the value of stock market capitalization of these companies and sectors in the Mexican Stock Exchange.

Furthermore, regarding to the results of the other experiments when we vary the number of retained factors, we can remark that in PCA the components retained have the same interpretation that in the experiment when 9 were conserved, fact that responds to the property of this technique of producing the same mathematic solution independently of the number of components extracted; since each extra component added represents only an extra dimension to the solution but without any change to the previously computed artificial synthetic variables. Concerning FA, the interpretation of the factors changed as the number of factors extracted fluctuated, as expected in theory, especially for the estimation technique used in this case, namely Maximum Likelihood[117].

Finally, the stocks that contributed more number of times in the formation of the components and factors estimated in PCA were, in the DBWR: ALFAA with seventeen times, CONTAL* with seven, ELEKTRA* with six and BIMBOA with three; in the DBWE: ALFAA in fifteen occasions, CONTAL* in seven, ELEKTRA* in six, and BIMBOA in three; in the DBDR: ELEKTRA* contributed in eighteen times, CONTAL* and TVAZTECPO in fifteen, and ALFAA in fourteen; finally, in the DBDE: ELEKTRA* eighteen did it in eighteen cases, CONTAL* and TVAZTECPO in

[117] In Maximum Likelihood Factor Analysis if we change the number of factors extracted we will have different solutions or estimations, i.e., the construction of the extracted factors will depend on the number of dimension that we choose to estimate. Consequently, the value and nature of those factors will change depending the dimension selected.

fifteen, and ALFAA in fourteen. ALFA was the stock with the major presence in the formation of the components of the weekly databases, while ELEKTRA* was it in the daily expressions. To the light of these results we dare to point to these stocks as one of the most important securities in our sample, given the frequency of their contribution to the systematic risk factors extracted. Therefore, they would represent securities that should be followed, analyzed and considered for the portfolios management in the context of the Mexican stock markets.

Concerning FA, the number of times that one stock contribute in the formation of a factor is smaller than in PCA. Nevertheless, the analogue results for this technique are as follows. In the weekly databases, the stocks with a clearly higher frequency and the number of times that contributed to the formation of the extracted factors was: CIEB (nine), GEOB (six), and TVAZTECPO (three); in the DBDR, TVAZTECPO (nine) and CIEB (seven), and finally, in the DBDE, TVAZTECPO (12) and GFNORTE and GEOB (four). In this technique, CIEB was the stock the higher number of contributions in the weekly datasets, and TVAZTECACPO in the daily ones.

Accordingly, we can point the importance of the stocks marked in both techniques as important market movers in the sample and period studied.

4.3.5. Results of the econometric contrast.

As stated in Chapter 3, in the first stage of our econometric contrast methodology we estimated the betas or sensitive to the underlying factors to use in expression 4.11[118],

$$\overline{R_i} = \lambda_0 + \lambda_1 \cdot \beta_{1i} + \lambda_2 \cdot \beta_{2i} + ... + \lambda_k \cdot \beta_{ki} + \overline{\varepsilon_i}\,, \tag{4.11}$$

by regressing the factor scores obtained by PCA and FA as a cross-section on the returns and excesses, by way of Weighted Least Squares (WLS) to estimate the entire system of equations at the same time.

[118] Where, β_{jig} represents the sensitivity of equity *i* to factor *j*, F_{jt} the value of the systematic risk factor *j* in time *t* common for all the stocks, and ε_i the idiosyncratic risk affecting only equity *i*.

The results of the regressions in the four databases were suitable, in both PCA and FA estimations, producing, in almost all cases, statistically significant parameters, high values of the R^2 coefficients and results in the Durbin-Watson test of autocorrelation[119], which lead us to the non-rejection of the null hypothesis of no-autocorrelation[120]. Tables 4.17 to 4.20 present the results of the coefficients estimated for PCA and Tables 4.21 to 4.24 the equivalent ones for FA, which represent the betas to use in the second stage of the econometric contrast. All the tables correspond to the case where 9 components or factors were extracted. These tables show the sensitivity of the stock (i) to the risk factor (k). We can observe that in both techniques the values of all sensitivities in the case of beta number one is very similar for all the stocks, since this factor has been related to the market factor. Regarding PCA, we can distinguish the strong sensitivity of PEÑOLES* to beta number two and of GEOB to beta number three in the four databases; and of ALFAA to beta number four in the weekly databases. Nevertheless, analyzing their periodicity, it can be observed that there are differences, for example in the sing of beta number one between the database of weekly returns and the database of daily returns, which imply that the apparently market factor has an indirect relation with the weekly returns, while it has a direct relation with the daily returns. Concerning FA, we can remark that in this case the betas or sensitivities are clearly much smaller than in PCA, in addition, the importance order changes as well.

[119] Value of the statistic more than 2. We are aware of the undefinition of this test related in the sense of the no-autocorrelation zone of order one is clear only with values close to 2, however, for practical reasons and in the context of our study we believe that this test is sufficient.

[120] For reason of saving space the complete results of the simultaneously estimation of the betas when nine factors were extracted is included in Appendix_1; Tables 1 to 4 correspond to PCA and Tables 5 to 8, to FA. The results of the betas estimation for the experiments when eight, seven, six, five, four, three and two factors were extracted are not included in this dissertation; nevertheless, the results are similar to those reported in this chapter.

Table 4.17. *Principal Component Analysis. Betas estimated simultaneously via Weighted Least Squares. Database of weekly returns.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.126897	0.914852	0.318767	0.038830	-0.072420	0.105669	-0.119725	0.020960	-0.064335
BIMBOA	-0.113679	-0.020017	0.201671	-0.012999	0.179627	-0.232653	0.586068	-0.005175	-0.530716
GMODELOC	-0.097420	-0.038412	0.070841	0.047867	-0.128884	0.049686	-0.150310	0.140175	0.089890
FEMSAUBD	-0.211808	-0.067626	0.105197	-0.099098	0.030042	0.013647	0.127503	0.166489	-0.016027
CONTAL*	-0.132309	0.080728	0.075499	0.160585	0.241953	-0.445564	0.223491	0.318993	0.659808
GEOB	-0.293667	0.269049	-0.765574	-0.367746	0.099028	0.015674	0.139301	0.122664	-0.033579
ARA*	-0.153875	0.081291	-0.077583	-0.012444	0.211205	0.069702	0.149491	-0.290541	0.208249
WALMEXV	-0.191070	-0.098287	0.061952	-0.077264	-0.087542	0.142707	-0.030179	0.348935	-0.009896
SORIANAB	-0.227527	-0.096796	0.060851	-0.172514	-0.023314	-0.058331	-0.335898	0.072029	-0.152850
COMERUBC	-0.216157	-0.012800	0.121731	-0.001803	0.079592	-0.311785	-0.236521	-0.197895	-0.068402
ELEKTRA*	-0.306461	0.016709	-0.160190	0.358791	-0.508578	-0.184630	0.221530	-0.459268	0.070003
TELMEXL	-0.170229	-0.064603	0.161386	-0.077970	-0.068125	0.260308	0.136312	0.003331	0.081760
TELECOA1	-0.233999	-0.081362	0.226844	-0.088706	-0.029744	0.401071	0.267766	-0.093510	0.115624
TLEVICPO	-0.275543	-0.080797	0.119662	-0.125244	-0.140376	0.136611	0.128401	0.344072	-0.020949
TVAZTCPO	-0.301458	-0.071828	-0.053150	0.088748	-0.454739	-0.222687	-0.094510	0.208810	-0.152757
GFNORTEO	-0.201459	-0.069185	-0.075840	-0.110932	-0.021209	0.085079	-0.318333	-0.141737	0.126113
GFINBURO	-0.188846	-0.038797	0.043815	-0.233515	0.257862	0.096592	-0.005313	-0.361445	-0.023839
GCARSOA1	-0.236767	-0.126960	0.166017	-0.077609	0.001292	0.162087	-0.030264	-0.173170	0.284472
ALFAA	-0.328798	-0.056609	-0.157671	0.706323	0.446003	0.256539	-0.169384	0.122174	-0.203166
CIEB	-0.263305	-0.059289	0.202602	-0.226510	0.246870	-0.409671	-0.214977	-0.086764	-0.102380

Table 4.18. *Principal Component Analysis. Betas estimated simultaneously via Weighted Least Squares. Database of weekly excesses.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.128621	0.914825	0.318410	0.038227	-0.072042	0.105108	-0.119753	0.020881	-0.064310
BIMBOA	-0.114174	-0.019511	0.201153	-0.013230	0.179744	-0.231994	0.588670	-0.004762	-0.529515
GMODELOC	-0.097772	-0.038033	0.070472	0.047743	-0.129052	0.050038	-0.151242	0.140286	0.087455
FEMSAUBD	-0.211574	-0.067898	0.104672	-0.099130	0.030077	0.013791	0.127362	0.166301	-0.015360
CONTAL*	-0.132138	0.080704	0.073680	0.161726	0.240403	-0.444461	0.222137	0.318488	0.661647
GEOB	-0.294405	0.268035	-0.766692	-0.365744	0.098299	0.016143	0.139059	0.122631	-0.033239
ARA*	-0.154042	0.081230	-0.078866	-0.011561	0.210551	0.070341	0.148204	-0.290667	0.206675
WALMEXV	-0.190599	-0.098560	0.061326	-0.077239	-0.087619	0.142942	-0.031129	0.348821	-0.011707
SORIANAB	-0.227958	-0.096911	0.061563	-0.173264	-0.022293	-0.059432	-0.334488	0.072405	-0.153292
COMERUBC	-0.216331	-0.012994	0.121894	-0.002108	0.079854	-0.312504	-0.235258	-0.197525	-0.070837
ELEKTRA*	-0.306127	0.015574	-0.159193	0.359006	-0.509815	-0.183407	0.220635	-0.459446	0.069949
TELMEXL	-0.170090	-0.064637	0.161012	-0.078322	-0.067872	0.260675	0.135428	0.003209	0.081848
TELECOA1	-0.233816	-0.081624	0.226978	-0.089406	-0.029093	0.401360	0.267023	-0.093712	0.117564
TLEVICPO	-0.275457	-0.081309	0.120165	-0.125915	-0.139772	0.136608	0.128621	0.343970	-0.019275
TVAZTCPO	-0.301306	-0.072680	-0.051863	0.088200	-0.454759	-0.222681	-0.093589	0.208999	-0.152320
GFNORTEO	-0.201024	-0.069594	-0.076854	-0.110365	-0.021605	0.084983	-0.320213	-0.141859	0.120912
GFINBURO	-0.188711	-0.038977	0.042821	-0.233256	0.258189	0.096026	-0.005264	-0.361612	-0.022350
GCARSOA1	-0.236775	-0.127194	0.166393	-0.078233	0.001903	0.161825	-0.030778	-0.173324	0.286234
ALFAA	-0.328755	-0.057635	-0.155695	0.706754	0.445655	0.255859	-0.169158	0.122277	-0.203508
CIEB	-0.262681	-0.059909	0.201921	-0.226608	0.247301	-0.411142	-0.213159	-0.086897	-0.099466

Table 4.19. *Principal Component Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of daily returns.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.117277	-0.973511	0.096652	-0.100518	0.085719	-0.086521	0.000798	0.012306	-0.029220
KIMBERA	0.117706	-0.004097	0.009729	0.181604	0.033397	-0.042078	0.012899	0.010925	0.113274
BIMBOA	0.148436	-0.036119	-0.015305	0.231567	-0.008874	0.152692	0.107816	0.334676	0.138036
GMODELOC	0.129918	-0.006767	0.095008	0.080014	0.021540	0.001719	-0.062749	-0.171372	0.003197
FEMSAUBD	0.197091	0.047015	0.044271	0.039223	0.018307	-0.120970	-0.089376	-0.050793	0.075617
CONTAL*	0.132065	-0.115742	0.034728	0.510560	-0.510300	0.536398	-0.203487	-0.156846	-0.186973
CEMEXCP	0.180871	0.022931	0.014058	0.036934	-0.006984	-0.026538	-0.041823	-0.072307	-0.081715
GEOB	0.225849	-0.059157	-0.891996	-0.168168	-0.112279	0.010028	-0.202801	0.006027	0.116431
ARA*	0.163555	-0.001398	-0.198275	0.075148	0.025236	-0.058643	0.037707	0.190285	-0.385155
WALMEXV	0.224860	0.027891	0.066353	0.061221	0.064257	-0.107477	-0.162189	-0.101101	-0.027224
SORIANAB	0.218567	0.013687	0.024749	0.088093	0.033299	-0.113927	-0.018807	-0.107152	0.198334
COMERUBC	0.194787	-0.004795	-0.047340	0.106974	0.089717	0.088346	0.375847	-0.638845	0.281432
ELEKTRA*	0.294896	0.032482	0.089370	-0.417701	-0.409545	0.135759	0.551258	0.116898	-0.161634
TELMEXL	0.190876	0.040909	0.088137	0.034310	0.074800	-0.121430	-0.213092	-0.029400	-0.082459
TELECOA1	0.251475	0.045548	0.098991	0.076606	0.171658	-0.132722	-0.192538	0.006824	-0.106576
TLEVICPO	0.297633	0.085528	0.110027	-0.112249	-0.109032	-0.174872	-0.322397	-0.024119	-0.076632
TVAZTCPO	0.313603	0.080714	0.258394	-0.360452	-0.351377	-0.082768	-0.200247	0.048858	0.211246
GFNORTEO	0.213796	0.060403	-0.123404	0.044131	0.148043	-0.203432	0.279897	-0.312871	-0.348748
GFINBURO	0.178957	0.053846	-0.011782	0.209839	0.137777	-0.065131	0.199550	0.284825	-0.399761
GCARSOA1	0.221710	0.035970	0.107254	0.140309	0.136466	-0.071374	0.011392	0.051382	-0.010589
ALFAA	0.278485	0.061667	0.055725	-0.271528	0.553027	0.682432	-0.081255	0.103866	0.061710
CIEB	0.228982	0.003136	-0.036193	0.336151	-0.013054	-0.154383	0.259536	0.387151	0.508508

Table 4.20. *Principal Component Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of daily excesses.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.118079	-0.972958	0.104142	-0.098391	0.086144	-0.084324	0.005527	-0.012651	0.026767
KIMBERA	0.117683	-0.004750	0.007423	0.181685	0.034709	-0.043325	0.014334	-0.010684	-0.116744
BIMBOA	0.148554	-0.034117	-0.014533	0.231737	-0.013885	0.154609	0.109080	-0.335570	-0.133567
GMODELOC	0.129964	-0.005979	0.093587	0.080585	0.022776	-0.000220	-0.064565	0.170599	-0.005777
FEMSAUBD	0.197273	0.049943	0.041920	0.036959	0.020576	-0.119149	-0.090113	0.045387	-0.069830
CONTAL*	0.132031	-0.113837	0.039342	0.516046	-0.519924	0.517525	-0.212240	0.158831	0.191227
CEMEXCP	0.180710	0.022115	0.014048	0.037865	-0.005807	-0.029204	-0.040273	0.073900	0.078389
GEOB	0.225912	-0.066407	-0.888977	-0.175217	-0.117905	0.015256	-0.204086	-0.015031	-0.113109
ARA*	0.163461	-0.004470	-0.199365	0.074394	0.025915	-0.059798	0.044059	-0.182403	0.393722
WALMEXV	0.224583	0.025755	0.063868	0.062880	0.068832	-0.112600	-0.159478	0.101917	0.018598
SORIANAB	0.218870	0.015463	0.020838	0.085677	0.035730	-0.111448	-0.021350	0.102211	-0.197457
COMERUBC	0.194981	-0.004605	-0.051674	0.103868	0.087896	0.095774	0.363958	0.642165	-0.303190
ELEKTRA*	0.294716	0.034451	0.098407	-0.417046	-0.414493	0.136446	0.549216	-0.105643	0.155258
TELMEXL	0.190680	0.039544	0.086025	0.036033	0.079554	-0.126301	-0.209399	0.029353	0.078784
TELECOA1	0.251431	0.044788	0.094781	0.077718	0.176687	-0.135186	-0.188568	-0.006760	0.104312
TLEVICPO	0.297497	0.085533	0.109895	-0.110632	-0.103030	-0.183195	-0.319764	0.021612	0.079015
TVAZTCPO	0.313559	0.083178	0.261388	-0.359072	-0.347054	-0.091471	-0.204962	-0.053859	-0.204059
GFNORTEO	0.213831	0.060804	-0.127953	0.039005	0.150508	-0.194530	0.280767	0.317314	0.356557
GFINBURO	0.178692	0.053612	-0.010548	0.211963	0.136967	-0.063631	0.213966	-0.275140	0.387564
GCARSOA1	0.221816	0.038297	0.105070	0.140427	0.137694	-0.068860	0.014821	-0.052385	0.007832
ALFAA	0.278381	0.061437	0.060906	-0.266147	0.539109	0.694619	-0.091003	-0.107861	-0.049547
CIEB	0.229171	0.005552	-0.041423	0.332039	-0.012116	-0.149154	0.261816	-0.390327	-0.502186

Table 4.21. *Factor Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of weekly returns.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.009629	0.004203	0.008389	0.003289	-0.002067	0.015692	-0.007586	0.013560	-0.006778
BIMBOA	0.009749	0.009747	0.001816	0.007814	0.001202	-0.004691	-0.002888	0.011802	-0.002531
GMODELOC	0.021039	-0.000397	-0.000014	-0.023029	-0.007402	0.000028	-0.000017	0.000003	-0.000008
FEMSAUBD	0.019823	0.013886	0.014335	0.000535	0.000828	-0.006752	0.007700	0.006005	0.001701
CONTAL*	0.012749	0.004389	0.008250	0.003650	-0.000274	0.000027	-0.003368	0.011949	0.003770
GEOB	0.023693	0.010908	0.030054	0.007289	0.009365	0.029412	-0.001585	-0.004425	-0.008015
ARA*	0.012591	0.010341	0.009801	0.005938	-0.001875	0.007792	-0.002889	0.003796	0.003231
WALMEXV	0.019203	0.012218	0.008153	0.002408	0.004630	-0.005041	0.015460	-0.001604	-0.000659
SORIANAB	0.025828	0.009555	0.009876	0.003841	0.001350	-0.006021	0.001045	-0.008807	-0.002127
COMERUBC	0.033530	-0.000911	-0.000259	0.023501	-0.019347	0.000052	0.000027	-0.000006	-0.000023
ELEKTRA*	0.032444	0.009432	0.008058	0.005220	0.011134	0.009093	-0.000512	0.006245	0.014227
TELMEXL	0.017544	0.020703	-0.003978	0.000488	0.002824	-0.000627	0.002124	0.000251	-0.002132
TELECOA1	0.022022	0.035284	-0.008214	0.000758	0.001975	0.002018	-0.001889	-0.000136	-0.000471
TLEVICPO	0.028704	0.017759	0.008797	0.002722	0.007136	-0.003890	0.012450	0.004494	-0.004526
TVAZTCPO	0.043241	-0.001596	-0.000411	0.005152	0.029489	-0.000012	-0.000079	-0.000009	-0.000034
GFNORTEO	0.020388	0.009793	0.010042	0.004801	0.001086	0.001053	0.002760	-0.009402	0.004587
GFINBURO	0.014630	0.016462	0.012985	0.006573	0.000535	-0.003244	-0.006876	-0.005041	0.001921
GCARSOA1	0.023859	0.019062	0.004728	0.002876	0.002349	-0.005364	-0.001397	-0.005880	0.009357
ALFAA	0.030779	0.014388	0.013717	0.004327	0.003554	0.004867	0.000977	0.004957	0.014523
CIEB	0.027029	0.012200	0.019444	0.006150	0.000869	-0.016698	-0.014130	0.001197	-0.004561

Table 4.22. *Factor Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of weekly excesses.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.009629	0.004203	0.008389	0.003289	-0.002067	0.015692	-0.007586	0.013560	-0.006778
BIMBOA	0.009749	0.009747	0.001816	0.007814	0.001202	-0.004691	-0.002888	0.011802	-0.002531
GMODELOC	0.021039	-0.000397	-0.000014	-0.023029	-0.007402	0.000028	-0.000017	0.000003	-0.000008
FEMSAUBD	0.019823	0.013886	0.014335	0.000535	0.000828	-0.006752	0.007700	0.006005	0.001701
CONTAL*	0.012749	0.004389	0.008250	0.003650	-0.000274	0.000027	-0.003368	0.011949	0.003770
GEOB	0.023693	0.010908	0.030054	0.007289	0.009365	0.029412	-0.001585	-0.004425	-0.008015
ARA*	0.012591	0.010341	0.009801	0.005938	-0.001875	0.007792	-0.002889	0.003796	0.003231
WALMEXV	0.019203	0.012218	0.008153	0.002408	0.004630	-0.005041	0.015460	-0.001604	-0.000659
SORIANAB	0.025828	0.009555	0.009876	0.003841	0.001350	-0.006021	0.001045	-0.008807	-0.002127
COMERUBC	0.033530	-0.000911	-0.000259	0.023501	-0.019347	0.000052	0.000027	-0.000006	-0.000023
ELEKTRA*	0.032444	0.009432	0.008058	0.005220	0.011134	0.009093	-0.000512	0.006245	0.014227
TELMEXL	0.017544	0.020703	-0.003978	0.000488	0.002824	-0.000627	0.002124	0.000251	-0.002132
TELECOA1	0.022022	0.035284	-0.008214	0.000758	0.001975	0.002018	-0.001889	-0.000136	-0.000471
TLEVICPO	0.028704	0.017759	0.008797	0.002722	0.007136	-0.003890	0.012450	0.004494	-0.004526
TVAZTCPO	0.043241	-0.001596	-0.000411	0.005152	0.029489	-0.000012	-0.000079	-0.000009	-0.000034
GFNORTEO	0.020388	0.009793	0.010042	0.004801	0.001086	0.001053	0.002760	-0.009402	0.004587
GFINBURO	0.014630	0.016462	0.012985	0.006573	0.000535	-0.003244	-0.006876	-0.005041	0.001921
GCARSOA1	0.023859	0.019062	0.004728	0.002876	0.002349	-0.005364	-0.001397	-0.005880	0.009357
ALFAA	0.030779	0.014388	0.013717	0.004327	0.003554	0.004867	0.000977	0.004957	0.014523
CIEB	0.027029	0.012200	0.019444	0.006150	0.000869	-0.016698	-0.014130	0.001197	-0.004561

Table 4.23. *Factor Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of daily returns.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.004406	0.001995	0.002206	0.002532	0.003044	0.001843	0.005437	0.003992	0.000570
KIMBERA	0.006252	0.001452	0.003115	0.001575	0.000684	0.001334	0.001781	-0.002668	0.001112
BIMBOA	0.007350	0.002033	0.002759	0.001877	0.003416	0.000856	0.000491	0.001596	-0.000844
GMODELOC	0.006974	0.001412	0.001527	0.001408	-0.003040	0.001587	0.003316	-0.000530	0.000227
FEMSAUBD	0.010816	0.001894	0.001182	-0.001317	-0.001098	0.004127	-0.002428	-0.001104	-0.002131
CONTAL*	0.006177	0.002546	0.001894	0.002714	0.002886	0.003102	0.004032	0.002289	0.000442
CEMEXCP	0.009883	0.001615	0.001175	-0.003057	0.000586	0.003264	-0.000190	0.000397	-0.001545
GEOB	0.010238	0.004078	0.002680	-0.003554	0.002849	-0.000616	0.000357	0.003062	0.002278
ARA*	0.008084	0.002684	0.002378	-0.002897	0.003426	-0.000448	-0.001327	0.001889	0.003203
WALMEXV	0.012047	0.002804	0.001747	0.001271	-0.004371	0.001190	0.000206	0.000992	0.002504
SORIANAB	0.011291	0.003894	0.001791	0.001600	-0.001580	0.000239	-0.000366	-0.000317	-0.000795
COMERUBC	0.009443	0.003613	0.002724	-0.001013	0.000223	-0.000641	0.001908	0.000928	-0.002796
ELEKTRA*	0.014104	0.006692	-0.002196	-0.001233	0.001050	-0.001434	0.000919	0.002105	-0.002324
TELMEXL	0.012857	-0.006884	-0.000509	-0.000201	0.000469	0.000112	0.000343	-0.000223	-0.000086
TELECOA1	0.015022	-0.003426	0.001394	0.001868	-0.000755	-0.002844	-0.000728	0.001070	-0.000077
TLEVICPO	0.016463	0.002259	-0.003104	-0.001938	-0.000845	0.002342	-0.001872	0.000164	0.002888
TVAZTCPO	0.016902	0.006641	-0.010784	0.001135	0.000812	-0.001268	0.000815	-0.001061	-0.000210
GFNORTEO	0.010954	0.003613	0.004103	-0.005958	-0.001681	-0.004571	0.002340	-0.002739	-0.000016
GFINBURO	0.009040	0.002436	0.003206	0.000578	0.001108	-0.002706	-0.002680	0.001036	-0.000281
GCARSOA1	0.011721	0.002417	0.002930	0.003680	-0.002162	-0.001671	-0.002181	0.000656	-0.000699
ALFAA	0.013488	0.003696	0.000707	-0.000110	-0.000648	-0.001457	-0.000046	0.003773	-0.001701
CIEB	0.011381	0.004892	0.004317	0.003249	0.004715	-0.000265	-0.001385	-0.004385	0.000550

Table 4.24. *Factor Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of daily excesses.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.004509	0.001781	0.002272	0.002361	0.002484	0.003027	0.007124	0.002491	-0.001249
KIMBERA	0.006293	0.001244	0.003108	0.001556	0.000052	0.001429	-0.001345	0.003250	-0.000639
BIMBOA	0.007417	0.001782	0.002702	0.001889	0.003077	0.001926	0.001242	-0.000221	0.001125
GMODELOC	0.007019	0.001161	0.001488	0.001424	-0.003584	0.000699	0.001481	0.002828	0.000128
FEMSAUBD	0.010844	0.001479	0.001054	-0.001073	-0.001880	0.003126	-0.002038	-0.001319	0.000825
CONTAL*	0.006236	0.002372	0.001846	0.002503	0.001658	0.003953	0.003432	0.002108	0.000602
CEMEXCP	0.009964	0.001421	0.001285	-0.003376	-0.000498	0.003859	-0.000399	-0.000721	0.002194
GEOB	0.010376	0.003901	0.002967	-0.003435	0.003323	0.000238	0.003506	-0.001502	-0.004135
ARA*	0.008145	0.002448	0.002454	-0.002498	0.003363	0.000505	0.000599	-0.001791	-0.003042
WALMEXV	0.012111	0.002382	0.001750	0.001500	-0.004465	0.000063	0.000872	-0.000556	-0.002282
SORIANAB	0.011419	0.003480	0.001766	0.001702	-0.001497	-0.000191	-0.000162	-0.000264	-0.000089
COMERUBC	0.009554	0.003301	0.002768	-0.000925	0.000286	-0.000371	0.001919	0.000659	0.002195
ELEKTRA*	0.014264	0.006459	-0.002070	-0.001111	0.001346	-0.000928	0.002140	-0.000696	0.002382
TELMEXL	0.012604	-0.006993	-0.000670	-0.000321	0.000434	0.000262	0.000010	0.000483	0.000058
TELECOA1	0.014978	-0.004053	0.001229	0.001935	0.000303	-0.002807	0.000728	-0.001107	0.000090
TLEVICPO	0.016500	0.001843	-0.003072	-0.001738	-0.001395	0.001865	-0.001217	-0.001517	-0.002720
TVAZTCPO	0.017049	0.006434	-0.010730	0.000871	0.001013	-0.001082	-0.000274	0.001362	0.000286
GFNORTEO	0.011103	0.003340	0.004402	-0.006111	-0.000750	-0.005231	-0.000627	0.003106	0.000292
GFINBURO	0.009111	0.002167	0.003245	0.000850	0.001925	-0.002113	-0.001223	-0.002835	0.001295
GCARSOA1	0.011811	0.001948	0.002834	0.003967	-0.001470	-0.002066	-0.000809	-0.002211	0.000920
ALFAA	0.013595	0.003317	0.000744	0.000140	-0.000110	-0.001185	0.002895	-0.002432	0.001845
CIEB	0.011516	0.004459	0.004229	0.003238	0.004426	0.000783	-0.004171	0.001939	-0.000817

Continuing with the methodology described in Chapter 3, in the second stage of the econometric contrast, we estimated the lambdas or risk premiums in expression 4.11 by regressing the betas obtained in the first stage as a cross-section on the returns and excesses, using ordinary least squared corrected by heteroscedasticity and autocorrelation by means of the Newey-West heteroscedasticity and autocorrelation consistent covariance estimates (HEC). Additionally, we verified the normality in the residuals by carrying out the Jarque-Bera test of normality and we used the Wald test to confirm the equalities assumed by the APT regarding the independent term.

In Tables 4.25 and 4.26, we present a summary of the results of the econometric contrast for PCA and in Table 4.27 and 4.28 for FA. The results of the explanation power, the adjusted R-squared (R^{2*}), the statistical significance of the multivariate test (F), and the Jarque-Bera normality test of the residuals are suitable in all the contrasted models, except in the cases where only two factors were extracted using PCA; nevertheless, using FA there are more models that do not produce a good level of explanation and they are not statistically significant in multivariate terms. The univariate tests for the individual statistical significance of the parameters (Statistic t) priced from one to six factors different from λ_0 in PCA and from one to eight in MLFA, thus giving evidence in favor of the APT in 30 models using PCA and 27 utilizing FA. The total number of tested models was 32. Nevertheless, only three models in PCA and three in MLFA fulfilled both the statistical significance of the parameters and the equality of the independent term to its theoretic value, in addition to the fulfilment of normality in the residuals. Concerning the PCA these models were the one expressed in weekly returns when seven components were extracted and those expressed in daily returns when three, and nine components were retained. Regarding the MLFA those models were the ones using five factors in the weekly returns database, and eight and nine, in the daily returns dataset. Expressions in excesses did not produce any model that fulfil all the conditions to be completely accepted as valid.

We can make cross validation of the accepted models and the interpretation of factors under the approach proposed above, although we have to make a distinction first. Table 4.13 represents our interpretation of the extracted factors when nine components were estimated, and in the case of PCA the same interpretation works for the cases of the models that were completely accepted under this technique, despite they correspond to experiments were a different number of components were computed, i.e. seven, six and three. This fact is derived by the property of PCA explained in the interpretation section about the unique mathematical solution produced by PCA, that implies that additional dimensions do not affect the previously components computed, and only add an extra dimension to the new projected space. Nevertheless, for FA and the rest of the techniques used in this dissertation the mathematical solutions will depend of the number of components or factors estimated.

Consequently, we can state de following about the proposed cross validation: The significant components that affect the weekly model accepted in PCA, are the mining and construction sector factor. For the accepted daily models expressed in returns, the previous components are significant as well; additionally, the model with nine factors is affected by the entertainment consume, the holding-beverage-Salinas group, and infrastructure-financial sector factors.

Concerning the accepted models in FA, for reason of saving space, the tables including the interpretation when five and eight factors were estimated and that correspond to the models completely accepted, one in the database of weekly returns and the other of the database of daily returns, are not included in the body of this document[121]; however, under the same methodology illustrated for the case of the experiment when nine factors were extracted, we can state the following. In the model with five factors of the weekly database of returns, the significant factors would be the market one, and a factor that contrasts the construction with the leisure sector.

[121] Interested reader can consult the tables with the interpretation for all the experiments in the electronic appendix of this dissertation.

Finally, for the daily databases of returns, those would be represented by the construction materials and the leisure sector factors, in the case of the model using 8 betas; and one factor that combine the holdings and beverage sector with the Salinas Group, and another one that contrasts the leisure sector to the mining-holdings-construction sectors, in the case of the model with 9 betas.

On the other hand, making a cross validation that relates the significant factors in the accepted models with the factors that explain the major amount of variance in their corresponding estimation, i.e., the first three components or factors, we can conclude that in the case of PCA only the significant factors related to the mining and construction sectors, correspond to the second and third components, while in FA, only the significant factor related to the market corresponded to the first one.

Regarding the risk premiums (lambdas) we can observe that in the accepted models, the sensitivities to the extracted risk factors (betas) produce both positive and negative effects in the average returns of the stocks studied, although in most of the cases the relation is inverse (negative); i.e., increases in the values of the betas will produce reductions in the average returns. Regarding the values of these lambdas in all cases they present undersized values, which it may be explained by the periodicity of the datasets used in the study. For example, the results of the model with seven factors, imply that a change of one unity of risk related to the mining sector risk factor would produce a variation of 0.0029 in the average logarithmic weekly returns of the stocks considered, and a change of one unity of risk related to the construction sector risk factor would generate a decrease of 0.0077 in those rates of returns. In PCA the values of risk premiums in the accepted models ranged from -0.0077 to 0.0029 in weekly models and from -0.0013 to -0.0005 in daily expressions. In FA, those values fluctuated from 0.0007 to 0.2107 in the weekly databases, and from -0.1435 to 0.0546, in daily definitions.

Additionally, in Tables 4.25 to 4.28, in order to establish a ratio that serves as an indicator of the relevance of the factors considered in each model, we also included a column with the percentage of factors statistically significant in relation to the total number of parameters estimated in the model. For the accepted models, this ratio ranged from about 28% to 66% of statistically significant estimated factors in the models accepted in the case of PCA, and from around 22% to 40%, in the case of FA.

Finally, calls the attention that market factor was statistically significant only in one of the accepted models; further research would be needed about this issue, as well as about the meaning of the undersized value and signs of the estimated individual parameters.

To summarize, for the sample and periods considered, we can accept only partially the validity of the APT using PCA and FA as a pricing model explaining the average returns (and returns in excesses) on equities of the Mexican Stock Exchange. On the other hand, the evidence showed that the APT is very sensitive to the number of factors extracted and to the periodicity and expression of the models.

Table 4.25. *Principal Component Analysis. Summary of the econometric contrast. Weekly databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{2*}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of weekly returns.															
Model with 2 betas	●	●	●								6.62%	0.00%	●	○	○
Model with 3 betas	0.00563	●	0.00296	-0.00770							51.99%	66.67%	○	●	○
Model with 4 betas	0.00574	●	0.00292	-0.00777	●						49.02%	50.00%	○	●	○
Model with 5 betas	0.00551	●	0.00300	-0.00762	●	●					46.62%	40.00%	○	●	○
Model with 6 betas	0.00572	●	0.00292	-0.00775	●	●	●				57.27%	33.33%	○	●	○
Model with 7 betas	0.00574	●	0.00292	-0.00776	●	●	●	●			53.72%	28.57%	○	○	○
Model with 8 betas	0.00583	●	0.00288	-0.00783	●	●	●	●	●		53.57%	25.00%	○	●	○
Model with 9 betas	0.00579	●	0.00290	-0.00780	●	●	●	●	●	●	48.98%	22.22%	○	●	○
Database of weekly excesses.															
Model with 2 betas	●	●	●								6.62%	0.00%	●	○	○
Model with 3 betas	0.00392	●	0.00298	-0.00769							51.99%	66.67%	○	●	○
Model with 4 betas	0.00403	●	0.00294	-0.00776	●						49.03%	50.00%	○	●	○
Model with 5 betas	●	●	0.00303	-0.00761	●	●					46.62%	40.00%	○	●	○
Model with 6 betas	0.00402	●	0.00295	-0.00775	●	●	●				57.35%	33.33%	○	●	○
Model with 7 betas	●	●	0.00294	-0.00776	●	●	0.00322	●			53.80%	57.14%	○	○	○
Model with 8 betas	●	●	0.00290	-0.00782	●	●	●	●	●		80.53%	25.00%	○	●	○
Model with 9 betas	●	●	0.00292	-0.00780	●	●	●	●	●	●	49.05%	22.22%	○	●	○

Notes:

* The level of statistical significance used in all the tests was 5%.

λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Non-rejection of H_0. Parameter not significant

R^{2*}: Explanatory capacity of the model.

$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.

F: Global statistical significance of the model. $H_0 = \lambda_2 = \lambda_3 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Non-rejection of H_0. Model globally not significant.

Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Non-rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.

J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Non-rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

Table 4.26. *Principal Component Analysis. Summary of the econometric contrast. Daily databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{2*}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of daily returns.															
Model with 2 betas	●	●	-0.00049								7.96%	50.00%	●	○	○
Model with 3 betas	0.00053	●	-0.00057	-0.00137							41.29%	66.67%	○	○	○
Model with 4 betas	●	●	●	-0.00129	●						48.22%	25.00%	○	○	○
Model with 5 betas	●	●	●	-0.00130	●	●					49.15%	20.00%	○	●	○
Model with 6 betas	●	●	●	-0.00130	●	●	●				46.66%	16.67%	○	○	○
Model with 7 betas	●	●	●	-0.00130	●	●	●	●			43.35%	14.29%	○	○	○
Model with 8 betas	●	●	●	-0.00131	●	●	●	●	●		65.02%	12.50%	○	○	○
Model with 9 betas	0.00066	●	-0.00050	-0.00136	-0.00051	0.00041	●	●	●	-0.00094	70.55%	55.56%	○	○	○
Database of daily excesses.															
Model with 2 betas	●	●	-0.00052								-1.42%	50.00%	●	○	○
Model with 3 betas	●	●	-0.00061	-0.00141							42.28%	66.67%	○	○	●
Model with 4 betas	●	●	●	-0.00132	●						49.80%	25.00%	○	○	○
Model with 5 betas	●	●	●	-0.00132	●	●					50.60%	20.00%	○	○	○
Model with 6 betas	●	●	●	-0.00133	●	●	●				48.44%	100.00%	○	○	○
Model with 7 betas	●	●	●	-0.00130	●	●	●	●			43.35%	14.29%	○	○	○
Model with 8 betas	●	●	●	-0.001343	●	●	●	●	●		45.03%	12.50%	○	○	○
Model with 9 betas	●	●	-0.00052	-0.001391	-0.00055	0.00041	●	●	●	0.00097	73.51%	55.56%	○	○	○

Notes:

* The level of statistical significance used in all the tests was 5%.

λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Non-rejection of H_0. Parameter not significant

R^{2*}: Explanatory capacity of the model.

$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.

F: Global statistical significance of the model. $H_0 = \lambda_2 = \lambda_3 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Non-rejection of H_0. Model globally not significant.

Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Non-rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.

J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Non-rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

Table 4.27. *Factor Analysis. Summary of the econometric contrast. Weekly databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{*2}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of weekly returns.															
Model with 2 betas	0.00457	●	●								0.20%	0.00%	●	●	○
Model with 3 betas	0.00337	●	●	0.12722							11.05%	33.33%	●	○	○
Model with 4 betas	0.00376	●	●	●	0.13780						14.79%	25.00%	●	○	○
Model with 5 betas	0.00309	-0.07078	●	●	●	0.21077					52.58%	40.00%	○	○	○
Model with 6 betas	0.00424	-0.09734	●	●	●	0.20782	-0.13978				68.40%	50.00%	○	●	○
Model with 7 betas	0.00473	●	●	●	-0.15198	-0.06563	0.07245	●			69.06%	42.86%	○	●	○
Model with 8 betas	0.00593	-0.10643	-0.05528	-0.06844	0.12686	-0.08073	0.09068	0.07573	0.17361		80.71%	100.00%	○	●	○
Model with 9 betas	0.00590	-0.14932	●	●	0.05005	●	0.16900	0.09160	-0.11678	0.10175	77.77%	66.67%	○	●	○
Database of weekly excesses.															
Model with 2 betas	0.00287	●	●								0.05%	0.00%	●	●	○
Model with 3 betas	●	●	●	0.12758							11.09%	33.33%	●	○	○
Model with 4 betas	0.00205	-0.05436	-0.00193	0.02853	●						14.81%	75.00%	●	○	○
Model with 5 betas	●	-0.07021	●	●	●	0.20969					52.20%	40.00%	○	○	●
Model with 6 betas	0.00255	-0.09697	●	●	●	0.20709	●				68.38%	33.33%	○	●	○
Model with 7 betas	0.00304	●	●	●	-0.15182	-0.06446	●	●			69.00%	28.57%	○	●	○
Model with 8 betas	0.00424	-0.10598	-0.05599	-0.06776	0.12691	-0.08090	0.08932	0.07557	0.17512		80.76%	100.00%	○	●	○
Model with 9 betas	0.00421	-0.14882	●	0.04280	0.04998	●	0.16767	0.09366	-0.11721	0.10273	77.84%	77.78%	○	●	○

Notes:
* The level of statistical significance used in all the tests was 5%.
λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Non-rejection of H_0. Parameter not significant
R^{2*}: Explanatory capacity of the model.
$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.
F: Global statistical significance of the model. $H_0 = \lambda_1 = \lambda_2 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Non-rejection of H_0. Model globally not significant.
Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Non-rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.
J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Non-rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

Table 4.28. *Factor Analysis. Summary of the econometric contrast. Daily databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{*2}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of daily returns.															
Model with 2 betas	0.00094	-0.04908	●								2.31%	50.00%	●	●	○
Model with 3 betas	0.00086	-0.03853	0.02121	0.01201							-2.64%	100.00%	●	○	○
Model with 4 betas	0.00043	0.00113	0.02701	0.05664	0.06924						5.03%	100.00%	●	○	○
Model with 5 betas	●	●	●	●	0.10101	●					23.10%	20.00%	●	○	○
Model with 6 betas	●	●	●	●	●	●	0.05257				33.30%	16.67%	●	○	○
Model with 7 betas	0.00107	-0.05676	●	●	-0.12533	0.07379	●	0.05998			65.17%	57.14%	○	●	○
Model with 8 betas	0.00078	●	●	●	●	0.05464	-0.14354	●	●		71.69%	25.00%	○	○	○
Model with 9 betas	0.00092	●	●	●	-0.1086	●	●	●	0.1059	●	70.26%	22.22%	○	○	○
Database of daily excesses.															
Model with 2 betas	0.00072	-0.04878	●								1.65%	50.00%	●	●	○
Model with 3 betas	●	●	●	●							42.28%	66.67%	●	○	○
Model with 4 betas	●	●	●	●	●						3.51%	0.00%	●	○	○
Model with 5 betas	●	●	●	●	0.10455	●					23.14%	20.00%	○	○	○
Model with 6 betas	●	●	●	●	●	●	●				32.27%	0.00%	●	○	○
Model with 7 betas	0.00087	-0.05971	●	●	-0.13575	●	0.06580	0.07526			67.22%	57.14%	○	●	○
Model with 8 betas	0.00084	-0.05614	●	●	0.06366	●	-0.14532	0.03899	●		75.19%	50.00%	○	●	○
Model with 9 betas	0.0008	●	●	●	-0.10328	●	●	0.09296	-0.07264	●	77.63%	33.33%	○	●	○

Notes:
* The level of statistical significance used in all the tests was 5%.
λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Non-rejection of H_0. Parameter not significant
R^{2*}: Explanatory capacity of the model.
$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.
F: Global statistical significance of the model. $H_0 = \lambda_1 = \lambda_2 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Non-rejection of H_0. Model globally not significant.
Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Non-rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.
J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Non-rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

4.4 Conclusions

In general, and in accordance with the scope and limitations of this study, the generative multifactor model of returns estimated by means of PCA and FA was capable to reproduce the observed returns on equities of our sample; thus we can state that both techniques performed an outstanding extraction of the underlying systematic risk factors driving the returns on equities of our sample, under an statistical approach to the systematic risk factors theory. Regarding the interpretation, according the basic approach carried on in this study, we uncover that factors or components driving the returns are sensitive to the technique used, the periodicity and the expression of the returns used in the model.

Conversely, for the sample and periods considered, we can accept only partially the validity of the APT using PCA and FA, as a pricing model explaining the average returns (and returns in excesses) on equities of the Mexican Stock Exchange, since we found certain evidence in favor of this asset pricing model such as several model with statistically significant risk premiums, but on the other hand, there were only a few models that fulfilled also the equality of the independent term to its theoretic value. On the other hand, the evidence showed that the APT is very sensitive to the number of factors extracted and to the periodicity and expression of the models.

Consequently, we conclude that the performance of the APT statistical approach with respect to the Mexican Stock Exchange presents some inconsistencies that make it unstable and sensitive to the different techniques used for extracting risk factors. Further research will be required to examine alternative approaches for underlying factor extraction, such as Independent Component Analysis (ICA) and Neural Networks Principal Component Analysis (NNPCA)[122], in order to uncover the true generative structure of returns on equities in this emerging market. Finally, our results are consistent with earlier studies in which this statistical approach was applied to other markets and with the number of priced factors found in Mexico through studies in which a macroeconomic approach was used[123].

[122] These techniques will be studied in the following chapters of this dissertation.
[123] See references in the introduction of this chapter.

Chapter 5

Independent Component Analysis: Estimation of the generative multifactor model of returns[*].

[*] The research related to this chapter has generate the following academic products:

1. REFEREED PUBLICATIONS:
   1.1. Ladrón de Guevara, R., & Torra, S. (2012). 'An improved methodology to extract underlying systematic risk factors using Independent Component Analysis.' Abstract. In: D. Agudelo *et al.* (Eds.), *Memorias del XII International Finance Conference.* Medellín, Colombia: Universidad EAFIT - American Academy of Financial Management - Bancolombia. ISBN: 978-958-8719-12-2.
   1.2. Ladrón de Guevara, R., & Torra, S. (2010). 'Estimation of the generative multifactor model of returns on equities using the Independent Component Analysis.' In: R. Santillán (Ed.) *Proceedings of the X International Finance Conference.* México, D.F: EGADE-ITESM / American Academy of Financial Management. (ISBN: 978-607-501-029-8).
   1.3. Ladrón de Guevara, R., & Torra, S. (2009). 'Independent Component Analysis for Extracting Underlying Risk Factors. An empirical contrast of the Arbitrage Pricing Theory on the Mexican Stock Exchange.' In P. Andrikopoulos (Ed.), *Contemporary Issues of Economic and Finance Integration: A collection of Empirical Work,* 221-242. Athens, Greece: ATINER. ISBN: 978-960-6672-57-6.

2. REFEREED CONFERENCES:
   2.1. Ladrón de Guevara, R., & Torra, S. 'Estimation of the underlying structure of systematic risk based in the ICASSO methodology.' *V Congreso de Investigación Financiera IMEF*. Instituto Mexicano de Ejecutivos de Finanzas – Universidad Panamericana. August 27 – 28, 2015. Mexico, D.F.
   2.2. Ladrón de Guevara, R., & Torra, S. 'An improved methodology to extract underlying systematic risk factors using Independent Component Analysis.' *XII International Finance Conference.* Universidad EAFIT - American Academy of Financial Management. October 8 – 11, 2012. Medellín, Colombia.
   2.3. Ladrón de Guevara, R., & Torra, S. 'Estimation of the generative multifactor model of returns on equities using the Independent Component Analysis.' *X International Finance Conference.* EGADE-ITESM - American Academy of Financial Management. November 22-26, 2010. México, D.F.
   2.4. Ladrón de Guevara, R., & Torra, S. 'Independent Component Analysis for extracting underlying risk factors. An empirical contrast of the Arbitrage Pricing Theory on the Mexican Stock Exchange'. *6th International Conference on Finance.* Athens Institute for Education and Research (ATINER). July 7 – 10, 2008, Athens, Greece.

3. CONFERENCES BY INVITATION:
   3.1. 'Independent Component Analysis (ICA) for Extracting Underlying Systematic Risk Factors'. *Risk Analysis in Economics and Finance*. Centro de Investigaciones en Matemáticas (CIMAT) y Universidad de Guanajuato. Guanajuato, Guanajuato. Febrero 2-4, 2011.

5.1. Introduction and review of literature.

The goal of the present chapter is to determine the statistical pervasive systematic risk factors in the Mexican Stock Exchange by means of a relatively new computational technique, namely, Independent Component Analysis (ICA). Also we intent to improve the results of the previous chapter and to detect a more realistic[124] structure of the underlying factors explaining the returns on equities in the Mexican Stock Exchange (BMV for its acronym in Spanish).

Because of its nature, ICA is designed assuming a linear mix of variables that are not normally distributed, which is a relevant property for the problem we are dealing with. This technique helps to reveal a linear combination of underlying time series that explain the pervasive sources in some observed parallel time series, by extracting their statistically independent components.

Studies about ICA have been done mainly in fields such as: signal and image processing, speech and audio separation, biomedical signals and image analysis, telecommunications, neurophysiology, text and document processing, bioinformatics, environmental issues and some industrial applications. Two groups of researchers, one from France and another from Finland, are the authors of many of the seminal works on ICA. Several papers concerning the algorithms for estimating the independent components have been developed through the years[125].

In recent years, studies about the applications of ICA in different fields of Finance have been made in some countries. They have used ICA for extracting: the factors influencing cash flow generation at a set of retail stores in Finland (Kiviluoto and Oja, 1998); the components producing variations in the Foreign Exchange in the USA, the UK and Finland

[124] As stated in the introduction of this dissertation, with more realistic, we make reference to the fact that ICA is capable to extract factors from non-Gaussian data which is the nature of our financial series, while the classic techniques PCA and FA are actually developed to extract factors from data normally distributed.

[125] See Hyvärinen *et al.* (2001) for a complete reference and revision about ICA.

(Moody & Wu, 1997; Moody & Yang, 2001; Lesch *et al.,* 1999; Cheung & Xu, 2001); the factors driving the yield curve dynamics of government bonds in Germany and the spot rate curve movements in Italy (Molgedey & Galic, 2001; Bellini & Sallinelli, 2003); the features moving the returns from index funds, hedge funds, thrift saving plan funds, and real estate investment trusts in the USA and the UK (Rojas & Moody, 2001; Pike & Klepfish, 2004; Robinson, 2007; Nestler, 2007; Lizieri *et al*., 2007); the underlying factors explaining the stock returns in Japan, the USA, China and Italy (Back & Weigend, 1997; Yip & Xu, 2000; Cha & Chan, 2000; Chan & Cha, 2001; Wei e*t al.,* 2005; Coli *et al.,* 2005; Korizis *et al*., 2007; Bonhomme & Robin, 2009), as well as in simulated stock markets (Vessereau, 2000); the features of the volatility process related to a stock index (Capobianco, 2002a, 2002b, 2003), and the relevant factors from implied volatility surfaces of index options (Ané & Labidi, 2001). Moreover, other uses of ICA in Finance have been to forecast financial time series[126] (Mălăroiu *et al*, 2000; Chan, 2002; Lo & Coggins, 2003; Mok *et al*., 2004; Cichocki *et al*., 2005; Huang *et al*., 2006; Huang & Zhong, 2006; Lu *et al*., 2009a, 2009b; Lu, 2010; Lu & Wang, 2010), to manage investment portfolios (Clémençon & Slim, 2007), to allocate assets (Madan, 2006; Madan & Yen, 2008); to compute improved portfolio risk measures such as VaR (Chin *et al*., 1999; Wu *et al.,* 2006; Chen *et al*., 2007, 2010; Broda & Paolella, 2009); to cluster multivariate financial time series (Wu & Yu, 2006a); to describe the conditional higher moments risk in international stock markets (Xu & Jiang, 2006); to model the term structure of multiple yield curves (Wu and Yu, 2006b), as well as the volatility of market price indexes (Wu *et al.* 2006); and to discover causality in the stock market (Zhang & Chan; 2006, 2007)[127].

To the best of our knowledge, there is no study concerning the application of the ICA in Finance focused on Mexico. Consequently, we shall try to fill this gap found in financial literature by contributing, with the application of a non-commonly used extraction technique to extract the underlying systematic risk factors in the Mexican Stock Exchange. Additionally,

[126] In some of these studies ICA has been used in combination with other advanced forecasting techniques such as: neural networks, growing hierarchical self-organizing maps and support vector regression, or they have employed extended versions of the ICA like the Nonlinear ICA.
[127] In these studies the authors employ some extensions of the ICA basic model, like the Nonlinear ICA.

we will test the econometric contrast of the Arbitrage Pricing Theory (APT), by using the systematic risk factors extracted by ICA from this stock market.

The outline of this chapter is as follows: In section 2, we briefly describe the ICA technique; in section 3, we present an empirical study; and finally in section 4, we draw the main conclusions.

5.2. Independent components analysis.

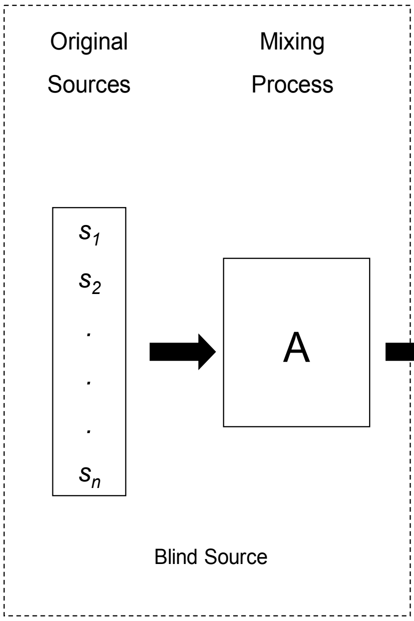
5.2.1. ICA basics.

Despite the widespread evidence concerning the non-Gaussianity of the returns on equities, the most popular latent variables analysis techniques used for extracting the pervasive factors underlying the financial multivariate data are, the Principal Component Analysis (PCA) and Factor Analysis (FA), which assume a Gaussian distribution of the latent factors.

ICA represents an improved extraction technique for this kind of data, since it is based on a multivariate non-normality approach and looks for mutually and statistically independent components. According to Hyvärinen *et al.* (2001), statistical independence means that ‘the value of any one of the components gives no information on the values of the other components’. Also following De Lathauwer *et al.* (2000), mutually and statistically independent can be interpreted as ‘of different nature’.

ICA was introduced in the field of signal processing and neural computation as a tool to solve the problem of Blind Source Separation (BSS) and Signal Reconstruction. According to Oja (2004): ‘Blind Source Separation is a computational technique for revealing hidden factors that underlie sets of measurements or signals'. The most basic statistical approach to BSS is ICA.’ In addition, he states that: ‘Blind means that we know very little if anything about the original sources’. Figure 5.1 shows a schematic representation of ICA.

Figure 5.1. *Schematic representation of Independent Component Analysis.*



Source: Own elaboration based on Back & Weigend (1997) and Wei *et al*. (2005).

This technique assumes that the observed variables are the result of an unknown mixing process of some latent original sources. Consequently, the observed variables can be decomposed by means of a demixing process, capable of estimating some statistically independent components that can be considered as reliable proxies for the original sources that generated the observed variables ($s \approx y$)[128]. The main characteristic of the latent sources is that they are assumed to be non-Gaussian and mutually independent. They are known as the independent components of the multivariate observed data. According to Cha & Chan (2000), the formal expressions of the mixing and demixing processes are as follows[129]:

$$\text{Mixing process:} \quad \mathbf{x} = \mathbf{As} \tag{5.1}$$

$$\text{Demixing process:} \quad \mathbf{y} = \mathbf{Wx} = \mathbf{WAs} \tag{5.2}$$

[128] This is true up to a scaling of variables and permutation of the variables.

[129] These expressions represent the most basic definition of the ICA model; some generalizations and modifications in them, such as the addition of a noise term, the case when the number of observed mixtures and the number of sources are different, or the mixing process is not linear, can be found in Hyvärinen *et al.* (2001).

Where **x** represents the vector of observed variables; **A**, the mixing matrix; **s**, the vector of original sources; **y**, the vector of the independent components; and **W**, the demixing matrix, which we assume that has inverse. Since we are ignorant[130] of both the input and output processes and also the original sources, the ICA methodology makes several assumptions: a) both the original sources and the components *y* are non-Gaussian[131] and mutually independent; b) the number of observed mixtures is equal to the number of original sources, so the unknown mixing matrix is square; c) if the independent components are equal to the original sources, the mixing matrix **A** will be the inverse of the demixing matrix **W**[132]:

$$\mathbf{A} = \mathbf{W}^{-1} \tag{5.3}$$

Under these assumptions we can estimate both **W** and **y** from **x** by looking for some components as statistically independent as possible. Thus, the objective of ICA is to find a demixing linear mapping **W** in which the components **y** would be as statistically independent as possible.

In relevant literature we can find mainly three estimation criteria for ICA[133]: a) the maximization of nongaussianity, b) the maximum likelihood estimation, and c) the minimization of mutual information. As it is expressed in Hyvärinen (1999a, 1999b) and Hyvärinen & Oja (2000), under some conditions, the three approaches are essentially equivalent or at least closely related. Next we describe the criteria:

[130] Since the input and output relationship is unknown.
[131] In the common ICA models only one component at most can be Gaussian. If there is more than one Gaussian component, ICA will not be able to separate them from each other; thus, all the Gaussian components will be linearly combined.
[132] This relation can be seen, too, as the demixing matrix **W** being the inverse of the mixing matrix **A** ($\mathbf{W}=\mathbf{A}^{-1}$).
[133] A deeper study of the different approaches to estimate the ICA model, including their concepts, algorithms, numeric methods, and extensions, is out of the scope of this research; however, the interested reader can find a detailed study of them in Hyvärinen *et al* (2001).

a) Maximization of nongaussianity poses that, by finding the maximum nongaussianity of the dataset, we can find its independent sources. The two measures of nongaussianity used are kurtosis and negentropy. Since the value of kurtosis is zero for Gaussian random variables, and nonzero for non-Gaussian, we will try to maximize its absolute value. The entropy of a random variable is the degree of information that the observation of a variable gives. The more Gaussian the variable is, the larger its entropy. On the contrary, the value of negentropy is zero for Gaussian variables[134]. Since the negentropy will always be nonnegative, we will try to maximize it in order to maximize the nongaussianity.

b) Maximum likelihood (ML) estimation, as a fundamental method of statistical estimation, can be used to estimate the independent components. This method consists in taking as estimates of the parameters the values that make the obtained measurements most likely given the model, i.e., the values of the parameters of the model that give the highest probability for the observations. Following Hyvärinen *et al.* (2001), in the context ICA, the derivation of the likelihood of the ICA model is based on a linear transform of the probability density function of the independent components. The likelihood is expressed as a function of the parameters of the model, which are the elements of the mixing matrix, where the likelihood is actually a function of the density of the independent components.

c) Mutual information (MI) represents a measure of dependence between random variables. Its value is always non-negative, and it is zero for statistically independent variables. Finding a linear transformation **W** that minimizes the mutual information, we will discover the directions in which the negentropy is maximized. MI, as a higher order statistic, considers not only the second order dependence provided by the covariance but also the whole dependence structure of the variables.

[134] Negentropy is a normalized version of entropy that is zero for a gaussian variable and always nonnegative. See details in Hyvärinen *et al.* (2001).

The former three criteria allow for different methods for computing the ICs, which resemble one another in the sense that the optimization step is done by means of an iterative algorithm. The two main methods are: the adaptive algorithms based on gradient methods, and the fixed-point iteration scheme algorithm, known as fast fixed-point or Fast-ICA algorithm.

The gradient method is a typical technique used for the optimization of objective functions. In this case, we aim either to maximize the absolute value of kurtosis, the negentropy or the likelihood, or to minimize the mutual information. By computing their gradients, we will obtain the direction in which the kurtosis, the negentropy, or the likelihood of the following expression is maximized:

$$\mathbf{y} = \mathbf{W}\mathbf{z} \tag{5.4}$$

Where, **z** represents the observed variables after a whitening pre-processing.

In the case of the mutual information approach, we will find the direction in which the mutual information of the foregoing expression is minimized. Then, we will move the vectors **w** in that direction. This method is closely related to the learning concept of the neural network and has the advantage of using the inputs **z** at once in the algorithm; nevertheless, it presents the drawbacks of slow convergence and dependence on the learning rate choice.

According to Hyvarinen & Oja (1997), the FastICA algorithm represents a transformation of a neural network learning rule into a fixed-point iteration scheme. The possible performance measurements or optimization criteria can be either of the two measures on nongaussianity used: on one hand, the maximum kurtosis, and on the other hand, the negentropy of a linear combination of the observed variables. It can find all the non-Gaussian independent components one by one, in spite of their probability distributions; besides, its convergence speed is faster and it is more reliable since there is no user-defined parameter to choose.

In addition, there are two methods to estimate several independent components: deflationary orthogonalization, where the independent components are estimated one by one, and the symmetric decorrelation, where they are estimated in parallel.

5.2.2 ICA compared to PCA and FA

In reference to PCA and FA, Hyvärinen *et al*. (2001) state: 'ICA is a much more powerful technique, capable of finding the underlying factors or sources when these classic methods fail completely'; furthermore, Oja *et al.* (2000) declare 'ICA might reveal some driving mechanisms that otherwise remain hidden'. PCA and FA present a limitation that ICA overcomes. It is often believed that PCA and FA generate independent components; however, this is only true if the data are multivariate normally distributed, since uncorrelated components are also independent for Gaussian data. The real world data and specially the financial time series usually are non-Gaussian. ICA will search statistically independent components for non-Gaussian data. In addition, independence represents a stronger property than uncorrelatedness, since the former implies the latter but not vice versa. Therefore, uncorrelatedness is not enough to separate the underlying components. From a different perspective, PCA and FA techniques use only the covariance matrix to obtain linear decorrelated components, i.e., they minimize second-order statistics. Another problem related to the use of these two methods on financial time series is the fact that, in finance, probability distributions have long tails, and therefore the outliers can distort the estimation of the parameters in both cases. The ICA techniques use statistics that are not considered in the covariance matrix, i.e., they additionally minimize higher-order statistics containing information not included in the covariance matrix[135]. Nevertheless, PCA generates a whitening or sphering[136] procedure very useful for pre-processing the data before applying

[135] This is the reason why ICA cannot be used for Gaussian variables, since they are defined only by the mean and the variance, and all the other statistics are zero.
[136] Whitening or sphering refers to the process of transforming linearly a set of random variables so as to get uncorrelated variables with variances equal to unity. Whitening is equivalent to performing PCA but conserving all the components.

ICA algorithms, since it reduces the search for the demixing matrix to the space of orthogonal matrices. Note that a whitening process is affected if the data has outliers, because of their influence in the covariance matrix. Therefore before the decision of doing a whitening preprocessing, the effect of the outliers on the covariance matrix should be checked. In our dataset, for instance the effect of the outliers was negligible on the covariance matrix. Another key difference between these methods is that while PCA and FA factorize the covariance matrix of the observed variables, ICA factorizes the joint probabilities of the independent signals. From a geometric standpoint, the directions obtained by the transformation can define the differences: PCA and FA will find the directions that capture the maximum amount of total and common variance, respectively; whereas ICA will find the directions most deviated from Gaussianity.

From a broad perspective the basic ICA model could be seen as a generalization of PCA or FA[137], taken to a higher-order independence of the components or factors extracted. Conversely, ICA presents a special problem absent in both PCA and FA: the estimated independent components (ICs) are not explicitly ranked as in the other methods, where the factors are automatically ranked by their eigenvalues. Additionally, therefore we have to apply an algorithm able to order the ICs according to some criteria.

Summarizing, as stated in Hyvärinen *et al.* (2001, p. 287): 'What distinguished ICA from PCA and classic factor analysis is that the nongaussian structure of the data is taken into account. This higher-order statistical information (i.e., information not contained in the mean and the covariance matrix) can be utilized, and therefore, the independent components can actually be separated, which is not possible by PCA and classic factor analysis'.

[137] In the case of FA, where there is no presence of the error term. Nonetheless, when the error term cannot be assumed to be zero, this generalization would imply the presence of the noisy ICA model or the Independent Factor Analysis, where the hidden factors are independent and non-Gaussian instead of uncorrelated and Gaussian.

5.2.3. ICA in Finance.

It is known that ICA assumes that there are independent components that generate the observed returns by means of a linear transformation. In the case of signal processing (i.e. blind source separation of audio signals), one has to posit the hypothesis that the functions of the original set are mutually independent, which can easily be checked by examining the physical process that generates the signals (i.e., different persons speaking can be assumed to generate independent signals). In the case of financial series, one has to posit the independence but the actual check of it by examining the physical process that generates the original signal is impossible. Nevertheless, it is reasonable to assume that there is a set of independent signals that underlie the observed time series, which might be related to political events, meteorological phenomena, short-time technical changes, internal dynamics of the markets and the economy. These signals could be assumed to be independent; and a linear combination of these markets (or a numerical expression of the factors), plus a component of noise could be a model for the generation of the observed time series.

Consequently, ICA is very suitable for use on financial time series for the following reasons: first, ICA deals with the problem of blind source separation or dealing with parallel time series, like those obtained from financial variables; secondly, ICA works with nongaussian random variables, the most common nature of the financial data; thirdly, from the statistical and financial standpoints, ICA produces more reliable underlying components or factors, since they are statistically independent and not only uncorrelated. This fact contributes directly to the aim of extracting systematic risk factors affecting the returns on equities in a multifactor asset-pricing model like the APT.

5.3. Empirical study. Methodology and Results.

5.3.1. Tests for univariate and multivariate normality.

In the previous chapter we found a good results in the estimation of the generative multifactor model of returns via Principal Component Analysis (PCA) and Maximum Likelihood Factor Analysis (MLFA); however, it is known (Hyvärinen, 2001) that PCA (implicitly) and FA (explicitly) require a normally distributed multivariate sample in order to produce completely reliable results, i.e., they will only produce uncorrelated and independent components if the sample data have no higher order statistics beyond the variance. Thus, if the samples do not fulfill these conditions, we will be prompted to use a more suitable technique such as ICA to uncover the underlying sources in a non-Gaussian sample.

Therefore, we first tested the univariate normality (UVN) of each individual series, since ICA requires that not more than one of the observed signals (the returns on equities) be non-Gaussian. We carried out the Jarque-Bera test for UVN (Jarque & Bera, 1980) on the four databases, rejecting the null hypothesis of normality at 5% of probability for all the stocks in the daily databases, but not rejecting it for only one stock in the weekly databases that was normally distributed. Table 5.1 presents these results.

Table 5.1. *Jarque-Bera's Test for Univariate Normality.*

STOCKS	DBWR		DBWE		DBDR		DBDE	
	Jarque-Bera	p-value	Jarque-Bera	p-value	Jarque-Bera	p-value	Jarque-Bera	p-value
ALFAA	257.08005	0.00000	253.82792	0.00000	680.80834	0.00000	680.81895	0.00000
ARA_01	**4.51024**	**0.10486**	**4.41149**	**0.11017**	506.94138	0.00000	508.46176	0.00000
BIMBOA	38.35626	0.00000	38.80787	0.00000	1287.20099	0.00000	1287.55675	0.00000
CEMEXCP					89.79688	0.00000	90.82310	0.00000
CIEB	155.16387	0.00000	153.78293	0.00000	2951.91390	0.00000	2960.07901	0.00000
COMERUBC	27.09040	0.00000	25.70275	0.00000	744.45079	0.00000	740.85038	0.00000
CONTAL_01	34.03192	0.00000	33.07250	0.00000	859.25423	0.00000	857.36127	0.00000
ELEKTRA_01	25.62004	0.00000	25.06947	0.00000	719.39733	0.00000	717.46530	0.00000
FEMSAUBD	39.99115	0.00000	40.11908	0.00000	1046.36974	0.00000	1055.20377	0.00000
GCARSOA1	27.80589	0.00000	29.54416	0.00000	607.23296	0.00000	606.28756	0.00000
GEOB	57.94051	0.00000	58.22178	0.00000	3051.90518	0.00000	3046.60283	0.00000
GFINBURO	73.50976	0.00000	72.26142	0.00000	256.99029	0.00000	260.06846	0.00000
GFNORTEO	31.31952	0.00000	29.15816	0.00000	858.25169	0.00000	855.28213	0.00000
GMODELOC	65.67019	0.00000	64.14730	0.00000	418.66316	0.00000	416.20179	0.00000
KIMBERA					2207.37871	0.00000	2213.97563	0.00000
PE_OLES_01	29.24151	0.00000	28.42667	0.00000	3051.74875	0.00000	3020.95408	0.00000
SORIANAB	38.24454	0.00000	38.52444	0.00000	154.15882	0.00000	156.49754	0.00000
TELECOA1	7.46268	0.02396	7.78122	0.02043	191.39299	0.00000	191.66132	0.00000
TELMEXL	293.25403	0.00000	299.96063	0.00000	544.60981	0.00000	551.65619	0.00000
TLEVICPO	98.94046	0.00000	100.67490	0.00000	790.30896	0.00000	792.82003	0.00000
TVAZTCPO	32.37142	0.00000	32.43913	0.00000	1552.43422	0.00000	1544.07832	0.00000
WALMEXV	30.87516	0.00000	30.63142	0.00000	512.84070	0.00000	513.11548	0.00000

Notes:
DBWR = Database of weekly returns. DBWE = Database of weekly excesses.
DBDR= Database of daily returns. DBDE= Database of daily excesses.
Numeric values in bold represent stocks with univariate normal distribution.
H_0 = Univariate Normality. p-value lower than 0.05 = Rejection of the H_0.

Although in statistical literature there are several approaches for assessing the multivariate normality (MVN) tests, for practical reasons we used two classical alternatives: the Mardia (1970) and the Henze-Zirkler (1990) MVN tests. Mardia's test is based on the multivariate skewness and kurtosis of the sample. Henze-Zirkler's (H-Z) test considers a measure of the distance between the characteristic function of the MVN and the empirical one, where the computed statistic will be lognormally distributed, if the data is multivariate normal. Both techniques have shown very good performance in measuring the MVN against other classic and newer alternatives, as Mecklin & Mundfrom (2004) remark in their study. We performed two tests following the accepted criteria of applying more than one MVN test when assessing this property of a sample[138]. Our results with both tests reject the null

[138] We performed both MVN tests using the Matlab scripts developed by Trujillo *et al.* (2003, 2007).

hypothesis of MVN at 5% of probability for all the databases. Tables 5.2 and 5.3 present the results of Mardia's and H-Z's tests, respectively.

Table 5.2. *Mardia Test for Multivariate Normality.*

	DBWR	DBWE	DBDR	DBDE
Multivariate Skewness (Ms)	3305.5000	3297.1000	6659.4000	6666.3000
p-value	0.00000	0.00000	0.00000	0.00000
Multivariate Skewness corrected (Msc)	3342.8000	3334.4000	6674.8000	6681.7000
p-value	0.00000	0.00000	0.00000	0.00000
Multivariate Kurtosis (Mk)	37.8253	37.7060	141.0476	141.1625
p-value	0.00000	0.00000	0.00000	0.00000

Notes:
1) DBWR = Database of weekly returns. DBWE = Database of weekly excesses.
2) DBDR= Database of daily returns. DBDE= Database of daily excesses.
3) H_0 = Multivariate Normality. p-value lower than 0.05 = Rejection of the H_0.

Table 5.3. *Henze-Zirkler Test for Multivariate Normality.*

	DBWR	DBWE	DBDR	DBDE
Henze-Zirkler's Statistic	1.05188	1.05174	1.22493	1.22283
p-value	0.00000	0.00000	0.00000	0.00000

Notes:
1) DBWR = Database of weekly returns. DBWE = Database of weekly excesses.
2) DBDR= Database of daily returns. DBDE= Database of daily excesses.
3) H_0 = Multivariate Normality. p-value lower than 0.05 = Rejection of the H_0.

Mardia's test generated three statistics with their associated *p*-values: multivariate skewness (Ms), multivariate skewness corrected for small samples (Msc), and multivariate kurtosis (Mk). The *p*-values of the three statistics made us reject the null hypothesis of MVN. We extended this analysis by making an experiment concerning the horizon of Mardia's test, i.e., we ran the test using different numbers of observations so as to check the multivariate normality in different scenarios. The results showed that from 101 observations on inclusive, the sample is non-Gaussian according to the three statistics[139]. H-Z's test computes the H-Z statistic and its associated probability, thereby leading us to reject the null hypothesis of multivariate normality for all the databases as well.

[139] The results of these additional tests are not reported in this work.

On the basis of the foregoing results[140], we cannot accept as completely reliable the outcomes of techniques assuming the multivariate normality of data such as Principal Component Analysis and Factor Analysis, thus we are led to the application of more suitable techniques like ICA. In fact, this part of our investigation represents an important, but in most cases ignored, aspect in empiric studies that uses classic multivariate techniques to extract the pervasive factors; since in many cases the MVN is assumed but not tested, the results and conclusions may be flawed.

5.3.2. Estimation of the ICA Model.

In order to estimate the ICA model in expression (2), we used the ICASSO methodology (Himberg *et al.,* 2004; Himberg & Hyvärinen, 2003), which is based on the FastICA algorithm (Hyvärinen & Oja, 1997, 2000; Hyvärinen, 1999a, 1999b) [141].

According to the foregoing authors, the FastICA algorithm is based on a fixed-point iteration scheme for finding the local extrema of the objective functions for ICA estimation from a linear combination of the observed variables. The basic iteration for the vector **w** for each IC obtained by this method is:

$$\mathbf{w} \leftarrow E\{\mathbf{z}g(\mathbf{w}^T\mathbf{z})\} - E\{g'(\mathbf{w}^T\mathbf{z})\}\mathbf{w} \qquad (5.5)$$

Where the nonlinearity "g" can be almost any smooth function such as[142]:

[140] Considering that the results of kurtosis are positive and large which reveal the presence of outliers, which will have implications on the election of the non-linearity in the ICA estimation.
[141] We used the Matlab package developed by Himberg & Hyvärinen (2005) to estimate the ICA model using the ICASSO methodology. At the same time the ICASSO software uses the FastICA Matlab package by Gävert *et al.* (2005) to estimate the FastICA algorithm.
[142] Where y is a random variable assumed to be zero mean and unit variance, and $1 \le a_1 \le 2$ is some suitable constant, often taken as $a_1 = 1$.

$$g_1(y) = \tanh(a_1 y), \tag{5.6}$$

$$g_2(y) = y \bullet \exp(-y^2/2) \tag{5.7}$$

$$g_3(y) = y^3, \tag{5.8}$$

and "g'" is the derivative of $g(.)$[143].

The final vector gives one of the ICs as a linear combination in $\mathbf{y} = \mathbf{w}^T\mathbf{z}$. To estimate n ICs we run the algorithm n times, including an orthogonalization projection inside the loop to ensure the estimation of a different IC. The specific resulting algorithm depends both on the estimation principle[144] used and the approach selected to estimate several numbers of ICs[145], i.e., the nonlinearity and the decorrelation method chosen[146].

Hyvärinen (A. Hyvärinen, personal communication, November 4, 2008) states that by setting the options, *tanh* nonlinearity (hyperbolic tangent) and symmetric approach, one can obtain a good estimation of the ICA model; this would be equivalent to performing three estimation approaches at the same time. In addition, the positive kurtosis obtained in the multivariate normality tests lead us to use the hyperbolic tangent function. Furthermore, as reported in Giannakopoulos *et al.* (1999) the best trade-off for estimating the ICA model, from statistical performance and computational load perspectives, is represented by the FastICA algorithm with symmetric orthogonalization and *tanh* nonlinearity estimation. This specification also yielded one of the best results performance for increasing the number of components, presented in the last cited reference. Note that the results are consistent with our results in the sense that a symmetric orthogonalization is not significantly affected by outliers, and that the best non linearity corresponds to a non-linearity fitted for long tail distributions, such as the *tanh*. In our study we followed these specifications, which implies the use of the algorithm presented in Table 5.4.

143 According Hyvärinen *et al.* (2001), nonlinearity *than* (a_1y) is optimal for leptokurtic long tail distributions; y^3 performs better for platykurtic short tail ones; and $y{\cdot}exp(+y^2/2)$ is recommended for highly leptokurtic distributions or when robustness is very important.
144 Maximum nongaussianity (kurtosis or negentropy), maximum likelihood or minimal mutual information.
145 Deflationary (one by one) or symmetric (in parallel).
146 For details on the different resulting algorithms see Hyvärinen *et al.* 2001.

Table 5.4. *FastICA algorithm for estimating several ICs, with symmetric orthogonalization.*

1. Center the data to make its mean zero. 2. Whiten the data to give **z**. 3. Choose *m*, the number of independent components to estimate. 4. Choose initial values for the $\mathbf{w}_i$, $i = 1, \ldots, m$, each of unit norm. Orthogonalize the matrix **W** as in step 6 below. 5. For every $i = 1, \ldots, m$, let $\mathbf{w}_i \leftarrow E\{\mathbf{z}g(\mathbf{w}_i^T\mathbf{z})\} - E\{g'(\mathbf{w}_i^T\mathbf{z})\}\mathbf{w}$, where *g* is the nonlinearity function, e.g. $g_1(y) = \tanh(a_1 y)$. 6. Do a symmetric orthogonalization of the matrix $\mathbf{W} = (\mathbf{w}_1, \ldots, \mathbf{w}_m)^T$ by $\mathbf{W} \leftarrow (\mathbf{W}\mathbf{W}^T)^{-1/2}\mathbf{W}$ 7. If not converged, go back to step 5.
Notes: 1) Convergence means that the old and new values of **w** point the same direction, i.e. their dot-product is almost equal to 1.

Source: Taken from Hyvärinen *et al.* (2001).

The election of the ideal number of ICs to estimate still represents an unsolved problem. Although in ICA literature we can find diverse criteria to determine this number, in most cases it is actually chosen by trial and error without any theoretical basis. One alternative is to reduce the number of dimensions in the whitening pre-processing stage, considering some criteria from among those used in PCA or FA, and to estimate the same number of ICs. For the sake of comparison with the results of the foregoing chapter, we use the same test window, which ranges from two to nine components. This window was given for the results of nine different criteria usually employed to select the number of components or factors in PCA and FA. The criteria adopted were: the arithmetic mean of the eigenvalues, the percentage of explained variance, the exclusion of the components or factors explaining a small amount of variance, the scree plot, the unretained eigenvalue contrast (Q statistic), the likelihood ratio contrast, Akaike's information criterion (AIC), the Bayesian information criterion (BIC), and the maximum number of components feasible to estimate in each technique.

As stated by Himberg & Hyvärinen (2003, 2005), one problem that the ICA estimation presents is that the reliability of the estimated ICs is not known since the results are stochastic, i.e., they might be dissimilar in different runs of the algorithm. Thus, the results of a single run of the FastICA algorithm could not be completely trusted and an additional analysis of the reliability of the estimation should be performed. In this context, reliability has two aspects the algorithmic[147] and the statistical[148]. The ICASSO methodology represents an alternative for dealing with this problem, since it ensures the algorithmic and statistical stability and reliability of the estimated components by running the FastICA algorithm many times, using different initial conditions and/or a differently bootstrapped data set. According to Himberg & Hyvarinen (2003) and Himberg *et al.* (2004), we can ensure the algorithmic reliability by randomizing the initial values of the optimization, and we can ensure the statistical reliability by resampling the data set through bootstrapping.

First, ICASSO runs the FastICA algorithm M times on data set $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots \mathbf{x}_N]$ composed of N samples of k vectors; then, ICASSO forms clusters with the ICs produced in each run according to their similarity. Mutual similarities between estimates are computed, using the absolute value of their linear correlation coefficient as the measure of similarity:

$$\sigma_{ij} = |r_{ij}|, \tag{5.9}$$

These elements form the similarity matrix, which can be obtained by:

$$\mathbf{R} = \hat{\mathbf{W}} \mathbf{\Sigma} \hat{\mathbf{W}}^T, \tag{5.10}$$

where, $\mathbf{\Sigma}$ is the covariance matrix of dataset $\mathbf{X}$, and $\hat{\mathbf{w}}$ is the estimates of demixing matrices $\hat{\mathbf{W}}_i$ from each run $i = 1,2,\ldots,M$ gathered in a single matrix:

$$\hat{\mathbf{W}} = \left[\hat{\mathbf{W}}_1^T \mathbf{W}_2^T \ldots \mathbf{W}_M^T\right]^T \tag{5.11}$$

[147] The algorithmic reliability is given by the fact that most ICA algorithms are based on the maximization or minimization of an objective function, whose global minimum or maximum cannot be found in some cases since it will depend on the point where the search starts; i.e. depending on the initial value of the optimization, different local minima or maxima of the contrast function could be found.

[148] The statistical reliability is given by the fact that the finite sample size (random sampling of the data) may induce statistical errors in the estimation. This statistical reliability can be understood basically as the notion of statistical significance.

Then the similarity matrix is transformed into a dissimilarity matrix with the elements:

$$d_{ij} = 1 - \sigma_{ij} \tag{5.12}$$

Some clustering methods and validity indices are also used in order to agglomerate the estimates and to measure their dissimilarities or distances between them[149].

According to Himberg and Hyvärinen (2003, 2005), reliable estimates of ICs correspond to tight clusters, since they agglomerate estimates generated by many runs of the algorithm which are similar, even when the initial values and datasets for the estimation have been changed. Conversely, estimates which do not belong to any cluster are considered unreliable estimates. The centrotype of each cluster is considered a more reliable estimate than that generated by any single run. This centrotype is the point that has the maximum sum of similarities[150] to other points of the cluster, i.e. the original estimate that is most similar to other estimates in the same cluster.

In addition to the previously declared parameters for FastICA[151], there are some additional parameters to set when using ICASSO, such as the resampling mode[152], number of resampling cycles (M) and number of clusters (L). In order to ensure both statistical and algorithmic reliability, in our study we used both resampling modes, i.e., each time the dataset was bootstrapped and the initial conditions of the algorithm were randomized. We used the default number of resampling cycles fixed by the software, i.e., 30, and we set the number of clusters according to the number of ICs (m) estimated in each experiment in order to obtain squared mixing (**A**) and demixing (**W**) matrices.

[149] The ICASSO software uses agglomerative hierarchical clustering with an average-linkage criterion as the clustering method, and a cluster quality index I_q to measure the compactness and isolation of a cluster. For details see Himberg and Hyvärinen (2003, 2005).
[150] As measured by the correlations coefficients.
[151] Contrast function, orthogonalization approach, etc.
[152] Different random initial condition and/or resampling the dataset by bootstrapping.

The demixing matrix (**W**) computed by ICASSO corresponds to the centrotypes of each cluster as well, which represents a more reliable estimate than that produced by a single run of FastICA; however, they are not strictly orthogonalized since the best estimates might correspond to several runs of the algorithm[153]. In the context of our research where we need to obtain orthogonalized ICs, we will have to make an orthogonalization procedure in a later step.

Consequently, we first took the demixing matrix (**W**) produced by ICASSO, then we computed the mixing matrix

$$\mathbf{A} = \mathbf{W}^{-1}, \tag{5.13}$$

and the matrix of independent components or sources

$$\mathbf{S} = \mathbf{WX}. \tag{5.14}$$

5.3.3 Ranking and orthogonalization of the Independent Components

Next, we ordered the independent components in terms of their explained variability by means of the criteria proposed by García-Ferrer *et al.* (2012). This criterion orders the components by energy. Note that the presence of high value spikes will give more significance to a given component, due to the fact that the components are squared. First, we compute the variance of the observed stocks by means of:

$$var(x_{it}) = \sum_{i=1}^{m} a_{ij}^2, \quad \forall\, i = 1, \ldots, m \tag{5.15}$$

[153] This feature represents one of the most important advantages of ICASSO, since it allows combining information from several runs of the algorithms. Thus, we can obtain a set of components that are better than any component obtained in any single run, since some components might be well estimated in some runs and other components in other runs. See details in Himberg and Hyvärinen (2005).

Where, x_{it} are the observed returns and a_{ij}, the elements of the mixing matrix A. The result is a vector where each element represents the variance of each observed stock.

Then, the estimated ICs are weighted by the load that each IC has on the considered stock.

$$s_t^{w(i)} = diag(a_{i1}, a_{i2}, \ldots, a_{im}) s_t \tag{5.16}$$

Once we have the weighted ICs (s_t), we compute their variance:

$$var\left(s_{jt}^{w(i)}\right) = a_{ij}^2, \quad \forall\ i, j = 1, \ldots, m \tag{5.17}$$

The result is a matrix where each row represents the variances of the weighted ICs for each stock, i.e. the first row shows the variances of the weighted ICs for the first stock and so forth.

Therefore, the variability of the *i*-th stock explained by the *j*-th weighted IC, is computed by:

$$v_i^j = \frac{a_{ij}^2}{\sum_{i=1}^{m} a_{ij}^2} \tag{5.18}$$

The result is a matrix where each element (*i*,*j*) represents the variability of each *i*-th stock, explained by the *j*-th weighted IC.

The total variance on the whole set of stocks explained by each weighted IC is obtained by:

$$\vartheta = \frac{\sum_{i=1}^{m} v_j^i}{\sum_{j=1}^{m}\left(\sum_{i=1}^{m} v_j^i\right)}, \quad \forall j = 1, \cdots, m \tag{5.19}$$

The resultant vector represents the variability of each IC; therefore we can rank them according to the amount of variance of the stocks that explains each one of them, thus obtaining a ranked matrix of independent components ($\mathbf{S}^r$), as well as sorted mixing ($\mathbf{A}^r$) and demixing matrices ($\mathbf{W}^r$).

Finally, we orthogonalized the matrix of ICs by means of the following process of transformation:

$$\mathbf{V} = 2 * \left(\left(\mathbf{S}^r * \mathbf{S}^{r^T} \right)^{-1} \right)^{1/2} \tag{5.20}$$

$$\mathbf{S}^o = \mathbf{V} * \mathbf{S}^r \tag{5.21}$$

Where $\mathbf{V}$ is a transformation matrix to decorrelate the matrix of sorted independent components, and $\mathbf{S}^o$ represents the matrix of orthogonalized ICs.

5.3.4 Extraction of underlying systematic risk factors via ICA

We estimated eight different multifactor models to extract from two to nine independent components for each one of our four databases[154]. Then, we proceeded to reconstruct the original variables according to the generation process of expression (1) but including the inverse of the transformation matrix $\mathbf{V}$ in order to orthogonalize the mixing matrix A as well.

$$\mathbf{X} = \mathbf{S}^0 \left(\mathbf{V}^{-1} * \mathbf{A}^r \right) \tag{5.22}$$

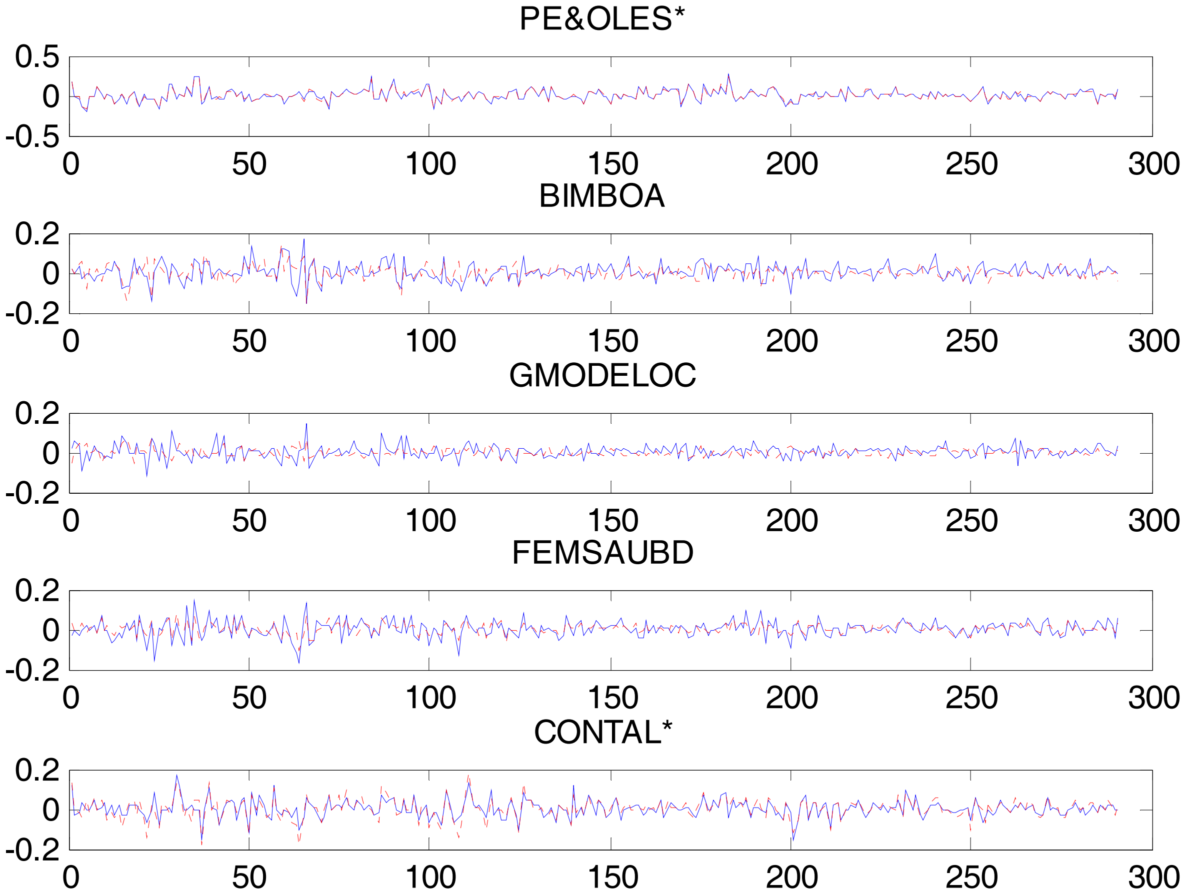
[154] The total number of estimated multifactor models was 32.

We carried out a graphical analysis in order to detect, from a visual stand point, the level of reconstruction of the observed returns, by way of our generative multifactor model of returns estimated by ICA. In order to observe the complete series of the dataset, we present the line plots of the first five stocks corresponding to the database of weekly returns when we extracted nine components; Figures 5.2 show the respective results[155].

We can easily observe that the generative multifactor model of returns estimated via ICA was capable to reproduce the observed returns in almost all cases. The reconstructed values were very similar to the observed returns or excesses for almost all the stocks in the four databases, which implies that the estimation of the generative multifactor model in the statistical approach of the APT performed by ICA was successful. Nevertheless, the highest and lowest peaks in some stocks were not very well reconstructed, specially in the cases of daily returns and excesses of GMODELO, CEMEX, SORIANA and GCARSO, due to the high volatility they presented during the studied period, whose reconstructions were deficient.

[155] For reason of saving space, in this chapter we only show this results; figures with the plots of all the stocks for the four databases when nine factors were extracted appears in Appendix_2 from Figure 1 to Figure 6 of Chapter 5. The results of the rest of the estimations when two, three, four, five, six, seven and eight components were extracted presented similar behavior; however, those results are not included in this document for representing too much information to be inserted in this Thesis.

Figure 5.2. *Independent Component Analysis. Observed and reproduced variables. Line plots. Database of weekly returns. Nine components extracted.*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

5.3.5. Independence test.

In order to test the independence of the computed ICs, we run the Hilbert-Schmidt Independence Criterion (HSIC) test (Gretton *et al.*, 2008). This test, which is based on a sample of observed pairs (x_i, y_i), tests whether random variables X and Y are independent. It uses, as a statistic test, the so called Hilbert-Schmidt Independence Criterion. The HSIC population is zero at independence, so the sample is unlikely to be independent when the empirical HSIC is large. The test computes both HSIC and a threshold; when HSIC exceeds this threshold, we reject the independence hypothesis[156]. We remark that we are interested in warranting that the systematic risk factors extracted are statistically independent because this attribute implies that they are also linearly uncorrelated; however, the inverse situation can be warranted especially in non-Gaussian data.

We tested all the possible pairs combination of ICs in or der to be able to determine if each couple of ICs were statistically independent, e.g., IC1 vs IC2, IC1 vs IC3, IC1 vs IC4, …, IC1 vs IC9, IC2 vs IC3, IC2 vs IC4, …, IC2 vs IC9, and so on[157]. The results of our independence tests on the databases and the cases presented were as follows: For the database of weekly returns, 33 of the 36 pairs of independent components compared were independent, i.e., 91.67% of the cases; while in the database of weekly excesses, there were 32 (88.89%). In the daily databases, there were 14 combinations that passed the independence test in the models expressed in returns (38.89%); while in the models expressed in excesses there were 12 (33.34%). Consequently, we can warrant that the estimated components are statistically independent in the terms of the test carried on. In addition, we can state that the statistical independence between each pair of components estimated from the weekly databases, showed a better performance than that computed from the daily ones.

[156] In order to perform this test we used the Matlab® code developed by Gretton (2007) available at: http://people.kyb.tuebingen.mpg.de/arthur/indep.htm For a detailed explanation of the test and software utilized, see also Gretton *et al.* (2008).

[157] For the sake of saving space, the results of this tests are not included in this document, since it was applied to the entire window of test and to the four databases; nevertheless, they generated the conclusion stated in this section.

5.3.6. Explanation of the variability using the extracted components or factors.

The amount of variance explained by means of the extracted independent components, as well as the accumulated one, is presented in Table 5.5. We can observe that in all cases the first four independent components explain between 19% and 68% of the variability, which gives some evidence as to the importance of those components. The extraction performed on the database of daily excesses overcomes the other three databases, since the first three components explain more than 60% of the variability. When a fourth component is considered the accumulated explained variance almost reaches 70%. In general, the components extracted from the daily databases explain higher amounts of variance than those estimated from the weekly ones.

5.3.7. Interpretation of the extracted factors.

Although this study is mainly focused on the extraction process of systematic risk factors of the Mexican Stock Exchange, but not on the risk attribution stage of statistical approach to the Arbitrage Pricing Theory, in this section we will just make a first attempt to propose an interpretation of the meaning or nature of the systematic risk factors extracted. We will follow an analogue methodology similar to the classic approach used when PCA and FA are used to reduce dimensionality or to extract features from a multifactor dataset. This approach is based on the use of the factor loading matrix estimated in the extraction process to identify the loading of each variable in each component or factor; high factor loadings in absolute terms indicate a strong relation between the variables and the factor. In our context, the factors will be saturated with loadings of one stock or a group of stocks that may help us to identify those factors with certain economic sectors, as a first approach to the interpretation of each component or factor. For the case of ICA, that factor loading matrix is represented by the mixing matrix A, which was extracted from the estimated mixing process and which, in the context of our study, is expressed as ranked and orthogonalized.

In line with the previously reported results, we only present the factor loading matrix plots from each database that belong to the experiment where we extracted nine underlying factors[158]. Figures 5.3 to 5.6 presents these results.

Table 5.5. *Variance explained and accumulated.*

	Independent Component Analysis			
	Independent Component		Explained	Accumulated
	Ranked	Original number	Variance (%)	Explained Variance (%)
Database of weekly returns	1	6	19.00	19.00
	2	8	14.00	34.00
	3	2	12.00	47.00
	4	4	11.00	58.00
	5	7	10.00	68.00
	6	1	9.00	78.00
	7	3	7.00	85.00
	8	5	7.00	93.00
	9	9	6.00	100.00
Database of weekly excesses	1	3	23.00	23.00
	2	1	14.00	38.00
	3	7	13.00	52.00
	4	9	9.00	61.00
	5	8	9.00	71.00
	6	4	9.00	80.00
	7	6	7.00	87.00
	8	5	6.00	94.00
	9	2	5.00	100.00
Database of daily returns	1	9	26.00	26.00
	2	6	16.00	43.00
	3	7	10.00	53.00
	4	4	9.00	63.00
	5	3	8.00	71.00
	6	8	7.00	79.00
	7	5	7.00	87.00
	8	2	7.00	94.00
	9	1	5.00	100.00
Database of daily excesses	1	6	29.00	29.00
	2	7	20.00	50.00
	3	3	10.00	60.00
	4	5	8.00	68.00
	5	8	7.00	75.00
	6	9	6.00	82.00
	7	2	6.00	89.00
	8	4	5.00	94.00
	9	1	5.00	100.00

[158] Results related to experiments where eight, seven, six, five, four, three and two, components were extracted are not included for the sake of saving space, as we have exposed before in this dissertation.

Figure 5.3. *Loadings matrices plots for interpretation of extracted factors.*
Independent Component Analysis.
Database of weekly returns.
Nine components extracted.

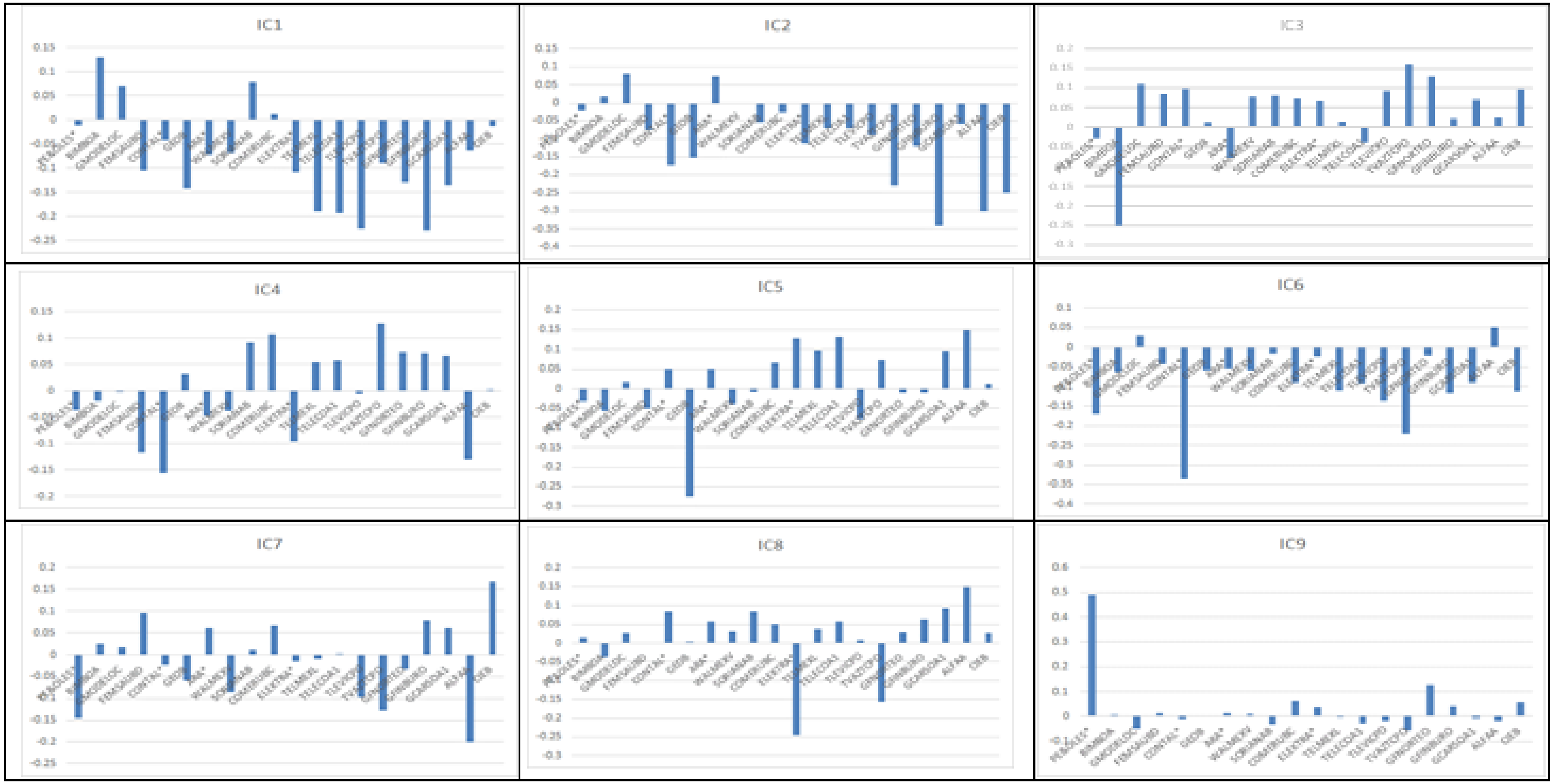


Figure 5.4. *Loadings matrices plots for interpretation of extracted factors.*
Independent Component Analysis.
Database of weekly excesses.
Nine components extracted.

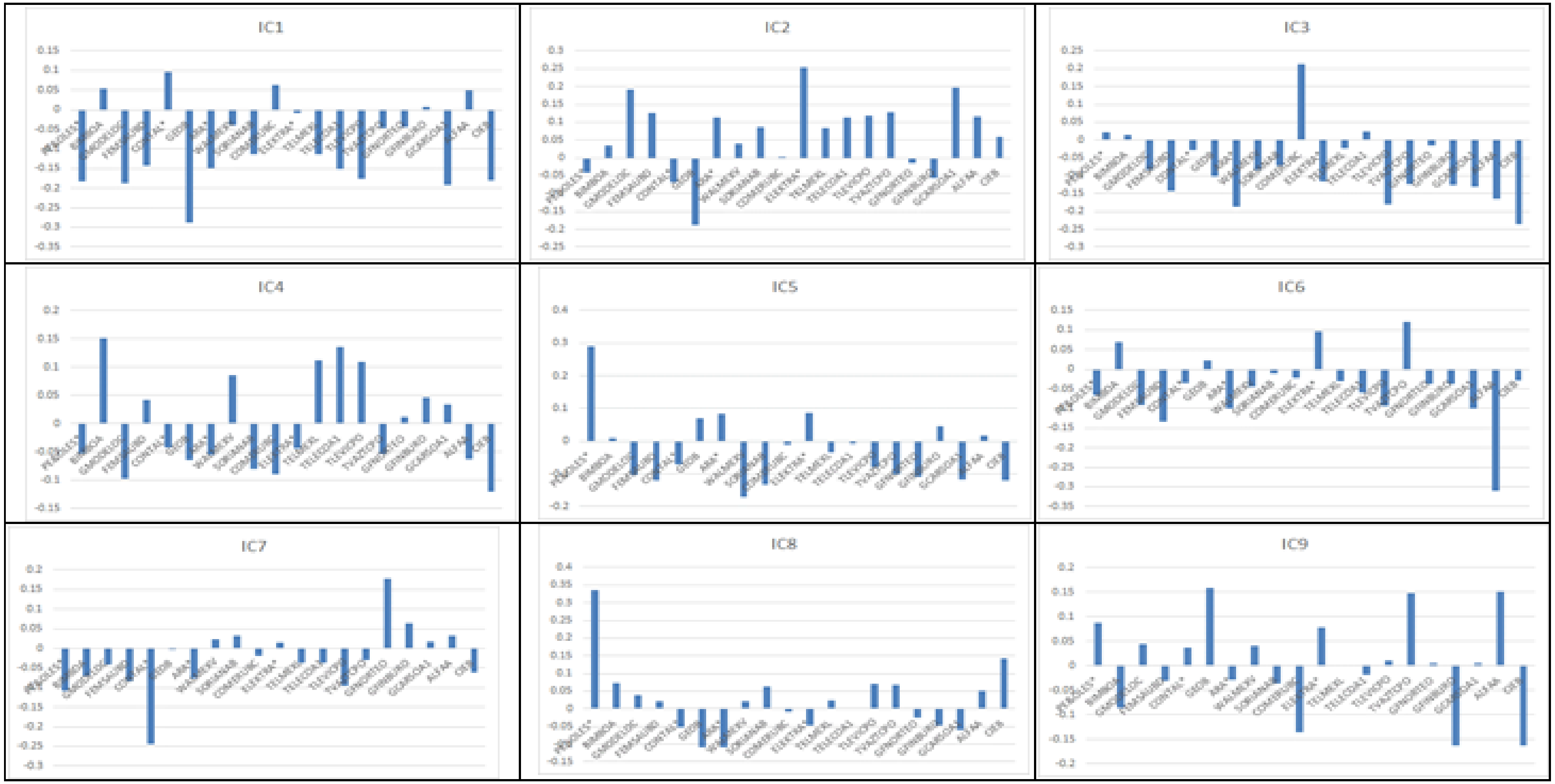


Figure 5.5. *Loadings matrices plots for interpretation of extracted factors.*
Independent Component Analysis.
Database of daily returns.
Nine components extracted.

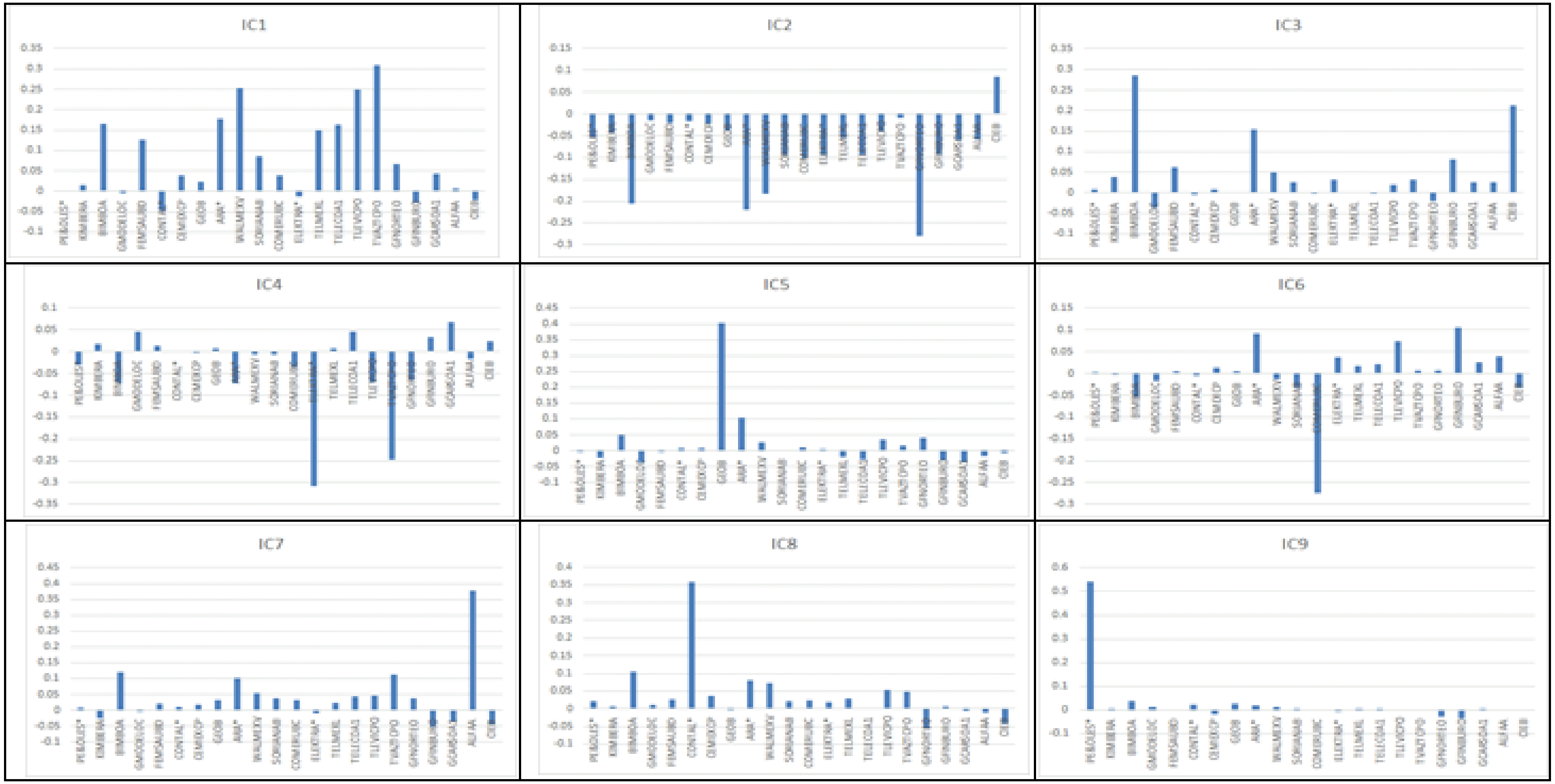


Figure 5.6. *Loadings matrices plots for interpretation of extracted factors.*
Independent Component Analysis.
Database of daily excesses.
Nine components extracted.

We constructed some tables summarizing the results derived from the analysis of the factor loading matrices and plots, where we propose a certain economic sector that may be related to each factor. We group together the stocks with the highest loading in each factor according to the official classification of the economic sectors used in the Mexican Stock Exchange. First, Tables 5.6 and 5.7 presents the details used for this interpretation which includes name of the stock, economic sector of each stock contributing to the formation of each factor, and sign of its loadings. Secondly, Table 5.8 presents a summary on the interpretation.

Daily databases provided clearer interpretations than weekly databases. In contrast to that expected in theory, the first component is not clearly related to the market factor[159], except in the case of the database of daily excesses; however, in the case of the database of daily returns, market factor is related to the second component[160].

On the other hand, in the database of weekly returns the first factor it is evidently related to the companies that form part of the Carso Group, owned by Carlos Slim Helú, for which reason we have named this first factor "the Slim Group", plus another important group in the communications media such as Televisa. Moreover, in the case of the daily database expressed in excesses, the first factor was related to the construction sector or GEO factor.

[159] We identify the market factor as the factor that is formed by a contribution of similar loadings of all the stocks considered, as explained in Chapter 1 for PCA and FA.

[160] Call the attention that in PCA and FA the first factor, which is the one with the major amount of variability explanation, is clearly identified with the market; whereas in ICA, although we have ranked the factors under the same criteria of variability explanation, in the cases when we could identify the market factor, this one was related to factor number two. In other words, when we have linearly uncorrelated but not statistically independent factors the market is the main source of risk; however, when we extract statistically independent factors that in addition are linearly uncorrelated, the marker factor is the second source of risk, and only for the daily periodicity of the data.

There is no a homogeneous interpretation of the factors in all the databases, except in some cases such as: factor number five, identified with the construction sector in the databases of weekly and daily returns; factor number six, in the daily databases, associated with the ordinary consumptive sector; and factor number nine in the data base of weekly returns and in both daily databases, which is related to the mining sector. Another factor that attracted our attention is the one pertaining to the companies of the Salinas Group, owned by Carlos Salinas Pliego, which are clearly identified as factor number eight in the database of weekly returns, and as number four in the databases of weekly and daily excesses.

Table 5.6. *Details of results. Sector interpretation of components. Independent Component Analysis. Nine components extracted.*

INDEPENDENT COMPONENT ANALYSIS							
Database of Weekly Returns				**Database of Weekly Excesses**			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
IC1	GFINBURO(-) TELEVICPO (-) TELECOA1 (-) TELMEXL (-)	Financial services: Financial groups Communication media: Radio & television services Telecommunications services: Wireless telecommunications services Telecommunications services: Wireless telecommunications services	Slim Group plus Televisa factor	**IC1**	GEOB (-)	Construction: House building	Construction sector factor (GEO factor)
IC2	GFINBURO(-) ALFA (-) CIEB (-) TVAZTECPO (-)	Financial services: Financial groups Capital goods: Industrial Conglomerate / Holdings Hotels, restaurants & leisure: Leisure facilities Communication media: Radio & television services	Financial service, Holdings, Leisure and Communication media sectors factor.	**IC2**	ELEKTRA* (+) GCARSOA1 (+) GMODELOC (+) GEOB (-)	Specialty retail: Home furnishing retail Capital goods: Industrial Conglomerate / Holdings Beverages: Brewers Construction: House building	Home furnishing, Holdings and Brewers / Construction sectors factor.
IC3	BIMBOA (-)	Food products: Production and commercialization of food products	Food products sector factor (Bimbo factor)	**IC3**	COMERUBC (+) CIEB (-)	Consumers staples: Hypermarkets and supercenters Hotels, restaurants & leisure: Leisure facilities	Consumer staples / Leisure sectors factor.
IC4	CONTAL* (-) ALFA (-) FEMSAUBD (-) TVAZTECPO (+) COMERUBC (+)	Beverages: Soft drinks Capital goods: Industrial Conglomerate / Holdings Beverages: Diversified beverages Communication media: Radio & television services Consumers staples: Hypermarkets and supercenters	Consume sector plus communication media sectors factor.	**IC4**	BIMBOA (+) TELECOA1 (+) TELMEXL (+) TELEVICPO (+) CIEB (-)	Food products: Production and commercialization of food products Telecommunications services: Wireless telecommunications services Telecommunications services: Wireless telecommunications services Communication media: Radio & television services Hotels, restaurants & leisure: Leisure facilities	Food products, Communication media and Telecommunications / Leisure sector factors.
IC5	GEOB (-)	Construction: House building	Construction sector factor (Geo factor)	**IC5**	PE&OLES (+) WALMEXV (-)	Metal and mining: Precious metals and minerals Consumers staples: Hypermarkets and supercenters	Mining / Consumer staples sector factor
IC6	CONTAL* (-)	Beverages: Soft drinks	Beverage sector factor (Contal factor)	**IC6**	ALFA (-)	Capital goods: Industrial Conglomerate / Holdings	Holding sector factor (Alfa factor)
IC7	ALFA (-) CIEB (+)	Capital goods: Industrial Conglomerate / Holdings Hotels, restaurants & leisure: Leisure facilities	Holdings / Leisure sectors factor	**IC7**	CONTAL* (-) GFNORTEO (+)	Beverages: Soft drinks Financial services: Financial groups	Beverage / Financial services sector factor
IC8	TVAZTECPO (-) ELEKTRA* (-)	Communication media: Radio & television services Specialty retail: Home furnishing retail	Salinas Group factor	**IC8**	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)
IC9	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)	**IC9**	GFINBURO (-) CIEB (-) GEOB (+) ALFA (+) TVAZTECPO (+)	Financial services: Financial groups Hotels, restaurants & leisure: Leisure facilities Construction: House building Capital goods: Industrial Conglomerate / Holdings Communication media: Radio & television services	Financial services and Leisure / House building, Holdings and Communication media sectors factor

Table 5.7. *Details of results. Sector interpretation of components. Independent Component Analysis. Nine components extracted. (Cont.)*

INDEPENDENT COMPONENT ANALYSIS							
Database of Daily Returns				**Database of Daily Excesses**			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
IC1	TVAZTECPO (+) WALMEXV (+) TELEVICPO (+)	Communication media: Radio & television services Consumers staples: Hypermarkets and supercenters Communication media: Radio & television services	Communication media plus consumer staples sectors factor.	**IC1**	IPC (+)	Market	Market factor
IC2	IPC (-)	Market	Market factor	**IC2**	TELEVICPO (+) TVAZTECPO (+) TELMEXL (+)	Communication media: Radio & television services Communication media: Radio & television services Telecommunications services: Wireless telecommunications services	Communication media and telecommunication sectors factor.
IC3	BIMBOA (+) CIEB (+) ARA* (+)	Food products: Production and commercialization of food products Hotels, restaurants & leisure: Leisure facilities Construction: House building	Food products, Leisure and House building sector factor	**IC3**	CIEB (-)	Hotels, restaurants & leisure: Leisure facilities	Leisure sector factor
IC4	ELEKTRA* (-) TVAZTECPO (-)	Specialty retail: Home furnishing retail Communication media: Radio & television services	Salinas Group factor	**IC4**	ELEKTRA* (+) TVAZTECPO (+)	Specialty retail: Home furnishing retail Communication media: Radio & television services	Salinas Group factor
IC5	GEOB (+)	Construction: House building	Construction sector factor (Geo factor)	**IC5**	ALFA (-)	Capital goods: Industrial Conglomerate / Holdings	Holdings sector factor (Alfa factor)
IC6	COMERUBC (-)	Consumers staples: Hypermarkets and supercenters	Ordinary consume sector factor (Comercial Mexicana factor)	**IC6**	COMERUBC (+)	Consumers staples: Hypermarkets and supercenters	Ordinary consume sector factor (Comercial Mexicana factor)
IC7	ALFA (+)	Capital goods: Industrial Conglomerate / Holdings	Holdings sector factor (Alfa factor)	**IC7**	CONTAL* (-)	Beverages: Soft drinks	Beverage sector factor (Contal factor)
IC8	CONTAL* (+)	Beverages: Soft drinks	Beverage sector factor (Contal factor)	**IC8**	GEOB (+)	Construction: House building	Construction sector factor (Geo factor)
IC9	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)	**IC9**	PE&OLES (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)

Table 5.8. *Summary of results. Sector interpretation of components. Independent Component Analysis. Nine components extracted.*

INDEPENDENT COMPONENT ANALYSIS							
Database of Weekly Returns		**Database of Weekly Excesses**		**Database of Daily Returns**		**Database of Daily Excesses**	
IC1	Slim Group plus Televisa factor	**IC1**	Construction sector factor (GEO factor)	**IC1**	Communication media plus consumer staples sectors factor.	**IC1**	Market factor
IC2	Financial service, Holdings, Leisure and Communication media sectors factor.	**IC2**	Home furnishing, Holdings and Brewers / Construction sectors factor.	**IC2**	Market factor	**IC2**	Communication media and telecommunication sectors factor.
IC3	Food products sector factor (Bimbo factor)	**IC3**	Consumer staples / Leisure sectors factor.	**IC3**	Food products, Leisure and House building sectors factor	**IC3**	Leisure sector factor
IC4	Consume sector plus communication media sectors factor.	**IC4**	Food products, Communication media and Telecommunications / Leisure sectors factors.	**IC4**	Salinas Group factor	**IC4**	Salinas Group factor
IC5	Construction sector factor (Geo factor)	**IC5**	Mining / Consumer staples sector factor	**IC5**	Construction sector factor (Geo factor)	**IC5**	Holding sector factor (Alfa factor)
IC6	Beverage sector factor (Contal factor)	**IC6**	Holdings sector factor (Alfa factor)	**IC6**	Ordinary consume sector factor (Comercial Mexicana factor)	**IC6**	Ordinary consume sector factor (Comercial Mexicana factor)
IC7	Holdings / Leisure sectors factor	**IC7**	Beverage / Financial services sectors factor	**IC7**	Holdings sector factor (Alfa factor)	**IC7**	Beverage sector factor (Contal factor)
IC8	Salinas Group factor	**IC8**	Mining sector factor (Peñoles factor)	**IC8**	Beverage sector factor (Contal factor)	**IC8**	Construction sector factor (Geo factor)
IC9	Mining sector factor (Peñoles factor)	**IC9**	Financial services and Leisure / House building, Holdings and Communication media sectors factor	**IC9**	Mining sector factor (Peñoles factor)	**IC9**	Mining sector factor (Peñoles factor)

Nevertheless, there are other factors that although had a different interpretation share certain sectors across the databases, e.g., factor number seven, in databases expressed in returns, that have in common the holdings sector; and in databases expresses in excesses, that share a strong contribution of the beverage sector. These results give certain indication of the importance of those sectors in the formation of the referred factors.

Furthermore, there are some factors that share the same interpretation in the different databases but are ranked in different order, such as: construction sector factor, beverage sector factor, holding sector factor, Salinas Group factor, mining sector factor and market factor. This fact make us to think about the importance of this sectors across the databases independently of their ranking.

Conversely, there are other factors whose meanings are not clearly identified since they are formed by stocks from different sectors, such as: factor number two in database of weekly returns; and two, four and nine, in database of weekly excesses. In some sense, those factors could be interpreted also as miscellaneous sector factors, which mix the effects of several economic sectors.

It is important to remark that there are some sectors or stocks which have a constant and strong contribution in the formation of several factors in the most of the databases, such as: communication media sector with TVAZTECPO and TLEVICPO, holding sector with ALFAA, the mining sector with PE&OLES*, the construction sector with GEO, and the leisure sector with CIEB[161]. This findings lead us to think in this stocks as important referents in the risk formation in the context of the Mexican Stock Exchange.

Finally, attending to the explained variance of each one of the factors extracted (See Table 5.5), we can point the first four of them in each dataset as the main factors in terms of the explained variance, which leads us to attribute them the interpretation presented in Table

[161] The sectors and stocks listed are ordered from higher to lower frequency in relation to its contribution to the formation of latent factors in the four databases.

5.8 for the first four factors in each database. Therefore we may conclude that the factors integrated by the companies of the Grupo Carso, Grupo Salinas, the market factor[162], as well as, sectors related to construction, ordinary consume and leisure are the ones that explain the most of the variability of the Mexican Stock Market, under the scope of the Independent Component Analysis.

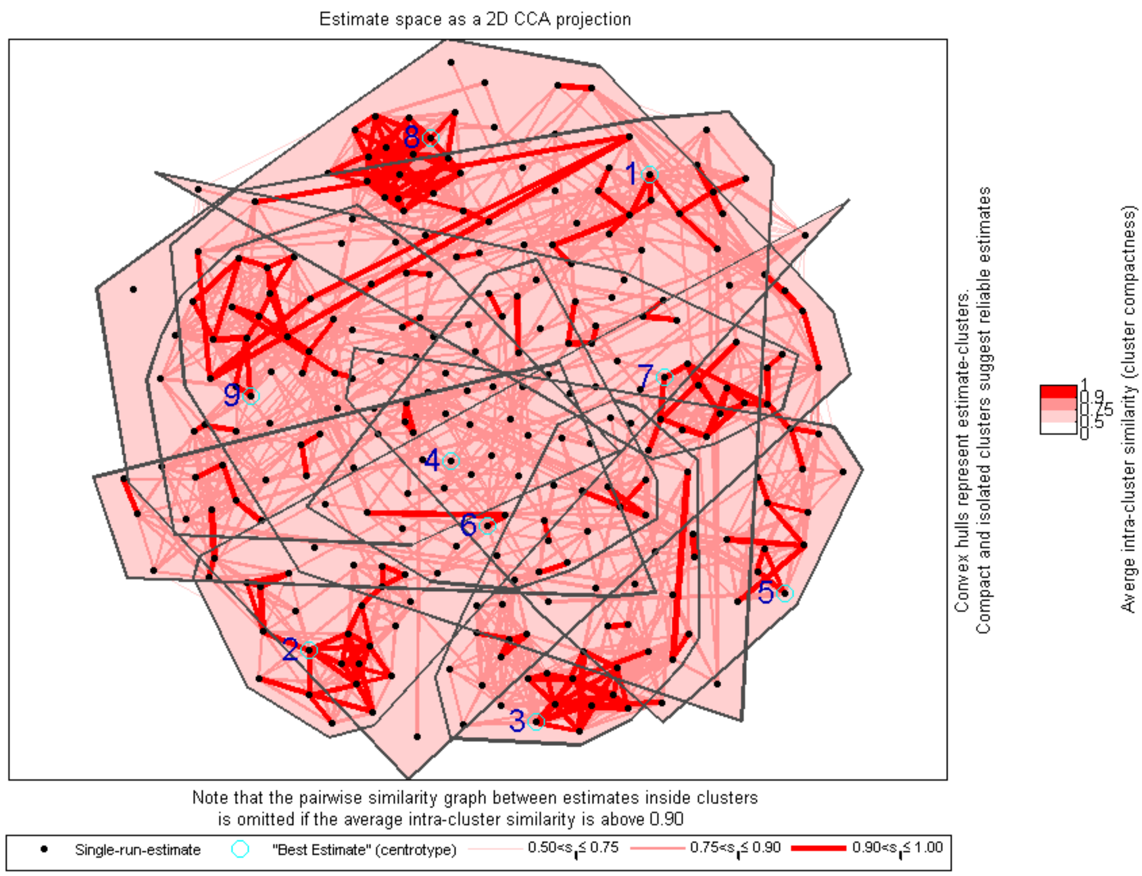
5.3.8. ICASSO Plots.

ICASSO also offers some graphic results in order to evaluate the reliability of the independent components via visualization of their clustering in the signal space. For illustrative purposes only, we will explain some of those that were found in the experiment, where nine independent components were extracted from the database of weekly returns[163]. The first one is the clusters plot, where each estimate computed in every run of the algorithm is represented by one point in the signal space and all the estimates which belong to the same cluster appear bounded by convex hulls. Points which appear close to each other and correspond to small clusters well-separated from the rest are considered reliable estimates; since in every run of the algorithm those estimates have been similar, it can be considered that they are very close to the real component. In contrast, points that do not belong to any cluster are considered unreliable estimates. In Figure 5.7, we show the clusters formed in the experiment described above. We can observe the formation of nine differentiated clusters where their centrotypes or best estimates of each one of them are surrounded with a blue circle. The thick/thin/color lines connecting the points represent the similarities $\sigma_{ij} = |r_{ij}|$ between them, the darker the line the stronger the similarity.

[162] Only in the case of daily databases.

[163] For the sake of saving space the results of the rest of our experiments are not included in this document; however, all these plots were elaborated for the four databases and for the entire window test which ranged from two to nine extracted factors.

Figure 5.7. *Clusters plot. Database of weekly returns. Nine components extracted.*



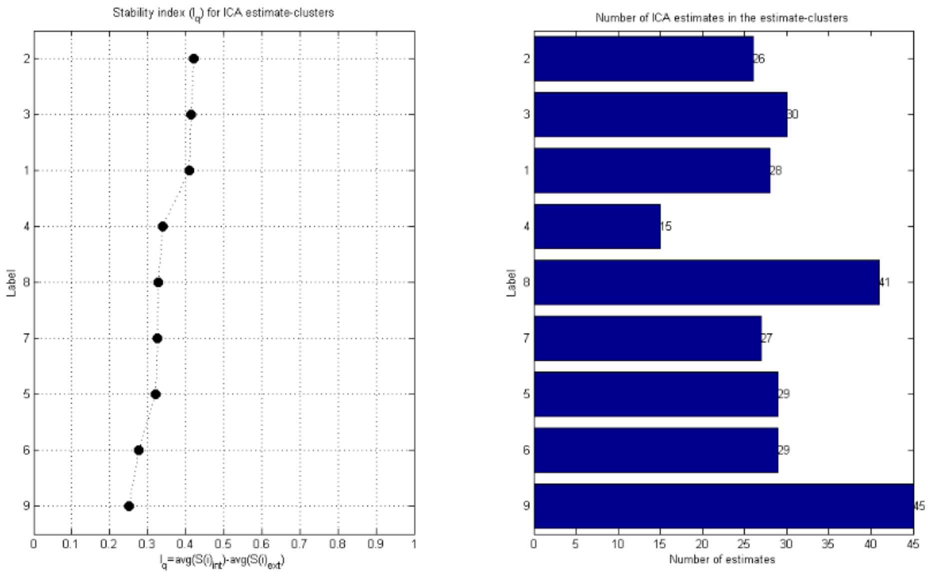
Source: Own elaboration using Gävert, *et al.* (2005) Matlab® software ICASSO.

Another interesting graphic result that ICASSO produces is the one concerning the cluster quality index I_q, which reflects the compactness and isolation of a cluster. The I_q index represents the difference between the average intracluster similarities and the average intercluster similarities and is computed by means of the following expression (Himberg and Hyvärinen, 2003, 2005).

$$I_q(C_m) = \frac{1}{|C_m|^2} \sum_{i,j \in C_m} \sigma_{ij} - \frac{1}{|C_m||C_{-m}|} \sum_{i \in C_m} \sum_{j \in C_{-m}} \sigma_{ij}, \tag{5.23}$$

where C is the set of indices of all the estimates; C_m, the indices that belong to the m-th cluster; $|C_m|$, the size of the m-th cluster and $|C_{-m}|$ the indices that do not belong to the m-th cluster. I_q will be equal to one for ideal clusters and its value will decrease when the clusters become less compact and isolated. Figure 5.8 presents the I_q index plot for the same experiment presented in Figure 8. The left panel shows the ICs ranked according to the quality of the estimation index I_q; i.e., in this experiment ICs 2, 3 and 1 are the best estimations which represent the most compact and isolated clusters. In addition, these results may indicate some interesting directions for further analysis and discussion on the nature of those ICs[164]. The left panel shows the ICs ranked according to the quality of the estimation index I_q. The right panel presents the number of estimates agglomerated in each cluster.

Figure 5.8. *Clusters Quality Index (I_q) plot. Database of weekly returns. Nine components extracted.*



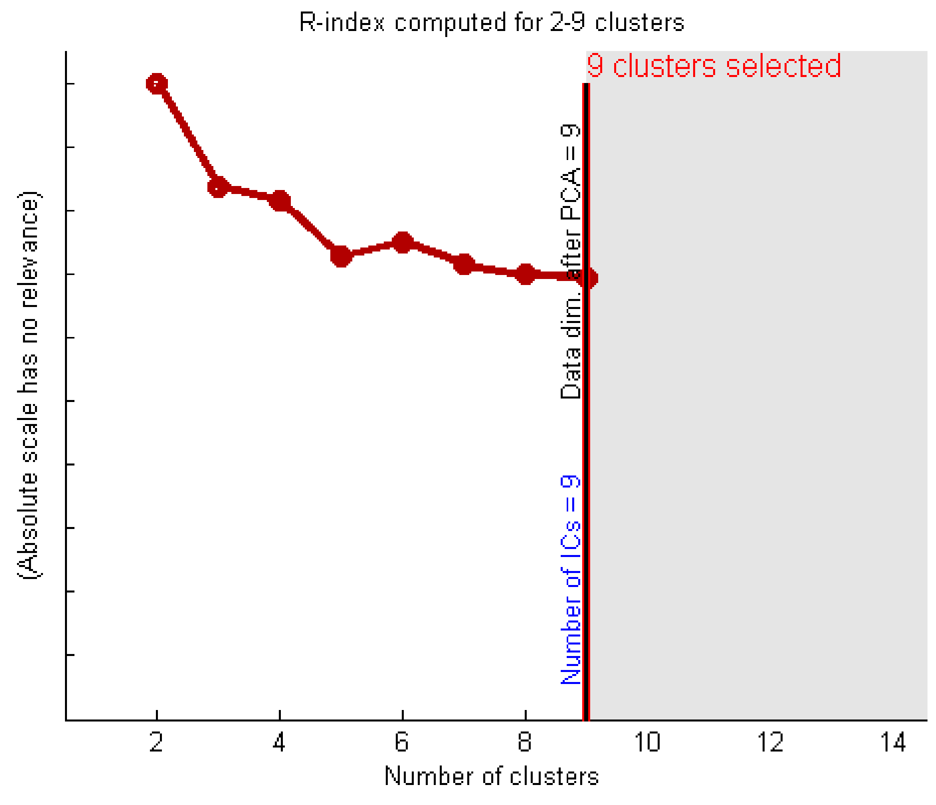
Source: Own elaboration using Gävert, *et al.* (2005) Matlab® software ICASSO.

[164] A deeper investigation on the estimated ICs derived from the results of the *Iq* index is out of the scope of this study. Although the *Iq* index could be used as a criterion to sort the ICs estimated by ICA, we used another ranking criterion, more suitable to the purposes of our research, which was explained in section 5.3.3. That is, the *Iq* index ranks the estimated components in function on the isolation or compactness of the cluster where each estimated independent component (the centrotype of each cluster) belongs; the most isolated cluster is considered the most independent and subsequently the best estimated. In our context, in order to be able to compare the factors extracted by the different techniques used in this study, we are more interested in obtaining a ranking in function of the amount of variability explained by each component, that is the reason for using the criteria proposed by García-Ferrer *et al.* (2012) explained in the section 5.3.3. and not the *Iq* index criteria included in the ICASSO methodology.

The ICASSO software generates three additional plots that offer information about the clustering quality, a dendrogram and a similarity matrix, and source estimates.

The first one plots a relative clustering quality index, R-index (I_R), which looks for compact and well-separated clusters. The minimum of I_R suggests the best partition[165]. Additionally, the plot shows the reduced data dimensions and the maximum number of independent components extracted. Figure 5.9 shows the R-index plot, where we can observe that, in an extraction of nine components, the best number of clusters is indeed nine.

Figure 5.9. *R-index plot. Database of weekly returns. Nine components extracted.*



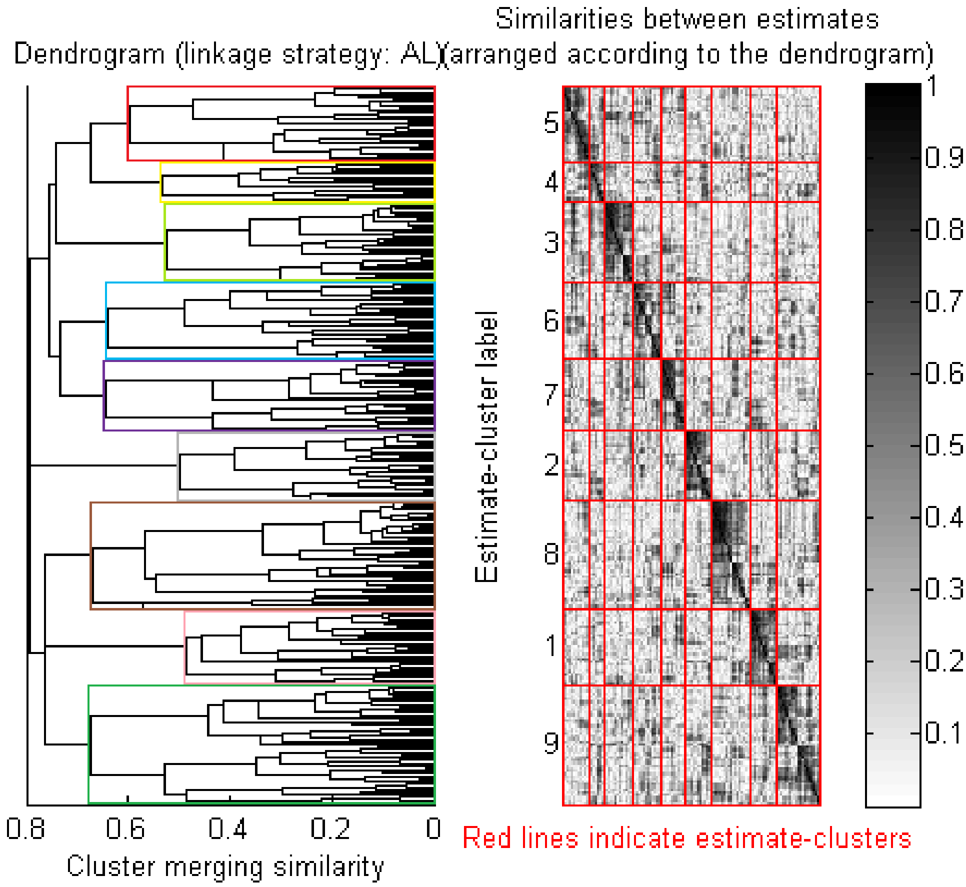
Source: Own elaboration using Gävert, *et al.* (2005) Matlab® software ICASSO.

[165] For details of the R-index, see Himberg and Hyvärinen (2003) and Himberg *et al.* (2004).

The second additional graph shows the correlation structure as a matrix and a dendrogram representation for L clusters. Its purpose is to visualize the clustering and the similarities between estimates as a dendrogram (tree visualizations) of the clustering hierarchy and a corrgram (the values of the similarity matrix visualized as a gray level matrix). The entries in the corrgram are ordered according to the leaf ordering in the dendrogram. The clusters in the corrgram are indicated by red lines. Figure 5.10 shows this plot. The left panel corresponds to the dendrogram where we can observe the nine clusters estimated. We have marked each cluster with rectangles of different colors to represent estimations that are very similar. We can find different levels of clustering when moving leftwards in the graph. The closer to the right the points are located, the more their similarity, i.e., when moving to the left of the plot, we can observe a diminishing level of similarity between the points. The right panel refers to the corrgram, which visually represents the correlation of the estimations arranged from the highest to the lowest level. The rows closer to the top show greater correlation with a darker scale of grays in the main diagonal of the matrix, while the rows closer to the bottom represent a lesser one with a lighter scale of grays in the same diagonal. Each row indicates the number of clusters that it represents, and its height permits us to distinguish the division of the nine clusters presented in the dendrogram, i.e., the rows help us to identify which hierarchy of clustering was last considered to form each of the nine clusters. In this case, the cluster whose estimations had the highest level of similarity was cluster number 5, whereas the one where they were least similar was number 9[166].

[166] Ranking according to the similarity of the estimations might be used as another criterion to sort the independent components, and might represent possible lines of interpretation of them; however, these lines of research are out of the scope of this work.

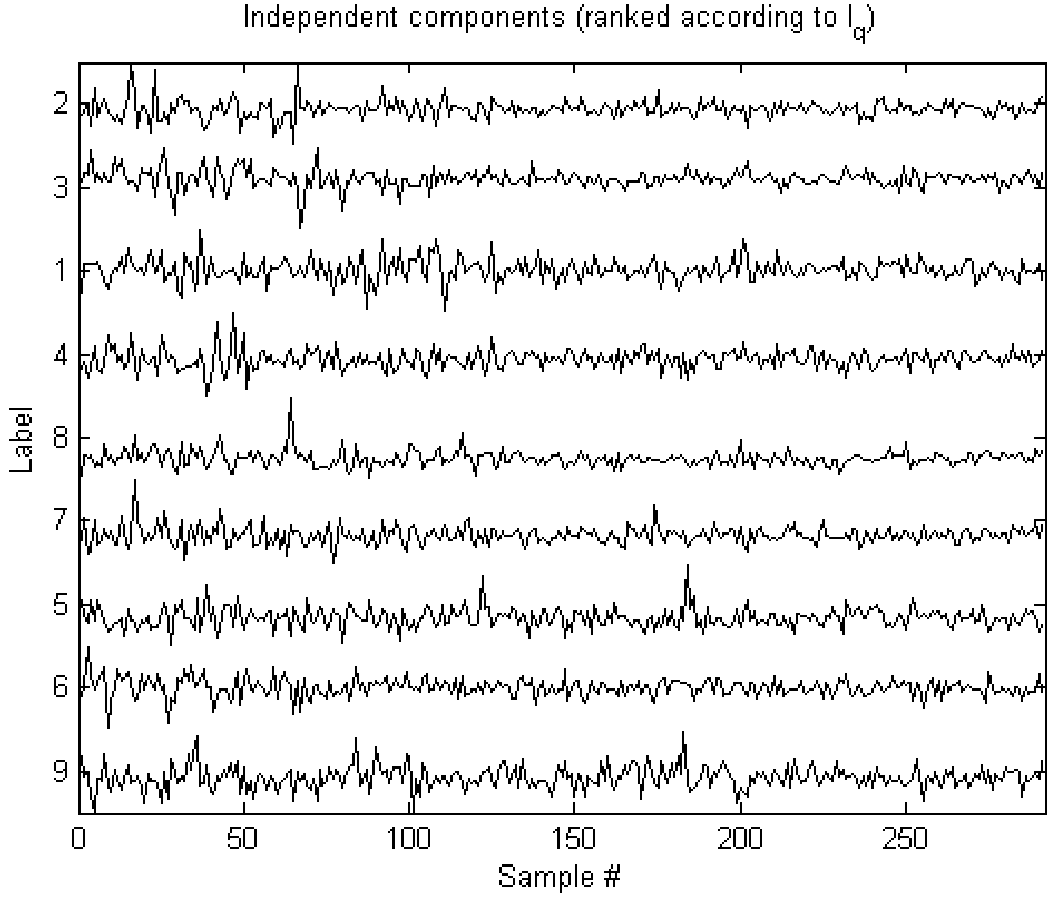
Figure 5.10. *Dendrogram and similarity matrix plots. Database of weekly returns. Nine components extracted.*



Source: Own elaboration using Gävert, *et al.* (2005) Matlab® software ICASSO.

Finally, the third additional graph plots the best estimated sources, i.e. the centroide or centrotype of each cluster of independent components extracted. Figure 5.11 shows those independent components ranked according to the cluster quality index (I_q).

Figure 5.11. *Source estimates. Database of weekly returns. Nine components extracted.*



Source: Own elaboration using Gävert, *et al.* (2005) Matlab® software ICASSO.

5.3.9. Results of the econometric contrast.

As stated in Chapter 3, in the first stage of our econometric contrast methodology we estimated the betas or sensitive to the underlying factors to use in expression 5.24[167],

$$\overline{R_i} = \lambda_0 + \lambda_1 \cdot \beta_{1i} + \lambda_2 \cdot \beta_{2i} + ... + \lambda_k \cdot \beta_{ki} + \overline{\varepsilon_i}\ , \qquad (5.24)$$

[167] Where, β_{jig} represents the sensitivity of equity i to factor j, F_{jt} the value of the systematic risk factor j in time t common for all the stocks, and ε_i the idiosyncratic risk affecting only equity i.

by regressing the factor scores obtained by ICA as a cross-section on the returns and excesses, by way of Weighted Least Squares (WLS) to estimate the entire system of equations at the same time.

The results of the regressions in the four databases were suitable, producing in almost all cases, statistically significant parameters, high values of the R^2 coefficients and results in the Durbin-Watson test of autocorrelation[168], which lead us to the non-rejection of the null hypothesis of no-autocorrelation in almost all the cases[169]. Tables 5.9 to 5.12 present the results of the coefficients estimated for ICA, which represent the betas to use in the second stage of the econometric contrast. All the tables correspond to the case where 9 components or factors were extracted[170].

Table 5.9. *Independent Component Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of weekly returns.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.012767	-0.012336	-0.034002	-0.036268	-0.035363	-0.174141	-0.154268	0.011862	0.516080
BIMBOA	0.012329	-0.134081	-0.189827	0.006463	0.013762	-0.167391	0.025539	-0.026878	-0.022708
GMODELOC	-0.028982	-0.025701	0.131136	0.001212	0.042247	-0.044834	-0.018247	0.022388	-0.004930
FEMSAUBD	-0.157323	-0.127534	0.110203	-0.105255	-0.020903	-0.093536	0.079821	0.015738	0.012016
CONTAL*	0.031415	-0.075419	0.059418	-0.172986	0.017206	-0.260805	-0.010615	0.070259	-0.022223
GEOB	-0.212195	-0.260124	0.035362	0.018874	-0.319361	-0.102635	-0.117817	-0.014985	0.045918
ARA*	-0.151417	-0.061775	-0.033847	-0.049611	0.027727	-0.095705	0.026926	0.058273	0.042625
WALMEXV	-0.136857	-0.073254	0.119958	-0.004769	-0.007609	-0.105899	-0.064269	0.045970	-0.028585
SORIANAB	-0.041651	-0.174562	0.144037	0.118244	0.012086	-0.103805	0.001242	0.074667	-0.006245
COMERUBC	-0.030499	-0.144437	0.101540	0.098050	0.080191	-0.145403	0.037597	0.051612	0.059106
ELEKTRA*	-0.194373	-0.230002	0.109354	-0.088996	0.136142	-0.085833	-0.036559	-0.260815	0.055082
TELMEXL	-0.176716	-0.055716	0.011342	0.055673	0.083757	-0.106982	-0.013046	0.036848	-0.006061
TELECOA1	-0.243882	-0.095438	-0.027511	0.070791	0.127036	-0.136893	-0.010093	0.062864	-0.005955
TLEVICPO	-0.225997	-0.114721	0.106550	0.012223	-0.010611	-0.181876	-0.067351	0.019521	-0.031829
TVAZTCPO	-0.082808	-0.220040	0.153903	0.124484	0.064322	-0.208528	-0.137382	-0.146965	-0.048224
GFNORTEO	-0.144652	-0.140925	0.145457	0.078824	0.005845	-0.013145	-0.007644	0.035280	0.058716
GFINBURO	-0.152498	-0.220113	-0.023794	0.059975	-0.007954	-0.037361	0.106724	0.057026	0.041651
GCARSOA1	-0.179941	-0.121136	0.086386	0.064333	0.111298	-0.120093	0.045973	0.077598	-0.003311
ALFAA	-0.105565	-0.379684	0.047561	-0.128422	0.157987	0.008243	-0.219870	0.151297	-0.010118
CIEB	-0.026916	-0.280997	0.112047	0.020773	0.015963	-0.146787	0.171918	0.041013	0.054851

168 Value of the statistic more than 2.

169 For reasons of saving space these results are not presented in this section, however the interested reader can consult the results of the estimation of the betas for all the equation system in the Appendix_1 of this dissertation, from Tables 9 to 12.

170 In line to the previously reported results, those corresponding to the rest of the experiments of the test window are not included in this document; nevertheless, the results are similar to those reported in this chapter.

Table 5.10. *Independent Component Analysis. Betas estimated simultaneously via Weighted Least Squares. Database of weekly excesses.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.227177	-0.027222	0.018121	-0.064798	0.307902	-0.077076	-0.130278	0.367506	0.087132
BIMBOA	-0.014020	0.071543	-0.102355	0.133377	-0.002661	0.016414	-0.106938	0.072439	-0.072367
GMODELOC	-0.085915	0.107972	0.007851	-0.063290	-0.075505	-0.042784	-0.020888	0.023930	0.036910
FEMSAUBD	-0.129522	0.096841	-0.138931	0.042600	-0.095134	-0.094311	-0.072260	0.024495	-0.023607
CONTAL*	0.001794	-0.003170	-0.094837	-0.065913	-0.069693	-0.081078	-0.284430	-0.018169	0.046644
GEOB	-0.373971	-0.120249	-0.226831	-0.084080	0.038431	-0.023132	-0.021412	-0.114226	0.186462
ARA*	-0.125621	0.078867	-0.122443	-0.046634	0.102040	-0.095682	-0.074784	-0.103418	-0.043887
WALMEXV	-0.108247	0.065488	-0.110329	0.073741	-0.152221	-0.066954	-0.003986	0.051321	0.060970
SORIANAB	-0.169153	0.106242	-0.106058	-0.084742	-0.149305	-0.042908	0.026472	0.065133	-0.031173
COMERUBC	-0.142283	0.150823	0.008284	-0.137738	-0.070358	-0.104248	-0.062056	0.018430	-0.086369
ELEKTRA*	-0.114833	0.329107	-0.222339	-0.075643	0.074187	0.058892	-0.017533	-0.031562	0.114778
TELMEXL	-0.144206	0.124157	-0.045100	0.096259	-0.050609	-0.062521	-0.032137	0.011638	0.001767
TELECOA1	-0.200016	0.178365	-0.055179	0.144794	-0.039581	-0.103512	-0.041436	-0.002702	-0.013111
TLEVICPO	-0.179406	0.126012	-0.171772	0.101795	-0.118754	-0.069637	-0.078233	0.057368	0.035504
TVAZTCPO	-0.137930	0.201054	-0.206934	-0.062244	-0.140475	0.080046	-0.036327	0.087234	0.151703
GFNORTEO	-0.154974	0.058549	-0.096937	-0.023351	-0.106642	-0.083053	0.126262	0.011981	0.021966
GFINBURO	-0.113793	0.023648	-0.218011	0.033178	0.022046	-0.078951	0.043449	-0.009902	-0.143292
GCARSOA1	-0.173625	0.176054	-0.098264	0.026367	-0.088692	-0.099184	-0.005512	-0.030770	-0.026170
ALFAA	-0.003896	0.170098	-0.262781	-0.073040	-0.021180	-0.354144	0.024540	0.036932	0.163243
CIEB	-0.148147	0.065302	-0.245903	-0.118529	-0.124645	-0.034527	-0.058188	0.118727	-0.167391

Table 5.11. *Independent Component Analysis. Betas estimated simultaneously via Weighted Least Squares. Database of daily returns.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.017825	-0.071532	0.017066	-0.037295	0.002327	0.002373	0.013725	0.027212	0.545156
KIMBERA	0.069789	-0.080806	0.072118	0.006285	-0.002726	-0.010078	0.009473	0.031072	0.010246
BIMBOA	0.050116	-0.093951	0.221996	-0.022390	0.015475	-0.051052	0.061919	0.069755	0.020740
GMODELOC	0.089915	-0.088661	-0.000148	0.000593	-0.019655	-0.016529	0.038902	0.047364	0.016753
FEMSAUBD	0.175436	-0.073934	0.074180	-0.017229	0.016530	-0.000973	0.046254	0.035813	0.000440
CONTAL*	-0.002412	-0.057722	0.020766	-0.015527	0.018122	-0.005381	0.029989	0.376939	0.027399
CEMEXCP	0.121940	-0.096468	0.044026	-0.037388	0.023611	0.010092	0.053221	0.056535	0.000707
GEOB	0.095509	-0.097057	0.038098	-0.024573	0.419657	0.005868	0.073757	0.020463	0.035254
ARA*	0.078563	-0.140830	0.108783	-0.027705	0.084755	0.087875	0.044563	0.042263	0.007662
WALMEXV	0.207020	-0.148236	0.028380	0.000561	0.013932	-0.004070	0.047324	0.055759	0.010772
SORIANAB	0.158036	-0.132436	0.059244	-0.027228	0.019469	-0.040607	0.053305	0.037768	0.012722
COMERUBC	0.093508	-0.160848	0.027296	-0.060858	0.026010	-0.276207	0.067940	0.037190	0.005429
ELEKTRA*	0.079657	-0.176873	0.075991	-0.358739	0.028552	0.040691	0.048156	0.043862	-0.001408
TELMEXL	0.189652	-0.092553	0.021104	0.000287	-0.002779	0.023777	0.049808	0.036087	0.006140
TELECOA1	0.224481	-0.150297	0.039664	0.014193	-0.008461	0.027326	0.075133	0.028608	0.010470
TLEVICPO	0.300127	-0.083979	0.036918	-0.087187	0.040676	0.065726	0.073374	0.069426	-0.001319
TVAZTCPO	0.315097	-0.012856	0.041183	-0.245562	0.015918	0.008446	0.109951	0.058721	0.004780
GFNORTEO	0.082357	-0.296812	-0.008843	-0.061881	0.042631	0.001896	0.029457	-0.038448	-0.023610
GFINBURO	0.056680	-0.176917	0.124597	-0.003960	-0.006157	0.107907	0.002572	0.031246	-0.022789
GCARSOA1	0.152550	-0.153670	0.076998	0.008727	-0.019060	0.026010	0.036341	0.032981	0.006784
ALFAA	0.074296	-0.122521	0.059019	-0.048551	-0.001870	0.039419	0.420289	0.011918	0.003390
CIEB	0.122768	-0.045258	0.290655	-0.034213	0.029070	-0.032606	0.020799	0.010831	0.016056

Table 5.12. *Independent Component Analysis.*
Betas estimated simultaneously via Weighted Least Squares.
Database of daily excesses.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	0.031453	0.016678	-0.031318	0.003498	-0.027512	0.018685	-0.016649	0.013230	0.549238
KIMBERA	0.091731	0.069932	-0.082432	-0.009987	-0.003873	0.024067	-0.030901	-0.003132	0.007666
BIMBOA	0.111691	0.021636	-0.136428	0.003590	-0.025652	-0.016057	-0.054930	0.016413	0.029529
GMODELOC	0.110765	0.093189	-0.008954	0.011703	-0.029344	0.024199	-0.048168	-0.032939	0.022111
FEMSAUBD	0.122709	0.156476	-0.066371	0.040762	-0.013752	0.016254	-0.026408	0.002579	0.001525
CONTAL*	0.070160	0.003313	-0.029169	0.010938	0.012761	0.011555	-0.382361	0.028242	0.038013
CEMEXCP	0.137193	0.107194	-0.036761	0.039116	-0.017672	0.015190	-0.043614	0.014817	0.011012
GEOB	0.149779	0.071752	-0.064429	0.030337	-0.071647	0.030360	-0.002757	0.410121	0.031078
ARA*	0.185545	0.063583	-0.090778	0.001844	0.026530	-0.023175	-0.029305	0.056304	0.028216
WALMEXV	0.170171	0.169453	-0.030913	0.029287	-0.039374	-0.008241	-0.037084	0.002315	0.019656
SORIANAB	0.139901	0.139454	-0.084166	0.028212	-0.009853	0.047273	-0.026130	0.011296	0.017195
COMERUBC	0.153648	0.082099	-0.035738	0.036753	-0.042645	0.313429	-0.031005	-0.002892	0.015754
ELEKTRA*	0.218433	0.007050	-0.068974	0.371244	-0.042131	0.016995	-0.034265	0.015514	0.031197
TELMEXL	0.133835	0.171736	-0.026638	0.015651	-0.025153	-0.026782	-0.025522	-0.003482	0.015218
TELECOA1	0.192995	0.185803	-0.049885	0.008133	-0.046396	-0.038774	-0.021927	-0.012226	0.023016
TLEVICPO	0.164617	0.278503	-0.062603	0.113878	-0.017378	-0.027908	-0.051477	0.034738	0.007384
TVAZTCPO	0.093744	0.270249	-0.105253	0.258821	-0.035683	-0.018184	-0.049580	0.016117	0.017564
GFNORTEO	0.320216	0.023462	-0.003832	0.025863	0.040032	0.029751	0.029971	0.012578	0.000430
GFINBURO	0.200712	-0.014624	-0.129070	0.007002	-0.024943	-0.077354	-0.013593	-0.007589	-0.003813
GCARSOA1	0.176324	0.105445	-0.083850	0.021429	-0.062612	-0.013604	-0.030341	-0.043782	0.013085
ALFAA	0.176618	0.090766	-0.098348	0.060669	-0.386188	0.005209	-0.046480	-0.015494	0.000284
CIEB	0.099355	0.077198	-0.348008	0.029199	0.026824	0.054270	-0.027821	0.004425	0.011871

The previous tables shows the sensitivity of stock (i) to the risk factor (k). In the case of this technique we can observe that in all the cases the sensitivity or beta related to the extracted factors are very small, which lead us to think that all these factors affects in a small measure to the returns of the studied stocks.

Ongoing with the methodology described in Chapter 3, in the second stage of the econometric contrast, we estimated the lambdas or risk premiums in expression 5.24 by regressing the betas obtained in the first stage as a cross-section on the returns and excesses, using ordinary least squared corrected by heteroscedasticity and autocorrelation by means of the Newey-West heteroscedasticity and autocorrelation consistent covariance estimates (HEC). Additionally, we verified the normality in the residuals by carrying out the Jarque-Bera test of normality and we used the Wald test to confirm the equalities assumed by the APT regarding the independent term.

In Tables 5.13 and 5.14, we present a summary of the results of the econometric contrast for ICA. As we can observed in the figures presented in the tables, the results of the explanation power, the adjusted R-squared (R^{2^*}), the statistical significance of the multivariate test (F), and the Jarque-Bera normality test of the residuals are suitable in almost all the contrasted models, except in the cases where only two factors were extracted; in some other cases, expressions such as the models with 7 and 9 betas in the database of weekly returns and the models with 5, 7 and 8, in the database of weekly excesses.

The univariate tests for the individual statistical significance of the parameters (Statistic t) priced from one to five factors exclusive of λ_0 in the weekly and daily databases, thus giving evidence in favor of the APT in 27 models[171]. Nevertheless, only four models fulfilled both the statistical significance of the parameters and the equality of the independent term to its theoretic value, in addition to the fulfilment of normality in the residuals. From the four models fully accepted, three models present only one statistically significant parameter outside of λ_0; this constitutes weak evidence in favor of the APT as a pricing model using these extracted factors, since as a multivariate asset pricing model, it should be expected that more than one underlying risk factor be priced. The referred models were the one expressed in weekly returns when six components were extracted, and those expressed in daily returns when three and five components were retained. The only model that presents two statistically significant parameters or priced factors is the one expressed in weekly returns when eight factors were estimated.

Moreover, there are ten other models which fulfil all the conditions for accepting the APT as a pricing model, except for the statistical significance of the independent term, and nine models that fail only in the equality of the independent term to its theoretical value, which provides some additional evidence in favor of this asset-pricing model.

[171] The total number of tested models was 32.

Table 5.13. Independent Component Analysis. Summary of the Econometric Contrast. Weekly databases.

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{2*}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of weekly returns.															
Model with 2 betas	●	●	●								5.78%	0.00%	●	○	○
Model with 3 betas	0.0053	●	●	0.01665							46.78%	33.33%	○	●	○
Model with 4 betas	0.005460	●	-0.01492	-0.01220	●						46.58%	50.00%	○	●	○
Model with 5 betas	0.005074	●	-0.01771	●	●	●					47.28%	20.00%	○	●	○
Model with 6 betas	0.005460	●	-0.01899	●	●	●	●				44.21%	16.67%	○	○	○
Model with 7 betas	0.00505	●	0.02036	●	●	●	●	●			38.45%	14.29%	●	●	●
Model with 8 betas	0.00557	●	0.01043	-0.01765	●	●	●	●	●		49.69%	25.00%	○	○	○
Model with 9 betas	0.00557	●	●	●	●	-0.01158	●	●	●	●	34.51%	11.11%	●	○	○
Database of weekly excesses.															
Model with 2 betas	●	●	●								17.81%	0.00%	●	○	○
Model with 3 betas	0.00376	●	●	0.01662							37.21%	33.33%	○	●	○
Model with 4 betas	0.00341	●	-0.01774	0.00891	●						45.25%	50.00%	○	●	○
Model with 5 betas	●	●	●	●	●	●					-29.79%	0.00%	●	○	○
Model with 6 betas	0.00249	●	●	●	●	●	0.01717				39.81%	16.67%	○	●	○
Model with 7 betas	●	●	●	●	●	●	0.01431	-0.00500			31.63%	14.29%	●	○	○
Model with 8 betas	●	●	●	●	●	●	●	●	-0.01046		9.34%	12.50%	●	○	○
Model with 9 betas	0.0045	●	-0.01257	●	●	0.01050	●	0.01247	-0.01057	0.00941	63.49%	55.56%	○	●	○

Notes:

* The level of statistical significance used in all the test was 5%.

λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Not rejection of H_0. Parameter not significant.

R^{2*}: Adjusted R-squared = Explanatory capacity of the model.

$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.

F: Global statistical significance of the model. $H_0 = \lambda_1 = \lambda_2 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Not rejection of H_0. Model globally not significant.

Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Not rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.

J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Not rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

Table 5.14. *Independent Component Analysis. Summary of the Econometric Contrast. Daily databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{2*}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of daily returns.															
Model with 2 betas	●	●	●								-2.48%	0.00%	●	○	○
Model with 3 betas	0.00055	●	-0.00302	●							30.49%	33.33%	○	○	○
Model with 4 betas	0.00108	●	0.00286	-0.00262	●						52.34%	50.00%	○	●	○
Model with 5 betas	0.00105	●	●	-0.00254	●	●	●				46.41%	20.00%	○	○	○
Model with 6 betas	●	●	●	●	●	0.00291	-0.00162				40.33%	33.33%	○	○	○
Model with 7 betas	●	●	●	●	0.00288	●	0.00119	●			40.22%	28.57%	○	○	○
Model with 8 betas	0.00131	0.00244	0.00329	●	0.00281	●	●	●	0.00267		56.08%	50.00%	○	●	○
Model with 9 betas	●	●	-0.00353	●	●	0.00288	●	●	●	0.00100	69.62%	33.33%	○	○	○
Database of daily excesses.															
Model with 2 betas	●	●	●								-1.91%	0.00%	●	○	○
Model with 3 betas	●	●	0.00318	●							34.55%	33.33%	○	○	○
Model with 4 betas	●	●	●	0.00245	●						50.53%	25.00%	○	○	○
Model with 5 betas	●	●	-0.00289	●	●	●					39.87%	20.00%	○	○	○
Model with 6 betas	●	●	●	●	0.00309	●	●				36.25%	16.67%	○	○	○
Model with 7 betas	●	●	0.00222	●	●	●	-0.00287	●			45.30%	28.57%	○	○	○
Model with 8 betas	●	-0.00197	●	●	0.00096	●	0.00283	●	●		44.95%	37.50%	○	○	○
Model with 9 betas	●	0.00300	-0.00183	0.00250	●	-0.00076	●	●	0.00274	0.00109	78.98%	66.67%	○	○	○

Notes:

* The level of statistical significance used in all the test was 5%.

λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Not rejection of H_0. Parameter not significant.

R^{2*}: Adjusted R-squared = Explanatory capacity of the model.

$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.

F: Global statistical significance of the model. $H_0 = \lambda_1 = \lambda_2 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Not rejection of H_0. Model globally not significant.

Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Not rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.

J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Not rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

After making a cross validation of the accepted models and the methodology for the interpretation of the factors proposed above, we could state the following[172]: The significant components that affect the weekly models accepted would be: the mining sector factor, in the model when six components were extracted; and the Group Carso factor and the communication media sector factor, in the model when eight components were estimated. For the accepted daily models the significant factors would be those of the construction sector factor, in the model when three components were extracted; and the mining sector factor, in the model when five factors were estimated.

On the other hand, after making a cross validation of those significant factors with the components that in each case explained the major amount of variability, i.e., the first four components[173], in all the cases the significant factors were identified with the second or the third components.

Regarding the premiums risks (lambdas) of the significant risk factors, we find both negative and positive relation with the average returns of the stocks, and in all the cases present very low values. Considering the interpretation given to the factors of the accepted models we can state that in the model when six components were extracted, the variations of one unity of the value of the beta corresponding to the mining sector factor have a negative effect of -0.01899 on the average weekly returns, while in the model with eight factors, the Group Carso factor, has a positive effect of 0.01043 and the communication media sector factor a negative one of 0.01765. On the other hand, the construction sector factor presents a negative effect of -0.00302 on the average daily returns, while the mining sector factor produces negative variations of -0.00254.

[172] We remark that Table 5.7 presents the interpretation of the components for the experiment when nine components were extracted. In ICA the components estimated will change depending on the number of them chosen to be computed; therefore, the interpretation of the components here stated corresponds to the results produced when three, five, six and eight components were extracted. The tables that contain those results are included in the electronic appendix of this dissertation.

[173] The same explanation of the previous note applies in this case. Table 5.5 refers to the experiment when nine components were estimated. The explained and accumulated variance that corresponds to the models when three, five, six and eight components were extracted, are included in the electronic appendix of this work.

Finally, concerning the ratio number of significant lambdas / total number of lambdas in the model, the accepted models presented figures that ranged from 16% to 33%, which indicates non-strong evidence in favor of the APT, since there were a small number of factors priced in each expression.

Interestingly, the market factor was statistically significant in only one of the accepted models again; in addition, datasets expressed in excesses did not produce any fully accepted model, as well. Further research will be needed regarding this issue, as well as the significance of the undersized values and signs of the estimated individual parameters.

To summarize, for the sample and periods considered, we can accept only partially the validity of the APT using ICA as a pricing model explaining the average returns (and returns in excesses) on equities of the Mexican Stock Exchange. On the other hand, as in PCA and FA, the evidence showed that the statistical approach to the APT using the risk factors estimated by way of ICA, is very sensitive to the number of factors extracted, to the periodicity of data and the expression of the models, as well.

5.4. Conclusions.

Our results showed that the data of the Mexican Stock Exchange used in the study presented univariate and multivariate non-Gaussianity, revealing that classic techniques such as PCA and FA will produce a biased estimation of the betas. To the light of evidence presented in this Chapter, this discovery led us directly to the use of techniques more suitable for non-Gaussian series such as ICA, which, by using the ICASSO software, produced a more reliable and realistic estimation of the underlying generative multifactor model of returns on equities in the Mexican Stock Exchange than those produced by PCA and FA, since this methodology is capable of extracting the underlying systematic risk factors from nongaussian financial time series, and solves the problem that the normal ICA model estimation presents, as explained in this Chapter.

Regarding the results of our empirical study, on one hand, the reconstruction of the observed signals, by means of a reduced number of factors with respect to the original variables with our estimated ICA model was suitable. On the other hand, our econometric contrast of the APT in the stocks and periods used in this study produced signals in favor of the APT, revealing from 1 to 5 factors priced in the statistically significant models.

The preceding results represent a first approach to the application of the ICA in this context, so they should be viewed in that light. The inexistence of unified criteria about the multiple aspects involved in the empirical application of the ICA, such as: estimation approach, estimation algorithm, nonlinear function, number of ICs to estimate, ordering algorithm and values to consider as betas; besides to the two differentiated elements of the APT, i.e., the returns generating model and the absence arbitrage principle, may lead us to unsuitable results in our empirical contrast. In addition, although theoretically the ICASSO methodology used produces better results for said model[174], other estimation algorithms should be tested in further research.

[174] In this context ICASSO methodology produces better results in terms of the algorithmic and statistical reliability explained in section 5.3.2.

Chapter 6

Neural Networks Principal Component Analysis: Estimation of the generative multifactor model of returns*.

* The research related to this chapter has generate the following academic products:

1. REFEREED PUBLICATIONS:
    1.1. Ladrón de Guevara, R., & Torra, S. (2012). 'Neural Networks Principal Component Analysis for estimating the generative multifactor model of returns in a statistical approach of the Arbitrage Pricing Theory. Evidence from the Mexican Stock Exchange'. In: P. Koveos (Ed.), *Financial Crisis, Impact and Response: The View from the Emerging World,* 399-422. Athens, Greece: ATINER. ISBN: 978-960-9549-71-4.

2. REFEREED CONFERENCES:
    2.1. Ladrón de Guevara, R., & Torra, S. 'Neural networks principal component analysis for estimating the generative multifactor model of returns in a statistical approach to the arbitrage pricing theory. Evidence from the Mexican stock exchange: An alternative topology of the autoassociative neural network for the interpretation of the extracted latent systematic risk factors'. Accepted in the: *2015 International Finance Conference.* PRIME Business School Universidad Sergio Arboleda – Colegio de Estudios Superiores en Administración (CESA) – American Academy of Financial Management.. November 26 – 27, 2015, Bogota, Colombia.
    2.2. Ladrón de Guevara, R., & Torra, S. 'Neural Networks Principal Component Analysis for estimating the generative multifactor model of returns in a statistical approach of the Arbitrage Pricing Theory. Evidence from the Mexican Stock Exchange'. 7^{th} *International Conference on Finance.* Athens Institute for Education and Research (ATINER). July 7 – 9, 2009, Athens, Greece.

6.1. Introduction and review of literature.

Principal Components Analysis (PCA) and Factor Analysis (FA) have been the classic techniques used for extracting the underlying systematic risk factors of the generative multifactor model of returns in the statistical approach to the Arbitrage Pricing Theory (APT). Both techniques make a strong assumption about the multivariate Gaussianity of the observed variables; however, real life data sets, especially financial time series, are not normally distributed neither univariate neither multivariate, nor this causes the application of PCA or FA to yield unreliable results. A solution to this problem is to extract the components by means of the Independent Component Analysis (ICA), which is capable of extracting statistically independent components from a set of nongaussian data. In addition, the underlying risk factors extracted by ICA represent better estimations than those extracted by PCA and FA, because the first are statistically independent, whereas the latter are only linearly uncorrelated.

Nevertheless, the three techniques (PCA, FA and ICA) make another strong assumption: the linearity of the model. In the present chapter we use another not commonly used extraction technique which deals with the nonlinearity problem: the Nonlinear Principal Components Analysis (NLPCA). This technique has been used in many fields of science as a dimensionality reduction or as a feature extraction technique[175]. For example, in Astronomy, Scholz & Vigario (2002) use NLPCA to detect nonlinearities, extract features and classify spectral data from a set of stars, showing that the nonlinear principal components perform better than standard PCA.

[175] The main difference between these two approaches is the required aim of the components or factors extracted. Whereas in the dimensional reduction the only interest is in achieving a smaller dimension of usually noise-free variables; in the feature extraction, the concern is for identifying unique and meaningful components or factors representing the main characteristics of the variables.

They also apply it in the Physiology field, analyzing data from electromyographic recordings of muscle activities and obtaining similar results. In Biochemistry and Bioinformatics, Scholz *et al.* (2005, 2007) and Scholz (2006a, 2007) apply NLPC to analyze molecular data from metabolite levels of a plant and from the reproductive cycle of a parasite. Their findings demonstrate that the nonlinear components extracted by NLPCA are more suitable for interpreting this kind of large multi-dimensional biological data as well.

Other fields of applications where there is an extensive list of studies are for instance: in Oceanography and Atmospheric Sciences, for extracting features from different atmospheric phenomena; in Chemical and Industrial Engineering, for detecting faults in nonlinear industrial and chemical separation processes; in Psychology, for dealing with nonlinear relationships applied to categorical data; and in Robotics, for characterizing humanoid motion and for transferring human skills to robots.

In the field of Finance, the application of NLPCA has been little developed. Fan *et al.* (2008), use NLPCA to determine the nonlinear principal components driving the variations of the implied volatility smile derived from FTSE-100 stock index options; Ravi & Pramodh (2008) employ it for bankruptcy prediction in banks, and Weigang *et al.* (2007) utilize it to analyze and predict the trend of withdrawals from an employment time guarantee fund. On the other hand, some works have used related techniques to extract nonlinear components in the field of finance, e.g., Ince & Trafalis (2007) and Lendasse *et al.* (2000), which employ Kernel PCA (KPCA) and Curvilinear Component Analysis (CLCA), respectively, to reduce the dimension from a set of technical analysis indicators that they use for predicting stock prices and a market index. In addition, Sun & Ni (2006) use KPCA to extract features from a set of stock prices with predictive purposes as well.

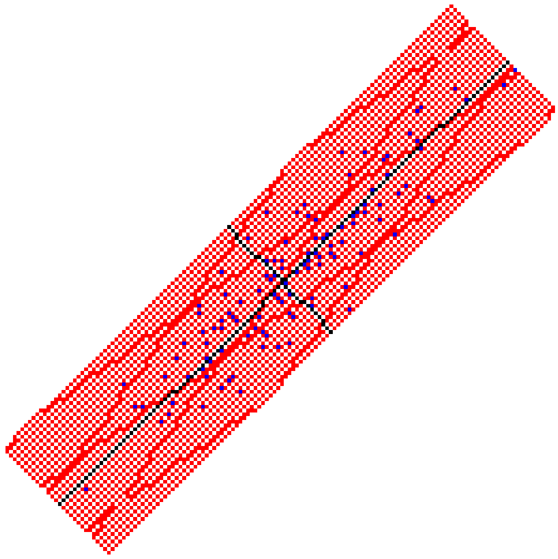
Applications in other related areas such as Economics and Business are limited too. Lagona & Padovano (2007) use NLPCA to evaluate the nonlinear relationship between budget rules and fiscal performance, and Ferrari & Salini (2008) utilize it as a dimensionality reduction technique to measure the perception of consumers about the quality of services.

As far as we are concerned, there is neither any reference using NLPCA to extract the underlying systematic risk factors affecting the returns on equities in the stock markets, nor any study using NLPCA applied to Mexico; consequently, the main objective of this research is to fill this gap in financial literature. The structure of this paper is as follows: Section 2 presents a brief review of the NLPCA, Section 3 explains the empirical study and Section 4 draws the conclusions.

6.2. Non-linear Principal Component Analysis (NLPCA).

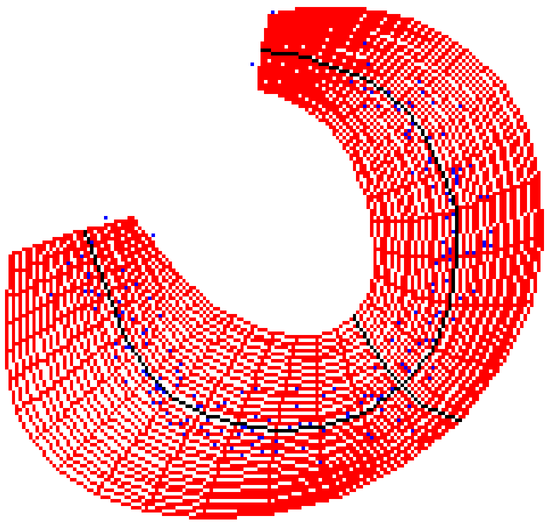
The objective of Non-linear Principal Component Analysis (NLPCA) is to extract nonlinear components from a data set. NLPCA represents a nonlinear generalization of the standard PCA capable of handling and of discovering nonlinear relationships among variables and between components and variables, in other words, the subspace produced in the original data space is curved. Figures 6.1 and 6.2, taken from Scholz (2008), show two examples of PCA and NLPCA where two components are estimated. In the linear case, the two principal components describing the data are the two main orthogonal straight lines in the center of the plane surface, while in the nonlinear case they are the two main curved lines in the center of the curve surface. In that sense, now we are interested in making a nonlinear extraction of the systematic risk factors and for this purpose we will estimate the generative multifactor model of returns by means of the Neural Networks Principal Component Analysis.

Figure 6.1. *Principal Component Analysis.*



Source: Figure taken from Scholz (2008).

Figure 6.2. *Non-linear Principal Component Analysis.*



Source: Figure taken from Scholz (2008).

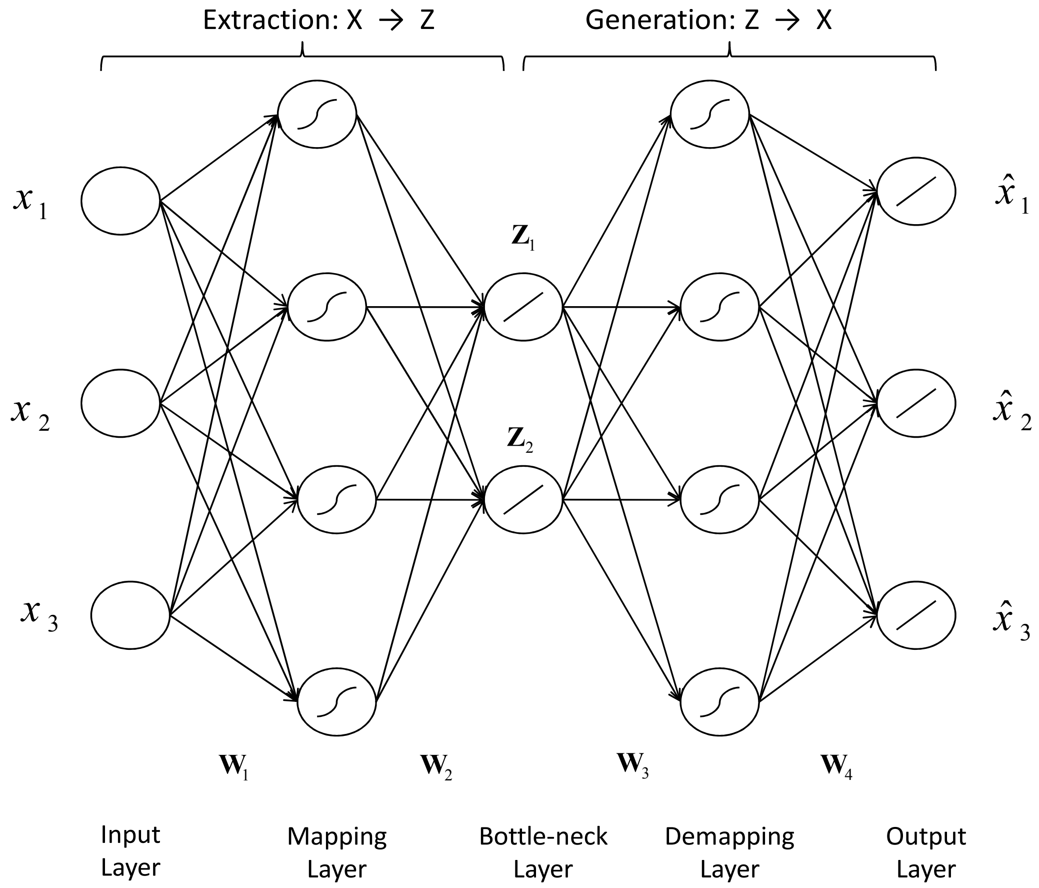
6.2.1. Neural Networks Principal Component Analysis (NNPCA).

In this study we will focus on one approach to perform NLPCA[176] based on artificial neural networks (ANN)[177]. This approach, known as Neural Networks Principal Component Analysis (NNPCA) or Principal Component Neural Networks (PCNN)[178], is commonly performed via an auto-associative neural network architecture named autoencoder, replicator network, bottleneck or sandglass type network[179]. This neural network (NN) is a multilayer perceptron[180] where the output layer of the network is required to be identical to the input layer (identity mapping) by minimizing the square error $\|x - \hat{x}\|^2$. In the middle of the network there is a layer (bottleneck) where the reduction of dimension is done and represents the values of the principal components or scores. Figure 6.3 shows a diagram of this kind of NN.

The first part of the process is the extraction of the principal components (bottle-neck layer) from the original data (input layer). The neural network estimates a first matrix of weights ($\mathbf{W}_1$) to generate the second hidden layer (mapping layer), which will represent a previous layer before the one of nonlinear principal components (NLPCs); then, the neural network estimates a second matrix of weights ($\mathbf{W}_2$), which will generate the bottle-neck layer or principal components ($\mathbf{Z}$).

[176] NLPCA belongs to the family of nonlinear versions of dimensionality reduction or feature extraction techniques, including Nonlinear Factor Analysis (NLFA) and Nonlinear Independent Component Analysis (NLICA). In addition, another related nonlinear approach in structural analysis is the Nonlinear Partial Least Squares (NLPLS). All these techniques are out of the scope of this dissertation.
[177] Other methods to extract nonlinear components are: the Locally Linear Embedding (LLE), the Isometric Feature Mapping (Isomap), the Principal Curves, the Self Organizing Maps (SOM), the Kernel PCA (KPCA), the Curvilinear Component Analysis (CLCA), and the Quantum-Inspired Evolutionary Algorithm (QIEA). All these techniques are out of the scope of this dissertation.
[178] The general technique used to extract non-linear principal components in this case is called Non-linear Principal Component Analysis (NLPCA); one of the particular methods or techniques to perform that estimation is based in the neural networks approach, which is known as Neural Networks Principal Component Analysis (NNPCA).
[179] Another approach used for estimating the NLPCA based on NN is the input training network (IT-net). For details see Martin & Morris (1999).
[180] For details on multilayer perceptron neural networks, and in general, on foundation of neural networks, see Bishop (1995).

Figure 6.3. *Auto-associative multilayer perceptron neural network or autoencoder.*



Source: Own elaboration based on Scholz (2007) and Martin & Morris (1999)

The second part of the process is the reconstruction of the variables from the NLPCs. The neural network computes a third matrix of weights ($\mathbf{W}_3$) to produce a fourth hidden layer (demapping layer) as a previous step to the reconstructed variables, which will be used join to the fourth matrix of weights ($\mathbf{W}_4$), in order to reproduce the original variables (output layer). Actually, the second and fourth hidden layers are the ones that perform the nonlinear mapping.

The formal expressions of the extraction and generation functions are:

Extraction function:

$$z = \phi_{extr} = (w,x) = \mathbf{W}_2 g(\mathbf{W}_1 x), \tag{6.1}$$

Generation function:

$$\hat{x} = \phi_{gen} = (w,z) = \mathbf{W}_4 g(\mathbf{W}_3 z) \tag{6.2}$$

Where z represents the scores or principal components; $\mathbf{W}_1$ and $\mathbf{W}_2$, the matrices of weights in the extraction process; $\hat{x}$, the reconstructed variables; $\mathbf{W}_3$ and $\mathbf{W}_4$, the matrices of weights in the generation process; and g, the nonlinearity performing the nonlinear transformation, usually a tangent sigmoid function[181].

According to Scholz (2006a) there are several architectures for the auto-associative neural network approach, such as: the standard, the hierarchical, the circular and the inverse model, and all of them can be used in combination. The standard NNPCA is the naive model, where both of the extraction and generation processes are included and no additional

[181] It is important to make a mention of differently to other types of neural networks, in NNPCA, as an unsupervised method there is not a training and testing stages (M. Scholz, personal communication, September 14, 2015). In this case the validation is done by using the error in missing data estimation as a criterion for model selection, i.e., the best model is the one able to predict missing values with the highest accuracy. (See: Scholz, 2012). Accordingly, the four techniques will be comparable in the sense that any of them make a separation of the dataset for the estimation of their models.

constraint regarding the order of components are imposed. The use of this version is recommended for non-periodic or non-cyclic data when the main interest is only the reduction of the dimensionality and not the extraction of meaningful features. In the hierarchical NNPCA, the order of the nonlinear components is enforced to respect the hierarchical ranking obtained in linear PCA, thus yielding more meaningful features for the analysis. The circular version allows extracting circular components which describe a closed curve, instead of a standard curve with an open interval, more suitable for periodic or cyclic phenomena. Finally, the inverse definition only models the generation process. This version is more efficient since we only train the second part of the neural network and not the two processes. It produces results more suited for real processes, since it models the natural process generating the observed data. In addition, it allows dealing with missing data because it does not need the sample data as an input. All the former extensions can be used in combination or separately[182].

6.2.2. Dealing with nonlinearity.

In many studies NLPCA has been used as a successful alternative to deal with the nonlinear relations among variables existent in different kinds of real data. Nevertheless, the use of NLPCA can be justified under a different perspective independently of the linear or nonlinear relation among the data set. Whereas PCA, FA and ICA represent linear models, NLPCA has the attribute of being a nonlinear system. As stated in Scholz (2006a): 'Linear models can be expressed as a (weighted) sum of their individual parts (factors …). Nonlinear models, by contrast, cannot simply be expressed by a sum. More precisely, the linear transformation … of a linear model is given by a linear function. A function $f(x)$ is termed linear when it satisfies both properties: additivity $f(x+y) = f(x) + f(y)$ and homogeneity $f(\alpha x) = \alpha f(x)$, otherwise it is a more complex nonlinear function.' In other words, PCA, FA and ICA express the variables in the model as linear combinations, while NLPCA does it as a nonlinear mixing. In NLPCA performed via an autoencoder neural network, the nonlinear hidden layers enable,

[182] For details about the different variants of the autoencoder neural network, see Scholz & Vigario (2002), Scholz *et al* (2005, 2007) and Scholz (2006a, 2007).

first, a nonlinear mapping from the observed variables in order to estimate the principal components, and then another nonlinear transformation (demapping) from the estimated components so as to approximate the reconstructed variables. As a nonlinear system characterized by the non-proportionality between its inputs and outputs, NLPCA will produce different insights of the studied phenomena. Particularly in the finance field, it could be assumed that simple variations in the underling systematic risk factors may generate complex effects in the returns on equities; i.e., the relation between the stock returns and the underlying systematic risk factors may be nonlinear.

6.3. Empirical Study. Methodology and results.

6.3.1. Extraction of underlying systematic risk factors via NNPCA.

The APT assumes the following generative multifactor model of returns[183]:

$$R_{it} = E(R_i) + \beta_{1i} \cdot F_{1t} + \beta_{2i} \cdot F_{2t} + ... + \beta_{ji} \cdot F_{jt} + \varepsilon_{it} \tag{6.3}$$

From the statistical approach, neither the factors nor their sensitivities are given and we must estimate them simultaneously by way of statistical or feature extraction techniques such as, in this case, the NNPCA. Although NNPCA is capable of extracting the scores of the components (the F_s), it is very difficult to obtain a single matrix containing the equivalent to the sensitivities to each factor (betas) in the same sense that in PCA, FA and ICA[184], because in this case there are two matrices of weights and a nonlinear transformation involved in the process of extraction the factors[185]. Consequently, we used the NLPCA for extracting only the scores of the underlying systematic risk (the Fs$_)$ in the expression 6.3.

[183] Where, β_{jig} represents the sensitivity of equity i to factor j, F_{jt} the value of the systematic risk factor j in time t common for all the stocks, and ε_i the idiosyncratic risk affecting only equity i.

[184] In NNPCA, in the extraction process we will get two loadings matrices ($\mathbf{W}_1$ and $\mathbf{W}_2$) which, along with the effect of the nonlinearity applied on the original variables, will produce one matrix of underlying factors (F).

[185] The analogous situation happens in the process of reproducing the variables, where there are two matrices of weights and a nonlinear transformation involved in the reproduction of the variables process.

For estimating the NNPCA model, we used its hierarchical extension (h-NNPCA) performed by an auto-associative neural network, which respects the ranking of the principal components in the linear PCA[186]. According to Scholz (2006a), this hierarchy implies the property of scalability which means that the first *n* components must explain, as much as possible, the variance in the *n*-dimensional subspace. In addition, hierarchical order will produce uncorrelated components.

In addition, following to Scholz & Vigario (2002), the hierarchy constraints are based on searching in the original data space for the smallest mean square reconstruction error while using the first *i-th* components according to the following expression[187]:

$$E = \frac{1}{dN}\sum_{n}^{N}\sum_{k}^{d}\left(x_k^n - \hat{x}_k^n\right) \tag{6.4}$$

Where, x and $\hat{x}$ represent the observed and reproduced data respectively; *N*, the number of samples; and *d*, the dimensionality. The hierarchical error function extended to *k* components, with $k<d$, implies minimizing:

$$E_H = E_1 + E_{1,2} + E_{1,2,3} + \ldots + E_{1,2,3,\ldots,k} \tag{6.5}$$

Therefore, as stated in Scholz (2006) the h-NLPCA can be interpreted as we look for a *k*-dimensional subspace of minimal mean square error (MSE), so that the (*k-1*)-dimensional

[186] We used the Matlab® code created by Scholz (2006b) to perform the NLPCA estimation, available at http://www.nlpca.org/matlab.

[187] In the hierarchical version of the NNPCA, one way to rank the components according to the variability they explained, is ordering in function of the error in reconstruction that they produced; i.e., in certain sense the component that produces the smallest error is the one that explain the most amount of variability. For details see Scholz & Vigario (2002) and Scholz (2006a).

subspace is also of MSE. Consequently, all the dimensional subspaces *1, ..., k,* are of minimal MSE and represent their dimensionality in the best way[188].

For the sake of comparison with our former studies, we estimated 8 different neural networks to extract from two to nine nonlinear principal components in each database.

In order to generate a loading matrix that make possible a fist attempt of interpretation of the latent risk factor extracted, as we did for PCA, FA and ICA in the previous chapters, we defined the neural network architecture as follows: a) five layers with the total number of stocks in each database (20 for the weekly databases and 22 in the daily ones as the number of neurons in the input and output layers, b) a mapping layer, a bottleneck layer, and a demapping layer with a number of neurons that ranged from two to nine[189]. In terms of the neural networks notation, the architectures used were: [20:2-9:2-9:2-9:20], in the weekly databases and [22:2-9:2-9:2-9:22], the daily expressions. Concerning the nonlinear transferring functions, following the recommendations of Martin & Morris (1999) for an autoencoder neural network to perform the NLPCA, we used a tangent sigmoid function from layer one to layer two and from layer three to layer four; and a linear function from layer two to layer three and from layer four to layer five.

We performed the NLPCA estimation on our four databases, in order to obtain the principal components hierarchically ordered, the four matrices of weights and the reproduced variables[190]. We emphasize that the objective of such estimation is to achieve a nonlinear transformation, first, from the observed variables to the principal components, and then to realize another nonlinear transformation capable of reproducing the observed variables from the extracted components.

[188] In each iteration of the network, the error with 1, 2, 3, …, *k* components is computed separately in order to get the estimation that produces the minimal square error adapting the order of the components in function of the total hierarchical error. For details on the hierarchical error function, see Scholz & Vigario (2002) and Scholz (2006a).

[189] The number of neurons considered in the mapping layer, bottleneck layer, and demapping layer ranged from 2 to nine, depending the number of factors extracted in each experiment, according to the test window used in all the techniques used in this dissertation.

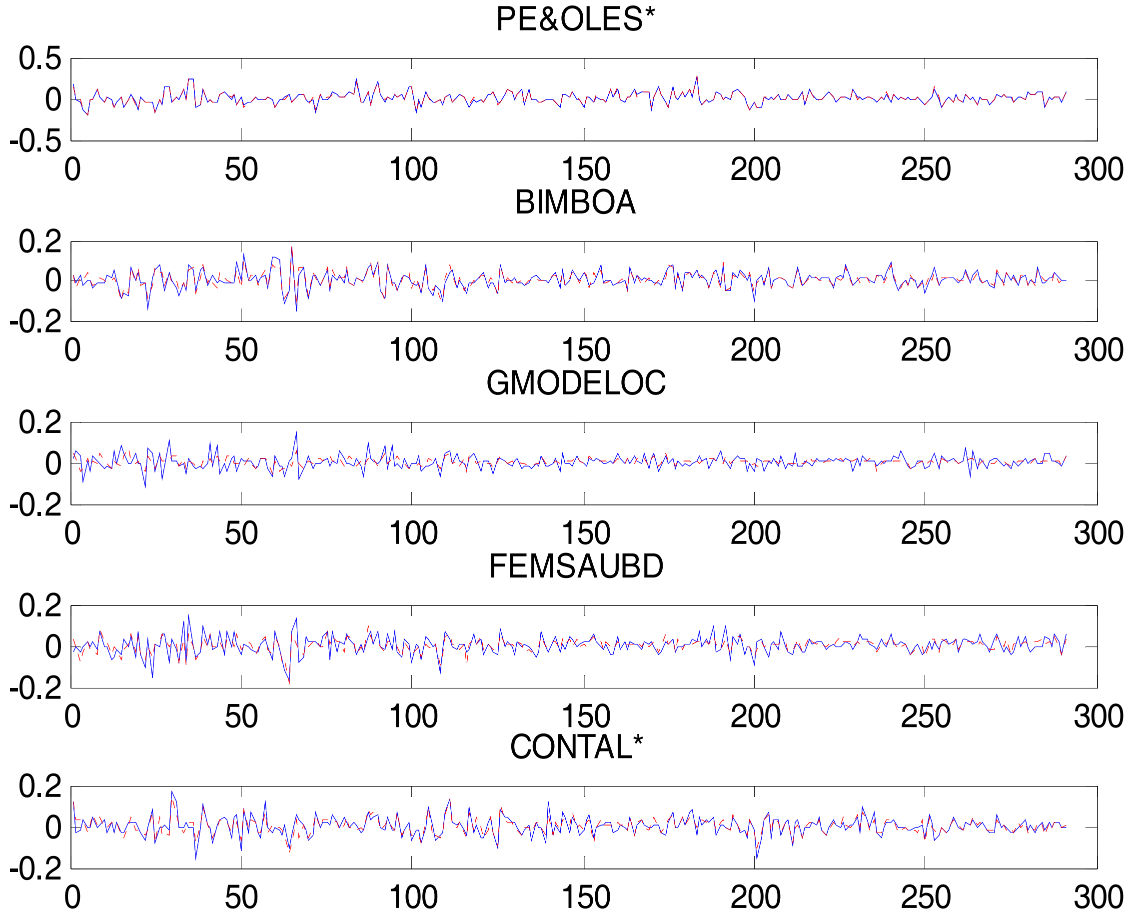
[190] We estimate the NNPCA model by way of the Matlab® code by Scholz (2006b) available at: http://www.nlpca.org/matlab.

We used a graphical analysis in order to visualize the level of reconstruction of the observed variables by way of our estimated generative multifactor model of returns via NNPCA. In order to observe the behavior of the reconstruction during all the time of our sample, we constructed the line plots of the observed and reconstructed returns, of all the stocks in the four databases, including the complete series of returns.

For reasons of saving space, in Figure 6.4 we present only the plots for the first five stock corresponding to the database of weekly returns when we extracted nine factors[191]. As we can observe in those graphics, the generative multifactor of returns estimated via NNPCA was capable to reproduce the observed returns and excesses for all the stocks in the four databases[192]. The only problem detected was in the reproduction of some observations in a few stocks presenting very high levels of volatility, where the reconstruction was not able to reach all the peaks completely[193]. These cases were mainly detected in the daily databases, especially in stocks such as: KIMBERA, BIMBOA and GMODELOC. Nevertheless, if we add more components to the extraction, the reproduction of all the series improves greatly, covering almost all the peaks of high volatility[194].

[191] In Appendix_2, from Figures 1 to 6 of Chapter 6; we show the line plots of the observed and reproduced returns and excesses for all the stocks and the four databases that belongs to the experiment where we extracted nine components. The results concerning the experiments when eight, seven, six, five, four, three and two components were are not included in this document for the sake of saving space; nevertheless, conclusions derived from their analysis are reported in this study.
[192] Evidently, the greater the number of components estimated, the better the reproduction capacity of the model.
[193] These results are similar to those obtained via ICA, FA and PCA.
[194] These experiments are not reported because we only focused on the range of estimation from two to nine components. In spite of these findings, further research about this loss of volatility in the reconstruction might be done, as an attempt to discover why these components fail in picking up the risk.

Figure 6.4. *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line plots. Database of weekly returns. Nine components extracted.*



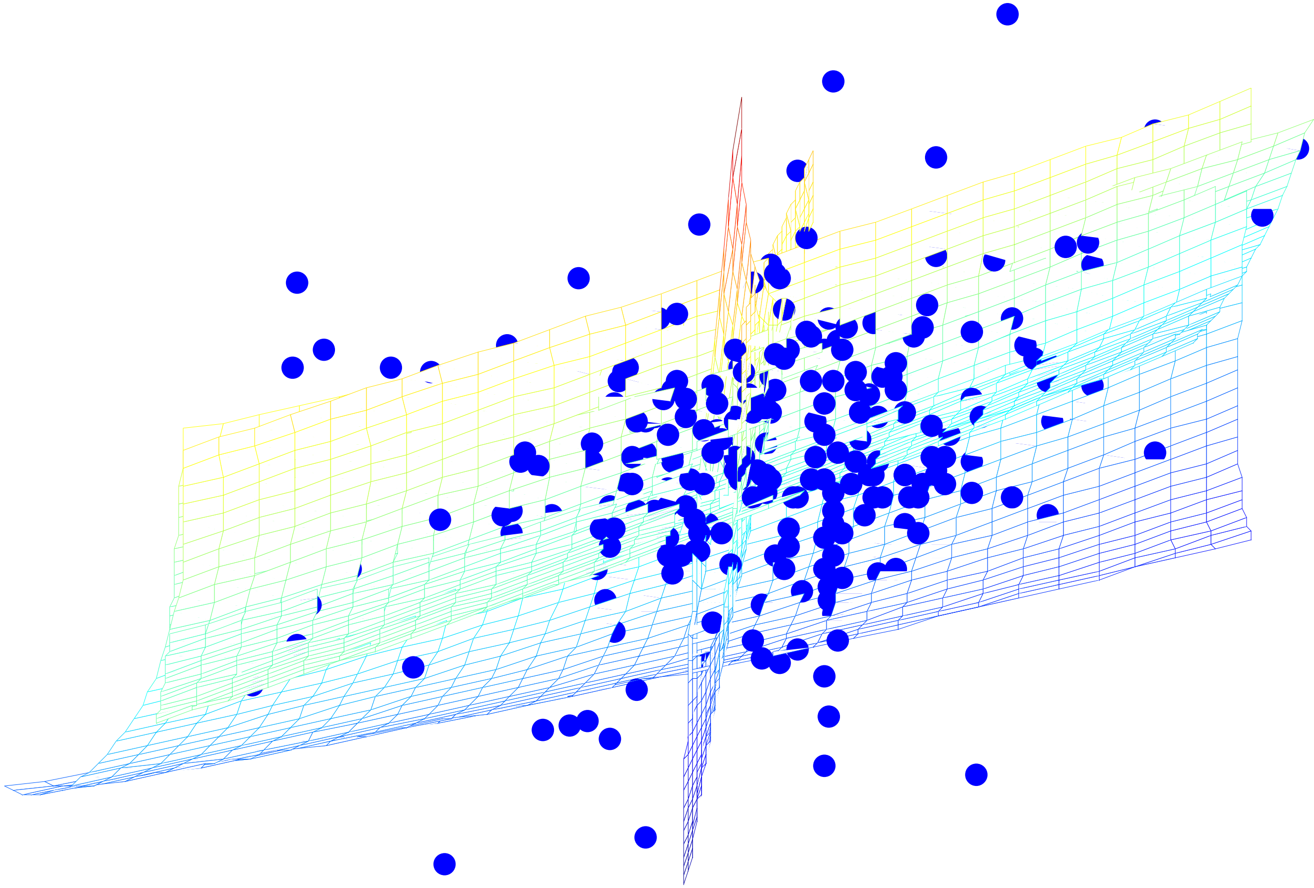
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

6.3.2. Nonlinear principal components plots.

In addition, for visualization purposes in Figures 6.5 to 6.8, we present the plots generated by the software used for the extraction, where the first three principal components of the NLPCA are plotted as a grid in the original data space[195]. In this case the grids represent the new coordinates of the component space, thus giving a nonlinear or curved description of the data. Although it is not completely conclusive, the four figures show certain adjustment of the data to a nonlinear surface. The grids represent the new coordinates in the space of the components and give a nonlinear or curved description of the data.

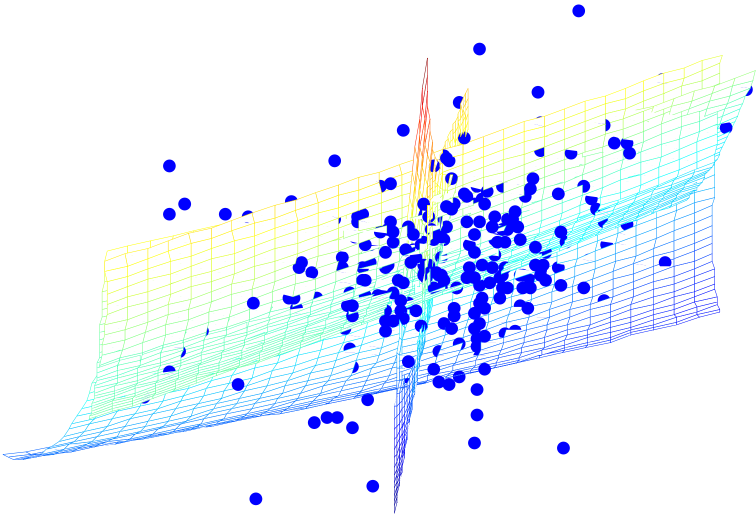
[195] These figures correspond to the experiment when nine components were extracted, for reasons of saving space the figures corresponding to the rest of experiments when eight, seven, six, five, four, three and two factors were extracted are not included in this document; nevertheless, the results were similar to those presented in this Chapter.

Figure 6.5. *Nonlinear PCA plot. Database of weekly returns. Nine components estimated.*



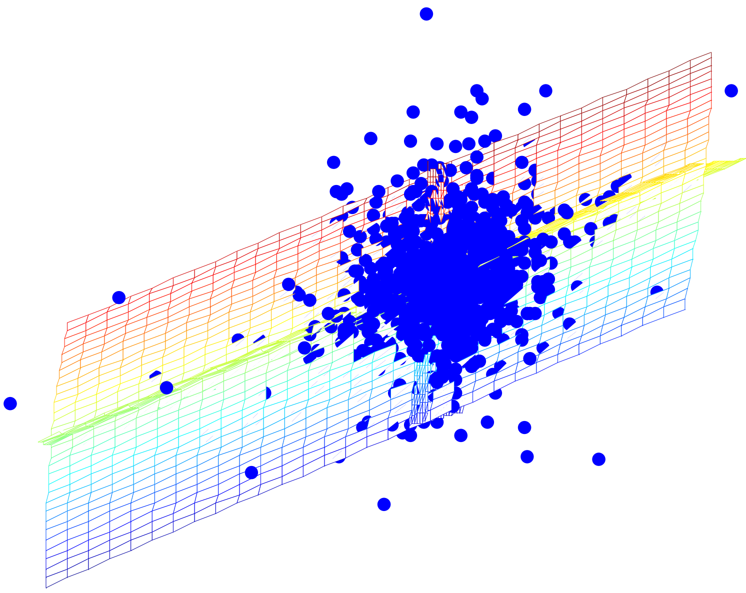
Source: Own elaboration using the Matlab® code by Scholz (2006b).

Figure 6.6. *Nonlinear PCA plot. Database of weekly excesses. Nine components estimated.*



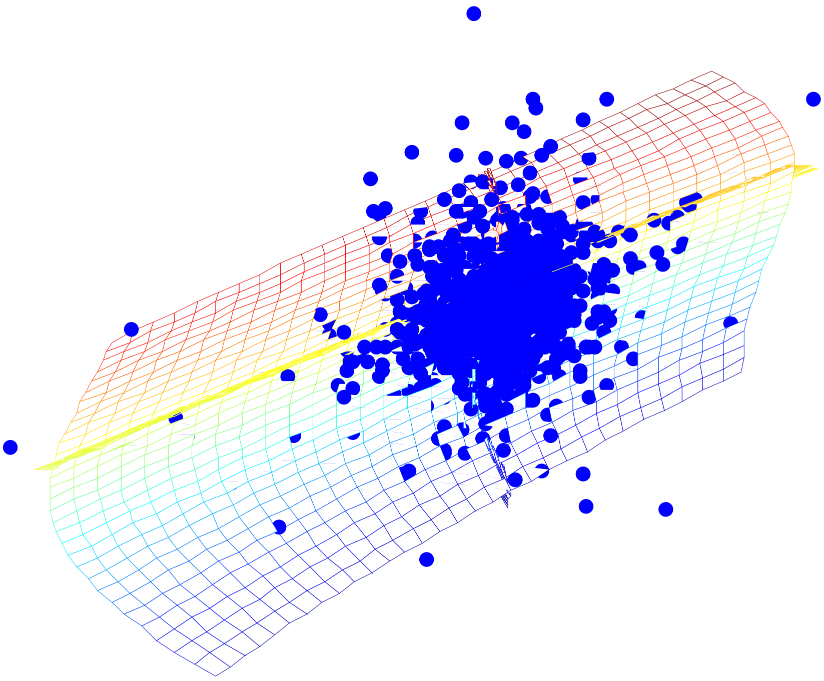
Source: Own elaboration using the Matlab® code by Scholz (2006b).

Figure 6.7. *Nonlinear PCA plot. Database of daily returns. Nine components estimated.*



Source: Own elaboration using the Matlab® code by Scholz (2006b).

Figure 6.8. *Nonlinear PCA plot. Database of daily excesses. Nine components estimated.*



Source: Own elaboration using the Matlab® code by Scholz (2006b).

6.3.3. Interpretation of the extracted factors.

Although this study is mainly focused on the extraction process of systematic risk factors of the Mexican Stock Exchange, but not on the risk attribution stage of statistical approach to the Arbitrage Pricing Theory, in this section we will just make a first attempt to propose an interpretation of the meaning or nature of the systematic risk factors extracted[196]. We will follow an analogue methodology similar to the classic approach used when Principal

[196] It is important to point that in this Chapter we have not been able to elaborate a table related to the variance explained and accumulated as in the other techniques, since in the case of NNPCA there is not a simple way to get the explained variance because there are not eigenvalues and eigenvectors like in PCA. In NNPCA the variance explained has to be approximated by relating it with the reconstruction error, since in NLPCA to minimize the square error is equivalent to maximize the variance. (Scholz, personal communication, July 29, 2015). This task represents a more difficult and not completely equivalent methodology to those used in PCA, FA and ICA which is out of the scope of this study. See: Scholz (2015).

Component Analysis (PCA) and Factor Analysis (FA) are used to reduce dimensionality or to extract features from a multifactor dataset.

This approach is based on the use of the factor loading matrix estimated in the extraction process to identify the loading of each variable in each component; high factor loadings in absolute terms indicate a strong relation between the variables and the factor. In our context, the factors will be saturated with loadings of one stock or a group of stocks that may help us to identify those factors with certain economic sectors, as a first approach to the interpretation of each component.

In the case of NNPCA, that factor loading matrix is not clearly defined, since the demixing process involves the combined effect of two loading matrices ($\mathbf{W}_1$ and $\mathbf{W}_2$) and a nonlinear function of transference; however, in order to use one of these matrices as an analogue one to those used in techniques such as PCA and FA, we can argument the following, considering the role that each matrix plays in the demixing process.

Following the network architecture displayed in Figure 6.3. Matrix $\mathbf{W}_1$ makes a projection into the space where we have an internal representation in the form of the hidden units, thus, it would be equivalent to a mixing matrix such as those used in PCA and FA.

In other words, from a structural point of view NNPCA makes a non-linear transformation given by $\mathbf{W}_1$. To that effect, it is necessary to subtract the medium value by way of the bias involved in the estimation and to scale the inputs somehow, so that the nonlinearity compress the margin properly. This makes the function of the first layer of the network to be different to that of other methods such as PCA and FA. On the other hand, matrix $\mathbf{W}_2$ makes a dimensionality change of the representation given the output of the first layer. Its function is to make a lineal transformation to rotate and scale the output, in such a way, the intermediate representation could be transformed by the second part of the network.

Furthermore, from a structural standpoint, the product ($\mathbf{W}_1 * x$) in expression 6.1, generates the representation that will pass through the nonlinearity later. The function of the nonlinearity is to make a compression of the space in order to make easy the function of the posterior part of the neural network. From this standpoint, the projection form given by ($\mathbf{W}_1 * x$) informs about the intermediate representation of the information and it could be compared with the latent factors estimated by PCA and FA; although it is important to remark that they are different things since they are obtained by way of different criteria.

According to the above stated, in this research we will use matrix $\mathbf{W}_1$ as a loading matrix to propose preliminary meanings to the extracted latent factors.

In line with the previously reported results, we only present the loading matrices plots from each database that belong to the experiment where we extracted nine underlying factors. Figures 6.9 to 6.12 present these results [197].

[197] For reason of saving space, the figures with the results regarding the experiments when eight, seven, six, five, four, three and two components are not included in this dissertation.

Figure 6.9. *Loadings matrices plots for interpretation of extracted factors.*
Neural Networks Principal Component Analysis.
Database of weekly returns.
Nine components extracted.

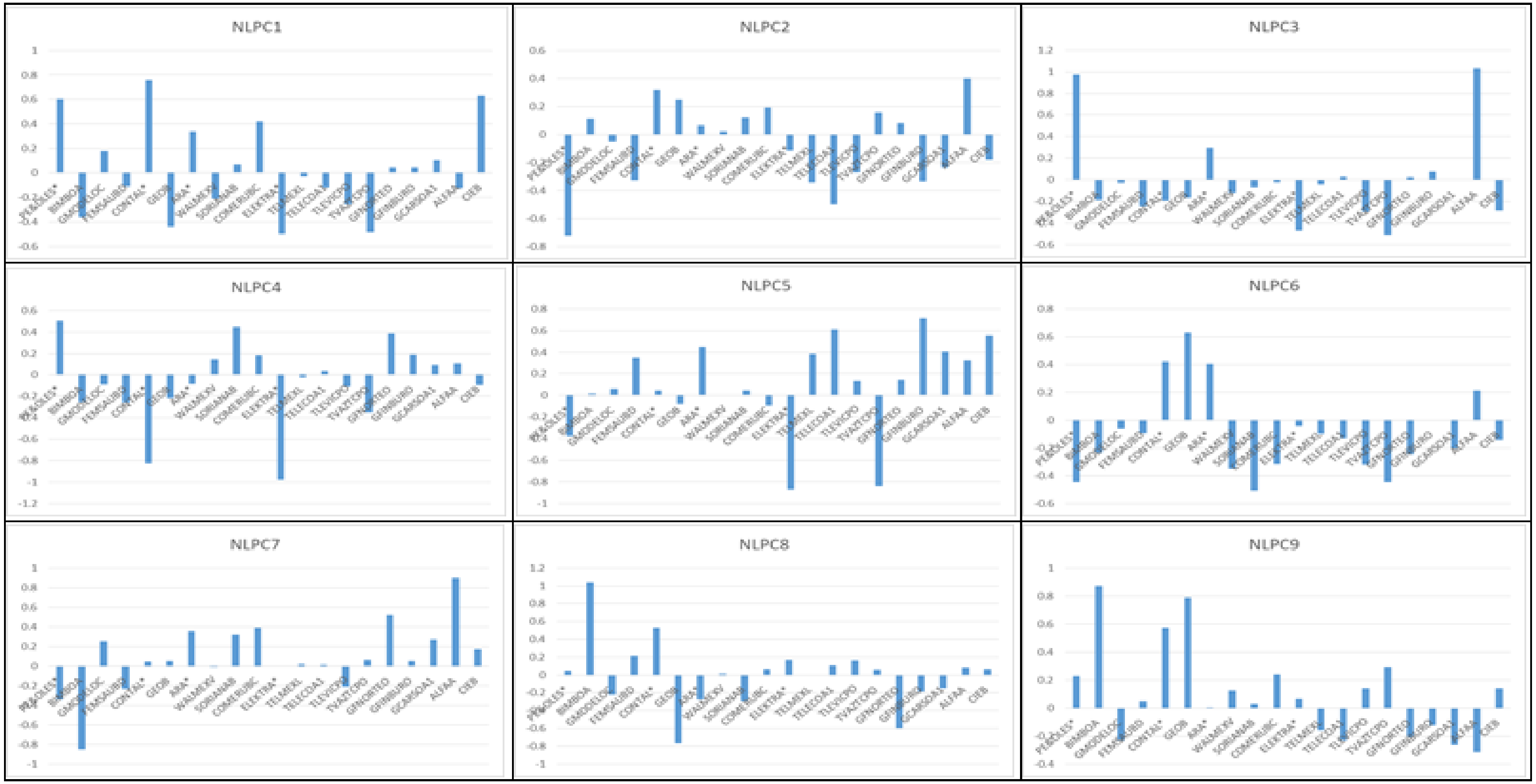


Figure 6.10. *Loadings matrices plots for interpretation of extracted factors.*
Neural Networks Principal Component Analysis.
Database of weekly excesses.
Nine components extracted.

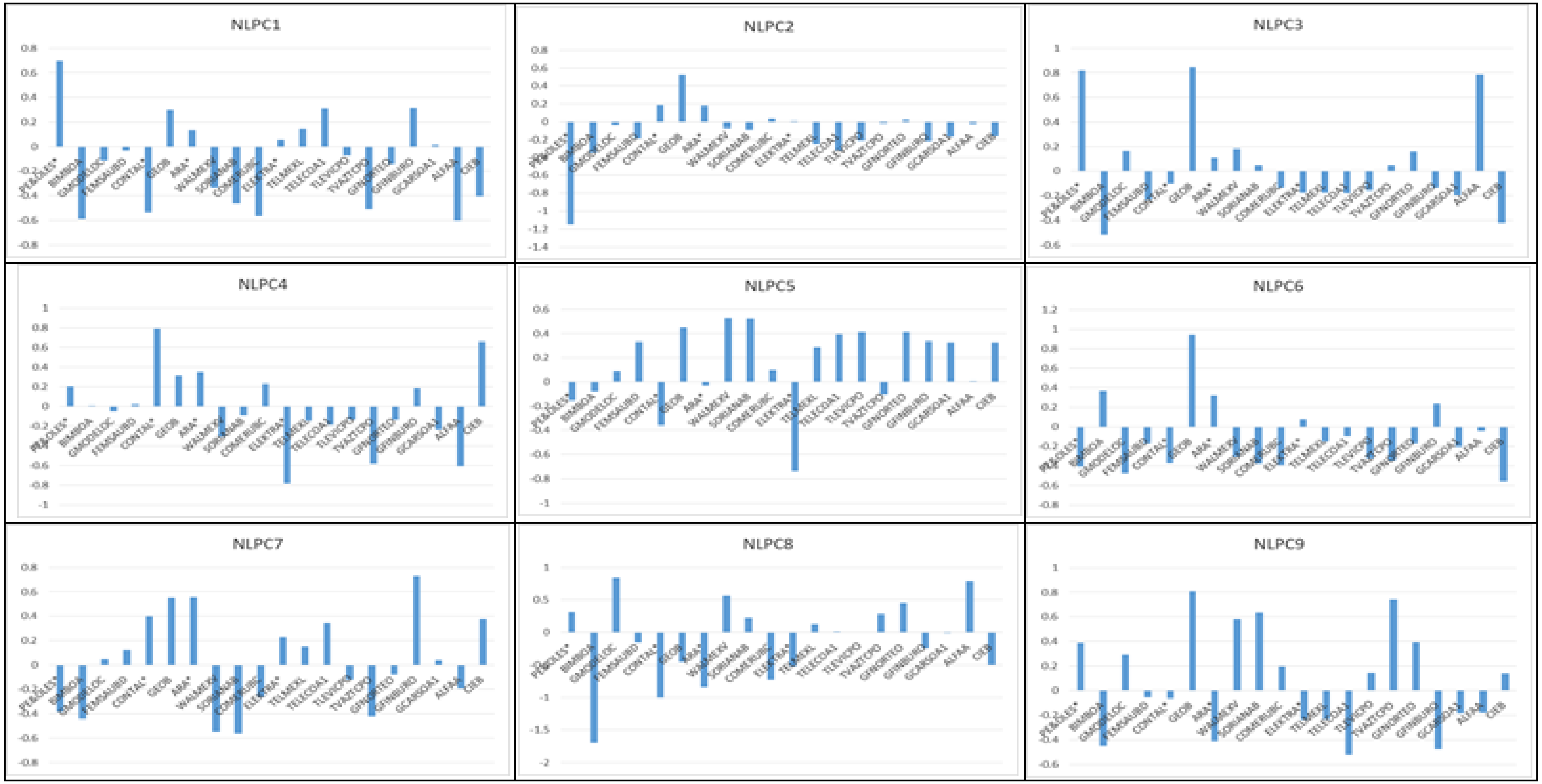


Figure 6.11. *Loadings matrices plots for interpretation of extracted factors.*
Neural Networks Principal Component Analysis.
Database of daily returns.
Nine components extracted.

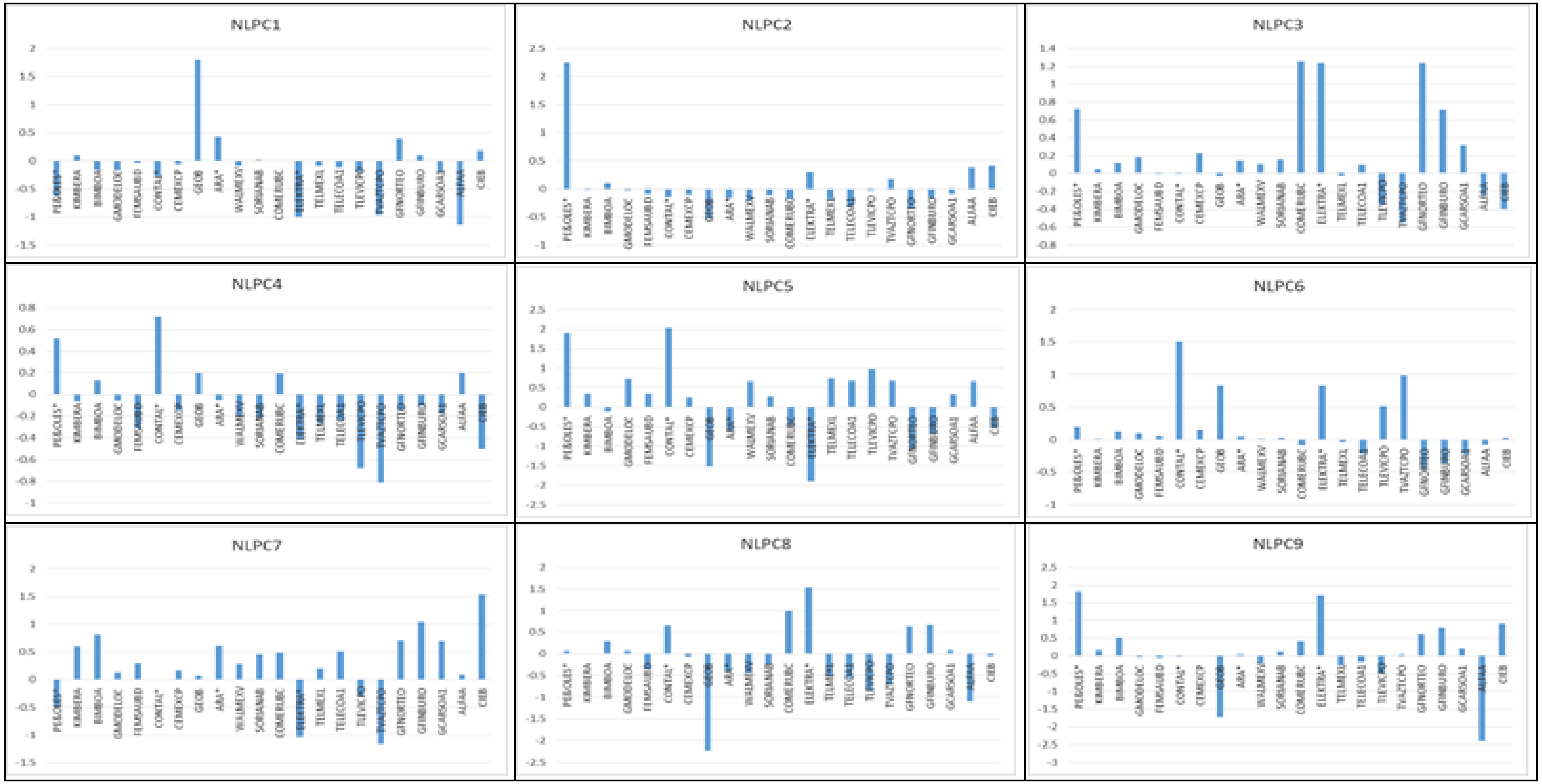
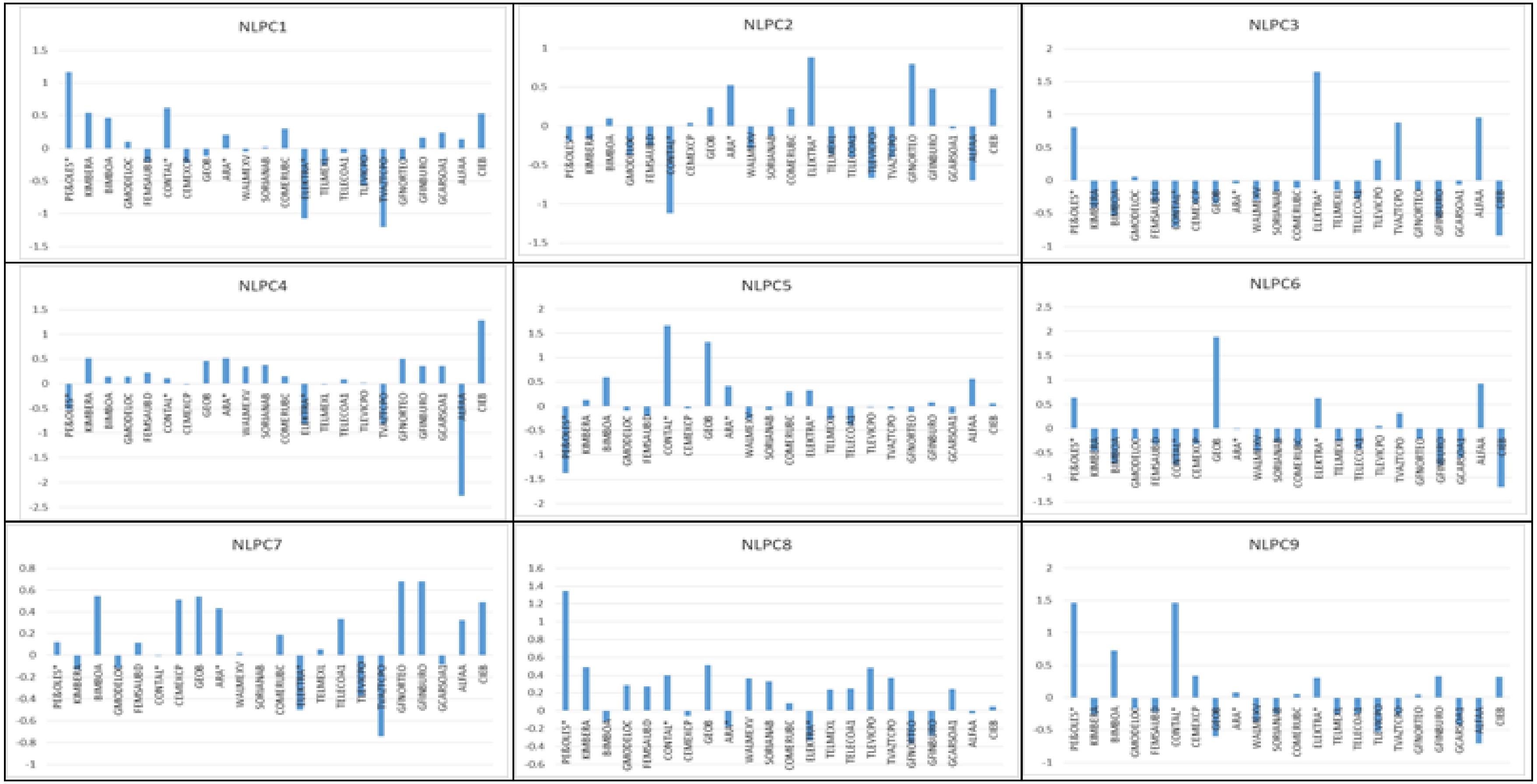


Figure 6.12. *Loadings matrices plots for interpretation of extracted factors.*
Neural Networks Principal Component Analysis.
Database of daily excesses.
Nine components extracted.



We constructed some tables summarizing the results derived from the analysis of the factor loading matrices and plots, where we propose a certain economic sector that may be related to each factor. We group together the stocks with the highest loading in each factor according to the official classification of the economic sectors used in the Mexican Stock Exchange. In Table 6.1 and 6.2 we present the details for this interpretation which include: the name of the stocks, the economic sector where they belong, and the sign of their loadings in each component. In Table 6.3 we present the summary of these interpretations. In line with the previous reported results, these tables contains those referred to the experiment when nine components were extracted[198].

There is not a clear interpretation of the factors using the matrix $\mathbf{W}_1$; however, we uncover that in this case the most of the factors are formed by a mixture of stocks from different industrial sectors instead of by a combination of shares from the same sector. In other words, excluding some factors that we could identify clearly; i.e.: number five (Salinas Group factor), in database of weekly returns; number five (Consumer sector factor), number six (Construction sector factor or GEO factor) and number eight (Food and Beverage sector factor), in database of weekly excesses; number one (Construction sector factor or Geo factor) and number two (Mining factor or Peñoles factor), in database of daily returns; and finally, number eight (Mining factor or Peñoles factor), in database of daily excesses; the rest of the factors represent a combination of sectors that in many cases have opposite signs.

[198] Tables with the results of the rest of experiments when eight, seven, six, five, four, three and two components were extracted are included in the electronic appendix of this research.

Table 6.1. *Details of results. Sector interpretation of components.*
Neural Networks Principal Component Analysis.
Nine components extracted.

NEURAL NETWORKS PRINCIPAL COMPONENT ANALYSIS							
Database of Weekly Returns				**Database of Weekly Excesses**			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
NLPC1	CONTAL* (+) CIEB (+) PE&OLES* (+)	Beverages: Soft drinks Hotels, restaurants & leisure: Leisure facilities Metal and mining: Precious metals and minerals	Beverages and Leisure / Mining sectors factor.	**NLPC1**	PE&OLES* (+) ALFAA (-) BIMBOA (-) COMERUBC (-) CONTAL* (-) TVAZTCPO (-)	Metal and mining: Precious metals and minerals Capital goods: Industrial Conglomerate / Holdings Food products: Production and commercialization of food products Consumer staples: Hypermarkets and supercenters Beverages: Soft drinks Communication media: Radio & television services	Mining / Food products and beverages, Consumer staples and Communication media sectors factor.
NLPC2	PE&OLES* (-) TELECOA1 (-) ALFAA (+)	Metal and mining: Precious metals and minerals Telecommunications services: Wireless telecommunications services Capital goods: Industrial Conglomerate / Holdings	Mining and Telecommunications / Holding sectors factor.	**NLPC2**	PE&OLES* (-) GEOB (+)	Metal and mining: Precious metals and minerals Construction: House building	Mining / House building sectors factor.
NLPC3	ALFAA (+) PE&OLES* (+)	Capital goods: Industrial Conglomerate / Holdings Metal and mining: Precious metals and minerals	Holding / Mining sectors factor.	**NLPC3**	GEOB (+) PE&OLES* (+) ALFAA (+)	Construction: House building Metal and mining: Precious metals and minerals Capital goods: Industrial Conglomerate / Holdings	House building, Mining and Holdings sectors factor.
NLPC4	ELEKTRA* (-) CONTAL* (-)	Specialty retail: Home furnishing retail Beverages: Soft drinks	Home Furnishing and Beverages sectors factor.	**NLPC4**	CONTAL* (+) CIEB (+) ELEKTRA* (-)	Beverages: Soft drinks Hotels, restaurants & leisure: Leisure facilities Specialty retail: Home furnishing retail	Beverages, Leisure and Home furnishing sectors factor.
NLPC5	ELEKTRA* (-) TVAZTCPO (-)	Specialty retail: Home furnishing retail Communication media: Radio & television services	Salinas Group Factor.	**NLPC5**	ELEKTRA* (-) WALMEXV (+) SORIANAB (+)	Specialty retail: Home furnishing retail Consumer staples: Hypermarkets and supercenters Consumer staples: Hypermarkets and supercenters	Consume sector factor
NLPC6	GEOB (+) CONTAL* (+) ARA* (+) SORIANAB (-) TVAZTCPO (-) PE&OLES* (-)	Construction: House building Beverages: Soft drinks Construction: House building Consumer staples: Hypermarkets and supercenters Communication media: Radio & television services Metal and mining: Precious metals and minerals	House building and Beverages / Consumer staples, Communication media and Mining sectors factors.	**NLPC6**	GEOB (+)	Construction: House building	Construction sector factor (Geo Factor).
NLPC7	ALFAA (+) BIMBOA (-)	Capital goods: Industrial Conglomerate / Holdings Food products: Production and commercialization of food products	Holdings / Food products sectors factors.	**NLPC7**	GFINBURO(+) ARA* (+) GEOB (+) SORIANAB (-) WALMEXV (-)	Financial services: Financial groups Construction: House building Construction: House building Consumer staples: Hypermarkets and supercenters Consumer staples: Hypermarkets and supercenters	Financial and House building /Consumer staples sectors factors.
NLPC8	BIMBOA (+) GEOB (-)	Food products: Production and commercialization of food products Construction: House building	Food products / Construction sectors factors.	**NLPC8**	BIMBOA (-) CONTAL* (-) ARA* (-) GMODELOC (+)	Food products: Production and commercialization of food products Beverages: Soft drinks Construction: House building Beverages: Brewers	Food and beverages sector factor.
NLPC9	BIMBOA (+) GEOB (+) CONTAL* (+)	Food products: Production and commercialization of food products Construction: House building Beverages: Soft drinks	Food products, Beverages and Construction sectors factors.	**NLPC9**	GEOB (+) TVAZTCPO (+) SORIANAB (+) WALMEXV (+)	Construction: House building Communication media: Radio & television services Consumer staples: Hypermarkets and supercenters Consumer staples: Hypermarkets and supercenters	House building, communication media and consumer staples sector factor.

Table 6.2. *Details of results. Sector interpretation of components.*
Neural Networks Principal Component Analysis.
Nine components extracted. (Cont.)

NEURAL NETWORKS PRINCIPAL COMPONENT ANALYSIS							
Database of Daily Returns				**Database of Daily Excesses**			
	Stocks	**Sector**	**Interpretation**		**Stocks**	**Sector**	**Interpretation**
NLPC1	GEOB (+)	Construction: House building	Construction sector factor (Geo factor)	**NLPC1**	TVAZTCPO (-) ELEKTRA* (-) PE&OLES* (+)	Communication media: Radio & television services Specialty retail: Home furnishing retail Metal and mining: Precious metals and minerals	Salinas Group / Mining sector factor.
NLPC2	PE&OLES* (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)	**NLPC2**	CONTAL* (-) ELEKTRA* (+) GFNORTEO (+)	Beverages: Soft drinks Specialty retail: Home furnishing retail Financial services: Financial groups	Beverages / Home furnishing and Financial services sectors factor.
NLPC3	COMERUBC (+) GFNORTEO (+) ELEKTRA (+) PE&OLES* (+) GFINBURO (+)	Consumer staples: Hypermarkets and supercenters Financial services: Financial groups Specialty retail: Home furnishing retail Metal and mining: Precious metals and minerals Financial services: Financial groups	Consumer staples, Financial services, Home furnishing and Mining sectors factors.	**NLPC3**	ELEKTRA* (+) ALFAA (+) TVAZTCPO (+) PE&OLES* (+) CIEB (-)	Specialty retail: Home furnishing retail Capital goods: Industrial Conglomerate / Holdings Communication media: Radio & television services Metal and mining: Precious metals and minerals Hotels, restaurants & leisure: Leisure facilities	Salinas Group, Holdings and Mining / Leisure sectors factor.
NLPC4	TVAZTCPO (-) TLEVICPO (-) CONTAL* (+)	Communication media: Radio & television services Communication media: Radio & television services Beverages: Soft drinks	Communication media and Beverage sectors factor	**NLPC4**	ALFAA (-) CIEB (+)	Capital goods: Industrial Conglomerate / Holdings Hotels, restaurants & leisure: Leisure facilities	Holdings / Leisure sectors factors.
NLPC5	CONTAL* (+) PE&OLES* (+) ELEKTRA* (-) GEOB (-)	Beverages: Soft drinks Metal and mining: Precious metals and minerals Specialty retail: Home furnishing retail Construction: House building	Beverages and mining / Home furnishing and house building sectors factor.	**NLPC5**	CONTAL* (+) GEOB (+) PE&OLES* (-)	Beverages: Soft drinks Construction: House building Metal and mining: Precious metals and minerals	Beverages and House building / Mining sectors factors.
NLPC6	CONTAL* (+) TVAZTCPO (+) GEOB (+) ELEKTRA* (+)	Beverages: Soft drinks Communication media: Radio & television services Construction: House building Specialty retail: Home furnishing retail	Beverages, Communication media, House building and Home furnishing sectors factor.	**NLPC6**	GEOB (+) ALFAA (+) CIEB (-)	Construction: House building Capital goods: Industrial Conglomerate / Holdings Hotels, restaurants & leisure: Leisure facilities	House building and Holdings / Leisure sectors factor.
NLPC7	CIEB (+) GFINBURO(+) TVAZTCPO (-) ELEKTRA* (-)	Hotels, restaurants & leisure: Leisure facilities Financial services: Financial groups Communication media: Radio & television services Specialty retail: Home furnishing retail	Leisure and Financial services sectors / Salinas Group factor.	**NLPC7**	TVAZTCPO (-) GFINBURO(+) GFNORTEO (+)	Communication media: Radio & television services Financial services: Financial groups Financial services: Financial groups	Communication media / Financial services sectors factor.
NLPC8	GEOB (-) ALFAA (-) ELEKTRA* (+) COMERUBC (+)	Construction: House building Capital goods: Industrial Conglomerate / Holdings Specialty retail: Home furnishing retail Consumer staples: Hypermarkets and supercenters	House building and Holdings / Home furnishing and Consumers staples sectors factor.	**NLPC8**	PE&OLES* (+)	Metal and mining: Precious metals and minerals	Mining sector factor (Peñoles factor)
NLPC9	ALFAA (-) GEOB (-) PE&OLES* (+) ELEKTRA* (+)	Capital goods: Industrial Conglomerate / Holdings Construction: House building Metal and mining: Precious metals and minerals Specialty retail: Home furnishing retail	Holdings and House building / Mining and Home furnishing sectors factors.	**NLPC9**	PE&OLES* (+) CONTAL* (+)	Metal and mining: Precious metals and minerals Beverages: Soft drinks	Mining and Beverages sectors factor.

Table 6.3. *Summary of results. Sector interpretation of components. Neural Networks Principal Component Analysis. Nine components extracted.*

INDEPENDENT COMPONENT ANALYSIS							
Database of Weekly Returns		**Database of Weekly Excesses**		**Database of Daily Returns**		**Database of Daily Excesses**	
NLPC1	Beverages and Leisure / mining sectors factor.	**NLPC1**	Mining / Food products and beverages, Consumer staples and Communication media sectors factor.	**NLPC1**	Construction sector factor (Geo factor)	**NLPC1**	Salinas Group / Mining sector factor.
NLPC2	Mining and Telecommunications / Holding sectors factor.	**NLPC2**	Mining / House building sectors factor.	**NLPC2**	Mining sector factor (Peñoles factor)	**NLPC2**	Beverages / Home furnishing and Financial services sectors factor.
NLPC3	Holding / Mining sectors factor.	**NLPC3**	House building, Mining and Holdings sectors factor.	**NLPC3**	Consumer staples, Financial services, Home furnishing and Mining sectors factors.	**NLPC3**	Salinas Group, Holdings and Mining / Leisure sectors factor.
NLPC4	Home Furnishing and Beverages sectors factor.	**NLPC4**	Beverages, Leisure and Home furnishing sectors factor.	**NLPC4**	Communication media and Beverage sectors factor	**NLPC4**	Holdings / Leisure sectors factors.
NLPC5	Salinas Group Factor.	**NLPC5**	Consume sector factor	**NLPC5**	Beverages and mining / Home furnishing and house building sectors factor.	**NLPC5**	Beverages and House building / Mining sectors factors.
NLPC6	House building and Beverages / Consumer staples, Communication media and Mining sectors factors.	**NLPC6**	Construction sector factor (Geo Factor).	**NLPC6**	Beverages, Communication media, House building and Home furnishing sectors factor.	**NLPC6**	House building and Holdings / Leisure sectors factor.
NLPC7	Holdings / Food products sectors factors.	**NLPC7**	Financial and House building /Consumer staples sectors factors.	**NLPC7**	Leisure and Financial services sectors / Salinas Group factor.	**NLPC7**	Communication media / Financial services sectors factor.
NLPC8	Food products / Construction sectors factors.	**NLPC8**	Food and beverages sector factor.	**NLPC8**	House building and Holdings / Home furnishing and Consumers staples sectors factor.	**NLPC8**	Mining sector factor (Peñoles factor)
NLPC9	Food products, Beverages and Construction sector factors.	**NLPC9**	House building, communication media and consumer staples sectors factor.	**NLPC9**	Holdings and House building / Mining and Home furnishing sector factors.	**NLPC9**	Mining and Beverages sectors factor.

In addition, we can distinguish the strong and constant contribution of some sectors or stocks in many factors in the four databases; e.g., mining sector with PEÑOLES (DBWR:4 + DBWE:3 + DBDR:4 + DBDE:5 = 16), beverage sector with CONTAL (DBWR:4 + DBWE:3 +DBDR:3 + DBDE:3 = 13), construction sector with GEO (DBWR:3 + DBWE:5 + DBDR:5 = 13), home furnishing sector with ELEKTRA (DBDR:6 + DBDE:3 = 9), holding sector with ALFA (DBWR:3 + DBDE:3 = 6), food products sector with BIMBO (DBWR:3), consumer staples with WALMEX (DBWE: 3) and SORIANA (DBWE:3), communication media sector with TVAZTECA (DBDR:3) and leisure sector with CIEB (DBDE:3).

In this case, under the methodology used in this study to give some meaning to the risk factors, none of the components in any database is clearly related to market factor. Likewise, there is no a homogeneous interpretation of the factors in all the databases. Nevertheless, there are two factors that could have the same interpretation in the different databases but are ranked in different order; e.g., the mining and the construction factors, as can be observed in the referred table.

6.3.4. Results of the Econometric contrast.

As stated in Chapter 3, in the first stage of our econometric contrast methodology we estimated the betas or sensitive to the underlying factors to use in expression 6.5[199],

$$\overline{R_i} = \lambda_0 + \lambda_1 \cdot \beta_{1i} + \lambda_2 \cdot \beta_{2i} + ... + \lambda_k \cdot \beta_{ki} + \overline{\varepsilon_i}\ , \tag{6.6}$$

by regressing the factor scores obtained by NNPCA as a cross-section on the returns and excesses, by way of Seemingly Unrelated Regression (SUR), to estimate the entire system of equations at the same time.

[199] Where, β_{jig} represents the sensitivity of equity i to factor j, F_{jt} the value of the systematic risk factor j in time t common for all the stocks, and ε_i the idiosyncratic risk affecting only equity i.

The results of the regressions in the four databases were very good, producing in almost all cases, statistically significant parameters, high values of the R^2 coefficients and results in the Durbin-Watson test of autocorrelation[200], which lead us to the non-rejection of the null hypothesis of no-autocorrelation[201]. Tables 6.4 to 6.7 present the results of the coefficients estimated for NNPCA, which represent the betas to use in the second stage of the econometric contrast. All the tables correspond to the case where 9 components or factors were extracted[202].

Table 6.4. *Neural Networks Principal Component Analysis.*
Betas estimated simultaneously via Seemingly Unrelated Regression.
Database of weekly returns.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.661146	0.404532	0.221154	-0.348588	-0.212235	0.231895	0.070423	-0.673661	5.852872
BIMBOA	-1.018037	-0.400656	0.438115	-0.625893	-0.096669	-0.791204	-1.111239	-0.635987	9.654203
GMODELOC	-3.890342	-1.713984	2.155201	-2.288916	-1.123985	-0.286422	0.422383	-5.831424	39.527120
FEMSAUBD	-1.991500	-0.850115	0.965746	-0.961114	-0.477731	-0.274462	-0.286570	-3.042211	18.786460
CONTAL*	-2.258178	-0.893738	1.203963	-1.529109	-0.467717	-1.087118	0.715768	-3.867295	22.248850
GEOB	0.511024	0.498312	-0.160461	1.147973	0.328838	-0.153578	-0.183413	1.111378	-8.338045
ARA*	-1.344151	-0.487022	0.738717	-0.704364	-0.126022	-0.156074	0.255672	-2.395672	12.489280
WALMEXV	-3.176441	-1.396400	1.689594	-1.685988	-0.834470	-0.268451	-0.152103	-3.970040	31.247020
SORIANAB	-2.760023	-1.198632	1.420615	-1.328995	-0.680395	-0.156491	0.461066	-2.989794	26.553090
COMERUBC	5.139106	2.362867	-3.117944	3.055385	1.485774	0.435959	0.481870	8.626535	-55.419980
ELEKTRA*	0.164280	0.198944	-0.188980	-0.037455	-0.410214	-0.016089	-0.131377	-0.040359	-4.652279
TELMEXL	1.110381	0.512345	-0.794749	0.805337	0.344741	0.364371	-0.344495	1.551578	-13.072150
TELECOA1	2.214760	1.014007	-1.487876	1.477933	0.712469	0.588877	-0.645929	3.066804	-25.108640
TLEVICPO	-0.921930	-0.356312	0.318817	-0.258356	-0.252440	-0.060988	-0.425646	-0.912894	7.067678
TVAZTCPO	0.217923	0.167963	-0.268234	0.237500	-0.263862	-0.061366	0.036825	1.370396	-5.149116
GFNORTEO	-3.074419	-1.340465	1.677342	-1.534849	-0.771012	-0.016945	0.581643	-3.956530	30.005960
GFINBURO	0.699775	0.349119	-0.542369	0.755233	0.441815	0.291611	-0.141626	0.850592	-9.004358
GCARSOA1	-0.453494	-0.197682	0.061953	-0.108553	-0.040953	0.233855	0.138577	-0.730015	2.539065
ALFAA	-0.052664	0.072603	-0.022153	-0.781726	0.395914	0.342193	-0.212150	0.667970	-2.643350
CIEB	0.707270	0.373413	-0.667428	0.733938	0.388800	-0.168995	0.617267	1.192863	-9.738467

[200] Value of the statistic more than 2.
[201] For reasons of saving space these results are not presented in this section, however the interested reader can consult the results of the betas for all the equation system for NNPCA when nine components were extracted in Appendix_1 from Tables 13 to 16.
[202] For the sake of saving space the results of the betas estimation for the experiments when eight, seven, six, five, four, three and two factors were extracted are not included in this dissertation; nevertheless, the results are similar to those reported in this chapter.

Table 6.5. *Neural Networks Principal Component Analysis. Betas estimated simultaneously via Seemingly Unrelated Regression. Database of weekly excesses.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.043163	0.486162	0.121661	0.004812	-0.499104	-0.086944	-0.030139	0.230848	1.280904
BIMBOA	0.153674	0.045729	0.147311	0.014452	-1.668440	0.461090	1.513013	1.654952	8.051806
GMODELOC	0.004531	-0.007567	0.047386	-0.010580	-0.797574	-0.000274	-0.186712	0.074784	2.403672
FEMSAUBD	-0.078199	-0.025567	0.068588	0.082091	-0.528778	0.036231	0.271890	0.186012	1.987517
CONTAL*	-0.220585	0.010571	-0.020720	-0.122170	2.065821	0.195926	-0.630877	-0.927799	-4.671980
GEOB	-0.148365	0.129246	-0.222991	0.327174	-0.461602	0.100265	0.218690	0.283212	1.990332
ARA*	-0.447752	-0.033100	-0.158602	-0.070679	3.722934	-0.335731	-0.714461	-1.644692	-12.184710
WALMEXV	-0.271972	-0.085520	-0.029591	0.009086	1.198038	-0.235595	-0.772432	-0.216296	-5.406945
SORIANAB	-0.204700	-0.066497	0.013455	0.074716	0.466036	-0.052683	-0.601527	0.106980	-2.186891
COMERUBC	-0.549244	-0.097007	-0.095963	-0.127488	4.095215	-0.195747	-1.466123	-1.380805	-14.655700
ELEKTRA*	-0.174958	0.015274	-0.041840	-0.219799	-1.255692	0.202962	0.551251	-0.204423	1.131834
TELMEXL	-0.205931	-0.052827	0.018535	0.007397	0.785378	-0.247164	-0.118289	-0.486135	-3.474624
TELECOA1	-0.289263	-0.068546	0.021333	-0.005011	1.249064	-0.375073	0.008123	-0.714292	-4.933621
TLEVICPO	-0.277070	-0.064901	0.015916	0.042153	0.694879	-0.152665	-0.366217	-0.261792	-3.654387
TVAZTCPO	0.052864	0.011772	0.077374	-0.007142	-3.159456	0.414829	0.426167	1.222152	8.869991
GFNORTEO	-0.162738	-0.050966	-0.028292	0.066173	0.181307	-0.118540	-0.375837	-0.099638	-1.109637
GFINBURO	0.194463	0.046816	0.132634	0.215212	-2.595970	0.177413	1.423572	0.891450	11.357310
GCARSOA1	-0.340196	-0.105147	-0.010619	-0.024488	1.698205	-0.305285	-0.456768	-0.916672	-6.726470
ALFAA	-0.088369	-0.000211	-0.036272	-0.326857	-0.395250	-0.147516	0.252845	0.685454	5.094150
CIEB	0.216224	0.042960	0.230983	0.222422	-3.062860	0.562687	0.988704	1.233040	13.611410

Table 6.6. *Neural Networks Principal Component Analysis. Betas estimated simultaneously via Seemingly Unrelated Regression. Database of daily returns.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.038338	-0.442438	0.030615	-0.046444	0.129480	0.003988	-0.014879	0.006439	1.019991
KIMBERA	0.077976	-0.014725	-0.028925	-0.013048	-0.010713	0.203777	-0.119361	0.053778	6.114341
BIMBOA	-0.573015	0.023321	0.086986	0.431654	-0.091011	-0.674661	0.415778	-0.475327	-20.779020
GMODELOC	0.116145	-0.019705	-0.003043	-0.091161	-0.012834	0.305166	-0.170306	0.223829	8.025039
FEMSAUBD	-0.001580	0.010911	-0.006309	-0.051264	0.048139	0.084701	-0.106962	0.081577	4.653299
CONTAL*	-0.047465	-0.055500	0.011448	0.129665	-0.757126	0.237908	-0.092710	0.143984	1.110448
CEMEXCP	0.010020	-0.000139	-0.016461	-0.060534	-0.012478	0.156311	-0.096419	0.133969	4.755374
GEOB	-0.160941	-0.022096	-0.315774	-0.088388	-0.080340	-0.113839	-0.029102	-0.003862	-1.311625
ARA*	-0.367559	0.022457	-0.022127	0.222848	0.031997	-0.470141	0.233205	-0.236326	-11.659020
WALMEXV	-0.278230	0.023390	0.053996	0.138225	0.090822	-0.308476	0.085523	0.013762	-6.415841
SORIANAB	-0.223950	0.013078	0.026909	0.115123	0.051610	-0.232138	0.073207	-0.031040	-4.269208
COMERUBC	0.192156	-0.027502	-0.080978	-0.152992	-0.013513	0.647395	-0.166292	0.444057	12.804310
ELEKTRA*	-0.278237	0.023310	0.064610	-0.136506	-0.301085	-0.119005	0.248398	-0.087945	-4.765151
TELMEXL	-0.257093	0.028976	0.062086	0.128207	0.113123	-0.327997	0.074919	-0.005984	-6.331497
TELECOA1	-0.607666	0.056768	0.126594	0.373054	0.205238	-0.810291	0.333888	-0.190420	-19.756100
TLEVICPO	0.292525	-0.001613	-0.045446	-0.367921	-0.019137	0.532455	-0.437547	0.312110	19.546310
TVAZTCPO	-0.258728	0.040846	0.122455	-0.126184	-0.169337	-0.333002	0.018069	-0.161110	-3.467456
GFNORTEO	0.085617	0.009229	-0.089211	-0.097295	0.168555	0.305925	-0.078290	0.365721	8.760370
GFINBURO	-0.247660	0.035318	0.018683	0.210425	0.093254	-0.207238	0.186200	-0.095708	-6.225637
GCARSOA1	-0.297732	0.028970	0.069805	0.198131	0.122770	-0.273227	0.144487	-0.075135	-7.335534
ALFAA	-0.083280	0.020138	0.006525	-0.146136	0.298487	0.711866	-0.129479	-0.124208	3.158050
CIEB	0.309391	-0.034740	-0.113025	-0.145258	-0.059051	0.582030	-0.305708	-0.208520	18.579130

Table 6.7. *Neural Networks Principal Component Analysis. Betas estimated simultaneously via Seemingly Unrelated Regression. Database of daily excesses.*

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
PE&OLES*	-0.097772	0.533503	-0.041415	0.001193	0.043114	0.077819	-0.061091	-0.044924	0.292448
KIMBERA	1.934205	0.527653	0.100114	-0.234403	0.030347	-0.999937	4.600877	6.940297	-24.656670
BIMBOA	1.731509	0.485822	0.089567	-0.211853	0.012837	-1.064735	4.533703	6.768506	-22.280610
GMODELOC	-2.387162	-0.601416	-0.140141	0.308304	0.054216	1.124880	-5.666746	-8.652569	28.595070
FEMSAUBD	0.737080	0.186177	0.016741	-0.094387	0.006069	-0.372734	1.877825	3.257826	-10.305150
CONTAL*	-1.715419	-0.373859	-0.066750	0.241707	-0.316650	0.280945	-3.978198	-5.931457	20.286010
CEMEXCP	0.624589	0.170146	0.019648	-0.083074	-0.004646	-0.369818	1.779183	3.036110	-8.783847
GEOB	1.223633	0.389409	0.479473	-0.189436	-0.125639	-0.628082	2.993219	4.886910	-16.425120
ARA*	-4.645785	-1.187565	-0.110229	0.602297	0.083047	2.257217	-10.660530	-16.902480	56.296290
WALMEXV	-0.195449	-0.040656	-0.032522	0.026580	0.057711	0.081098	-0.393842	-0.320910	0.990996
SORIANAB	0.381649	0.118982	0.018920	-0.046906	0.013540	-0.199454	1.042065	1.666630	-6.095472
COMERUBC	2.416777	0.660070	0.136078	-0.316441	0.032710	-1.263438	6.099257	8.910342	-31.058270
ELEKTRA*	-0.376405	-0.081354	-0.056572	-0.023416	-0.393025	0.245721	-0.069912	-1.245614	2.832206
TELMEXL	-0.654118	-0.172661	-0.068693	0.081955	0.066340	0.296039	-1.474741	-1.779940	6.893578
TELECOA1	-1.496942	-0.385918	-0.110092	0.192542	0.166826	0.698404	-3.384455	-4.728460	16.912070
TLEVICPO	-3.168261	-0.840688	-0.179648	0.386420	-0.082192	1.544202	-7.463439	-11.004340	37.229890
TVAZTCPO	2.772315	0.706448	0.020152	-0.415274	-0.371423	-1.350791	6.806987	10.821610	-36.124720
GFNORTEO	-2.715507	-0.713770	-0.071300	0.355004	0.119207	1.417318	-5.889119	-9.371779	32.226650
GFINBURO	1.766658	0.450304	0.079845	-0.211588	0.101461	-0.926617	4.722877	7.065137	-22.862060
GCARSOA1	0.050808	0.019478	-0.034159	-0.003266	0.118251	-0.043357	0.282761	0.198584	-2.065460
ALFAA	-0.341686	-0.086610	-0.022527	-0.050329	0.486563	-0.126613	-0.465215	-0.755529	2.507180
CIEB	0.781452	0.232376	0.060058	-0.061175	0.026148	-0.423187	2.274551	2.986473	-11.115940

The previous tables shows the sensitivity of the stock (i) to the risk factor (k). As we can observe in this technique, in many cases the values of the betas are higher than those obtained in ICA, FA and PCA, especially in those related to beta number nine, which would imply a higher influence of these systematic risk factors in the formation of the returns of the studied stocks than those found in the other three techniques[203].

Continuing with the methodology described in Chapter 3, in the second stage of the econometric contrast, we estimated the lambdas or risk premiums in expression 6.5 by regressing the betas obtained in the first stage as a cross-section on the returns and excesses, using ordinary least squared corrected by heteroscedasticity and autocorrelation by means of the Newey-West heteroscedasticity and autocorrelation consistent covariance estimates (HEC). Additionally, we verified the normality in the residuals by carrying out the Jarque-Bera test of normality and we used the Wald test to confirm the equalities assumed by the APT regarding the independent term.

[203] In previous experiments we used the recommended architecture for this kind of neural network (Autoencoder) which considered the number of neurons for the input, demapping, mapping and output layers equal to the number of observed variables (See: Martin & Morris, 1999), e.g. [20-20-9-20-20] in the case of the weekly databases when we extracted nine factors. In that case the results of the betas estimated simultaneously were very similar to those obtained in the other techniques; those results are not included in this document. Nevertheless, for comparative reasons regarding the interpretation of the factors extracted in the four techniques used in this study, we decided to use a neural network architecture that considered the number of neurons of the demapping, bottleneck and mapping layer equal to the number of extracted factors, in order to produce a loading matrix with the dimensions needed for the interpretation methodology employed. Consequently, the results obtained in the simultaneously estimation of the betas, using the nonlinear principal components estimated under this new architecture, are those presented in these tables, which generate higher values specially concerning the beta number nine. We remark that in those experiments NNPCA produced the best results across the four techniques in terms of the reproduction accuracy and the econometric contrast; conversely, that topology of the neural network was not capable to produce a loading matrix with the suitable dimensions needed to interpret the extracted factors. Consequently, to the light of evidence found, we uncover an interesting trade-off produced in the different topologies of the neural network used between, on one side, the accuracy in the reproduction of the observed variables and the results of the econometric contrast, and on the other side, the capability to get a matrix for the interpretation of the extracted factors. For the purpose of counting with a preliminary interpretation to the risk factors extracted by the four techniques, we decided to weight more the interpretation side.

In Tables 6.8 and 6.9, we present a summary of the results of the econometric contrast. In general, the results of the explanation power (R^2), the statistical significance of the multivariate test (F), and the residual test are very good in all the contrasted models, except in the cases where only two factors were extracted. The univariate tests for the individual statistical significance of the parameters (Statistic t) priced from one to three factors different from λ_0, thus giving evidence in favor of the APT in 29 models[204]. Nevertheless, only four models fulfilled both the statistical significance and the equality of the independent term to its theoretic value, in addition to the fulfilment of the requirements imposed by the residual test. These two models were those expressed in weekly returns when six, seven and eight factors were extracted; and the one expressed in daily returns when three components were estimated.

Moreover, there are sixteen other models which fulfil all the conditions for accepting the APT as a pricing model, except for the statistical significance of the independent term, and seven models that fail only in the equality of the independent term to its theoretical value, which provides some additional evidence in favor of this asset-pricing model. Furthermore, in all the accepted models there were more than one priced factor which gives additional evidence in favor of the APT as well.

Making a cross-validation with the interpretation of the factors proposed in section 6.3.3, the meaning of the significant factors corresponding to the fully accepted models are the following[205]. In the four models the statistical significant factors were the number two and number three, which correspond to the following interpretation derived from the analysis of the results referred to the number of components estimated in each case. Regarding the database of weekly returns, when six components were extracted, factor number two mixes the effect of the mining, telecommunications and beverage sectors; and factor number three is

[204] The total number of tested models was 32.

[205] We remark that in the case of NNPCA, each estimation that consider a different number of components extracted implies different values of the components, therefore, the interpretation may be different depending on the number of components computed. Table 6.1 and 6.2 represents the interpretation of the experiment when nine components were extracted; tables containing the meanings given to the significant factors of the accepted models are included in the electronic appendix of this work.

clearly related to the holdings sector. In the model with seven components, the two priced factors were identified with the mining a leisure sector, respectively. Finally, in the model that considered eight factors, the second one was related to the beverage sector factor, while the third one contrasted the mining to the specialty retail sector. Concerning the model in the database of daily returns, factor number two was related to the Mining sector factor (Peñoles Factor); and number three corresponds to the construction sector.

Concerning the value of the risk premiums (lambdas), in all the cases they were very small, which presents negative and positive effects on the average returns on equities. With respect to the accepted models, these values ranged from -0.002117 to 0.00378, in the weekly models, and from -.00104 to 0.00113 in the daily model. In this sense, we can observe that in the database of weekly returns, in the model with six betas, the factor that combine the mining, telecommunication, beverage and sectors yields increases of 0.00378 in the average weekly returns of the stocks studied, while the holdings sector factor produces decreases of -0.00997. In the model with seven betas, the mining sector factor, generates changes of 0.00362 and the leisure sector of -0.01168; and in the model with eight betas, the beverage sector factor causes fluctuations of 0.00303, while the factor that contrast the mining to the specialty retail sectors originates variations of -0.02117.

Regarding the accepted daily model, the mining sector factor makes variate the average returns in 0.00113, whereas the construction sector factor, does it in -0.00104.

Interestingly, using this technique, the market factor was not clearly identified in any of the accepted models; however, the mining sector factor was repeatedly significant in the many of them. Once again in this technique, datasets expressed in excesses did not produce any fully accepted model. Further research will be needed regarding this issue, as well as the significance of the undersized values and signs of the estimated individual parameters.

Finally, regarding the ratio number of significant lambdas / total number of lambdas in the model, the results in the accepted models ranged from 25% to 66%, which give some evidence in favor of the APT, as well. To summarize, for the sample and periods considered, we can accept only partially the validity of the NNPCA-APT as a pricing model explaining the average returns (and returns in excesses) on equities of the Mexican Stock Exchange. On the other hand, the evidence showed that the APT is sensitive to the number of factors extracted and to the periodicity and expression of the models.

Table 6.8. *Summary of the econometric contrast. Weekly databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{2*}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of weekly returns.															
Model with 2 betas	●	●	●								9.45%	0.00%	●	●	○
Model with 3 betas	0.005078	●	0.01034	0.02173							51.89%	66.67%	○	●	○
Model with 4 betas	0.005582	●	0.00193	0.01002	●						48.58%	50.00%	○	●	○
Model with 5 betas	0.005411	●	-0.00892	0.02423	●	0.00348					50.84%	60.00%	○	●	○
Model with 6 betas	0.004886	●	0.00378	-0.00997	●	●	●				47.96%	33.33%	○	○	○
Model with 7 betas	0.005458	●	0.00362	-0.01168	●	●	●	●			55.59%	28.57%	○	○	○
Model with 8 betas	0.005605	●	0.00303	-0.02117	●	●	●	●	●	●	50.58%	25.00%	○	○	○
Model with 9 betas	0.005782	●	●	0.02016	●	●	●	●	●	●	46.35%	11.11%	●	○	○
Database of weekly excesses.															
Model with 2 betas	●	●	●								6.61%	0.00%	●	○	○
Model with 3 betas	0.003488	●	-0.00195	-0.02129							47.35%	66.67%	○	●	○
Model with 4 betas	0.003945	●	-0.00237	-0.00481	●						49.04%	50.00%	○	●	○
Model with 5 betas	●	●	-0.00505	-0.03206	●	●					48.14%	40.00%	○	○	○
Model with 6 betas	●	●	-0.00404	-0.00882	●	0.00147	●				52.74%	50.00%	○	○	●
Model with 7 betas	●	●	0.00218	-0.00650	●	0.00168	●	●			51.67%	42.86%	○	○	●
Model with 8 betas	●	●	0.00439	-0.02272	●	●	●	●	●		53.24%	25.00%	○	○	○
Model with 9 betas	0.0433	●	0.00613	-0.02391	●	●	●	●	●	-0.00040	57.13%	33.33%	○	●	●

Notes:
* The level of statistical significance used in all the test was 5%.
λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Not rejection of H_0. Parameter not significant.
R^{2*}: Adjusted R-squared = Explanatory capacity of the model.
$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.
F: Global statistical significance of the model. $H_0 = \lambda_2 = \lambda_3 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Not rejection of H_0. Model globally not significant.
Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Not rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.
J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Not rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

Table 6.9. *Summary of the econometric contrast. Daily databases.*

	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	R^{2*}	$\lambda_{sig} / \lambda_{tot}$	*F*	*WALD*	*J-B*
Database of daily returns.															
Model with 2 betas	●	●	●								0.00%	0.00%	●	○	○
Model with 3 betas	0.00047	●	0.00113	-0.00104							38.93%	66.67%	○	○	○
Model with 4 betas	●	●	0.00090	-0.00184	●						38.11%	50.00%	○	○	○
Model with 5 betas	●	●	●	-0.00229	●	●					44.15%	20.00%	○	○	○
Model with 6 betas	0.001226	●	●	0.00401	●	●	●				56.56%	16.67%	○	○	○
Model with 7 betas	●	●	●	0.00211	●	●	●	●			50.05%	14.29%	○	○	○
Model with 8 betas	●	●	●	-0.00163	●	●	●	●	●		49.49%	12.50%	○	○	○
Model with 9 betas	●	●	●	-0.00361	●	●	0.00058	●	●	●	61.79%	22.22%	○	○	○
Database of daily excesses.															
Model with 2 betas	●	●	0.00046								-1.36%	50.00%	●	○	○
Model with 3 betas	●	●	0.00085	0.00162							41.19%	66.67%	○	○	○
Model with 4 betas	0.000636	●	-0.00043	-0.00140	●						50.91%	50.00%	○	●	●
Model with 5 betas	●	●	-0.00080	-0.00174	●	●					36.09%	40.00%	○	○	●
Model with 6 betas	●	●	●	0.00402	●	●	●				48.02%	16.67%	○	○	○
Model with 7 betas	●	●	●	0.00146	●	-0.00065	●	●			44.49%	28.57%	○	○	○
Model with 8 betas	●	●	●	-0.00284	●	-0.00069	●	0.00028	●		62.43%	37.50%	○	○	○
Model with 9 betas	●	●	●	0.00281	●	●	●	●	●	●	55.92%	11.11%	○	○	○

Notes:
* The level of statistical significance used in all the test was 5%.
λ_j: Estimated coefficients. H_0: $\lambda_j = 0$. Numeric value of the coefficient = Rejection of H_0. Parameter significant. ● = Not rejection of H_0. Parameter not significant.
R^{2*}: Explanatory capacity of the model.
$\lambda_{sig} / \lambda_{tot}$: Ratio number of significant lambdas / total number of lambdas in the model.
F: Global statistical significance of the model. $H_0 = \lambda_2 = \lambda_3 = \ldots = \lambda_k = 0$. ○ = Rejection of H_0. Model globally significant. ● = Not rejection of H_0. Model globally not significant.
Wald: Wald's test for coefficient restrictions. Databases in returns: H_0: λ_0 = Average riskless interest rate. Databases in excesses: H_0: $\lambda_0 = 0$. ○ = Not rejection of H_0. The independent term is equal to its theoretic value. ● = Rejection of H_0. The independent term is not equal to its theoretic value.
J-B: Jarque-Bera's test for normality of the residuals. H_0 = Normality. ○ = Not rejection of H_0. The residuals are normally distributed. ● = Rejection of H_0. The residuals are not normally distributed.

6.4. Conclusions.

The theoretical attributes of the NLPCA present desirable features when we extract the underlying systematic factors via this alternative technique, since they represent nonlinearly uncorrelated factors and not only linearly uncorrelated ones. NNLPCA performed via NNPCA is capable of uncover both linear and nonlinear correlations while PCA for example identifies only linear correlations. In that sense, we may conclude that the factors obtained in this study represent a more desirable estimation of the underlying systematic risk factors under a statistical approach to the APT[206]. In our case, we believe that the extracted factors should be better estimations[207], for use in a statistical approach to the APT because: first, they represent factors that have eliminated both linear and nonlinear correlations among variables, and second, they are the result of a nonlinear transformation, not only a linear mapping, which deals with any nonlinear effect of the systematic risk factors over the returns on equities.

We should like to remark that our main goal in this chapter has been the estimation of the generative multifactor model of returns of the APT by way of the NNPCA, that is, the risk extraction stage of a statistical approach to the AP. Therefore, the interpretation of the components extracted represents only a first attempt to give meaning to the latent factors; however, further research will be needed about the risk attribution process of this statistical approach.

[206] More desirable in the sense that under the scope of the APT in general and the statistical approach in particular, we look for obtaining risk factors as much independent or different as possible, in that sense having nonlinearly uncorrelated factors would suppose a better attribute of those extracted factors.
[207] Although this statement is object of academic discussion.

In the same way, the econometric contrast corresponds only to a first approach to the validation of the APT as a pricing model using the systematic risk factors estimated via this extraction technique; therefore its results should be seen under this perspective. For now, we could attribute the unsatisfactory results of the econometric contrast to two possible reasons: a) The methodology used for the contrast might not be the most suitable for a statistical approach to the APT, and perhaps it would be necessary to use time series moving regressions to estimate the sensitivities to the risk factors or betas (Nieto, 2001b; Roll & Ross, 1980), or mimicking portfolios as proxies of the underlying factors (Marin & Rubio, 2001; Zivot & Wang, 2003). b) The origin of the problem might not be in the first assumption of the APT, the generative multifactor model of returns, but in the second, the arbitrage absence principle (Khan & Sun, 2003); aspect that we have not investigated yet. Further research would be needed concerning these two possible causes of the results in the econometric contrast.

Chapter 7

Comparison of different latent factors extraction techniques*.

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* The research related to this chapter has generate the following academic products:

1. REFEREED PUBLICATIONS:
   1.1. Ladrón de Guevara, R., & Torra, S. (----). 'Comparative study of the underlying multi-factorial structure of systematic risk estimated by feature extraction techniques'. Accepted for publication en In: P. Koveos (Ed.), *The Crisis and Emerging Markets: A Multidisciplinary Analysis,* pp. TBA. Athens, Greece: ATINER. ISBN: TBA.
   1.2. Ladrón de Guevara, R., & Torra, S. (----). 'Techniques for estimating the generative multifactor model of returns on equities: Comparative study of the Principal Component Analysis. Factor Analysis, Independent Component Analysis and Neural Networks Principal Component Analysis.' Accepted for publication en In: P. Koveos (Ed.), *The Crisis and Emerging Markets: A Multidisciplinary Analysis,* pp. TBA. Athens, Greece: ATINER. ISBN: TBA.
   1.3. Ladrón de Guevara, R., & Torra, S. (2011). 'Comparative study of the underlying multi-factor structure of systematic risk estimated by feature extraction techniques (Abstract)'. In G. Papanikos (Ed.), *Abstract Book from 9th International Conference on Business: Accounting, Finance, Management & Marketing*, 35. Athens, Greece: ATINER. (ISBN: 978-960-9549-14-1).
   1.4. Ladrón de Guevara, R., & Torra, S. (2010). 'Techniques for estimating the generative multifactor model of returns on equities: Comparative study of the Principal Component Analysis. Factor Analysis, Independent Component Analysis and Neural Networks Principal Component Analysis (Abstract).' In G. Papanikos (Ed.), *Abstract Book from 8th International Conference on Business: Accounting – Finance – Management – Marketing*, 51. Athens, Greece: ATINER. ISBN: 978-960-6672-80-4.

2. REFEREED CONFERENCES:
   2.1. Ladrón de Guevara, R., & Torra, S. 'Comparative study of the underlying multi-factorial structure of systematic risk estimated by feature extraction techniques'. *9th International Conference on Business: Accounting – Finance – Management – Marketing*. Athens Institute of Education and Research (ATINER). July 4-7, 2011, Athens, Greece.
   2.2. Ladrón de Guevara, R., & Torra, S. 'Techniques for estimating the generative multifactor model of returns on equities: Comparative study of the Principal Component Analysis. Factor Analysis, Independent Component Analysis and Neural Networks Principal Component Analysis.' *8th International Conference on Business: Accounting – Finance – Management – Marketing*. Athens Institute of Education and Research (ATINER) July 5-8, 2010, Athens, Greece.

7.1. Introduction and review of literature.

In the previous chapters we have presented three different dimension reduction or feature extraction techniques for extracting the underlying systematic risk factors driving the returns on equities in a statistical approach to the Arbitrage Pricing Theory (Ross, 1976). This approach assumes a priori neither the number nor the nature of either the systematic risk factors or the sensitive to them; therefore, we have to estimate both of them by using extraction and econometric techniques in two different stages. Our efforts to extract underlying factors with better statistical attributes led us to advance from classical multivariate techniques, such as Principal Component Analysis (PCA) and Factor Analysis (FA), to more advanced and sophisticated techniques - usually applied in fields like engineering, telecommunications, astronomy, biochemistry, bioinformatics, artificial intelligence and robotics - such as Independent Component Analysis (ICA) and Neural Networks Principal Component Analysis (NNPCA).

Although the main objective of each technique is similar - to reduce the dimension or to extract the main features from a set of variables -, they are different in nature, assumptions, principles and internal algorithms; this makes it difficult to compare their results, i.e., the matrices used in the processes of extraction and generation, and the underlying factors extracted. In order to solve this problem, in this chapter we propose a set of statistical measures to compare the level of reconstruction of the four techniques, based on the degree of the accuracy in the reconstruction of the observed variables using the underlying systematic factors extracted by means of each technique.

Comparative studies of all four techniques in literature are scarce. To the best of our knowledge, only Scholz (2006a) uses and compares three of them in the same study, i.e. PCA, ICA and NNPCA, carried over to molecular data in biochemistry in order to extract biologically meaningful components. The author explains the benefits and drawbacks of each kind of analysis to understand biological issues, concluding that, depending on the characteristics of the data and the purpose of the research, one specific kind of analysis is more suitable than the others.

Comparative studies in economy and finance are not very frequent in literature, and they have dealt with only two of these techniques in the same review[208]. Some relevant references in these fields are the following[209]. Regarding PCA and FA, Ince & Trafalis (2007) use the components and factors extracted through PCA and FA as the input variables for two different forecasting models to compare their performance for stock price prediction on the NASDAQ. They found that the factors extracted through FA performed better than the components extracted through PCA.

Concerning ICA, Bellini & Salinelli (2003) find that the immunization strategies to the US Treasury spot rates curve movements based on ICA perform better than those based on PCA. Lesch *et al.* (1999) apply PCA and ICA to perform feature extraction from currency exchange data of the British Pound against the US Dollar, showing that both techniques are capable of detecting deterministic structure in the data, but independent components are much closer in their morphology to the signals. Back & Weigend (1997) apply ICA and PCA on the Tokyo Stock Exchange, showing that while the reconstruction of the observed stock prices derived from the independent components extracted is outstanding, the reproduction resulting from the principal components is not. Yip & Xu (2000) carry ICA and PCA over to stocks from the S&P 500, finding that ICA gives a better indication of the underlying structure of the US stock market, in terms of the linear relationship between the components extracted through both techniques and some predefined macroeconomic factors. Rojas & Moody (2001) compare ICA and PCA by investigating the term structure and the interactions between the returns of iShares MSCI Index Funds and the returns of the S&P Depositary Receipts Index; they demonstrate that ICA has more influence in the average mutual information. Lizieri *et al.*

[208] Comparative studies in fields different to finance and economics are out of the scope of this research; nevertheless, the interested reader can easily find some references of comparative studies between some of these techniques in literature.

[209] Although in the following papers the authors made a theoretical comparison of the techniques utilized, we will focus on the comparison of their empirical results. For detailed information about both the theoretical and the empirical comparison made in those works, the interested reader can consult the original sources.

(2007) compare the ICA and PCA components' capability of capturing the kurtosis in real estate investment trusts (REIT) in the USA, therefore proving that ICA overcomes PCA. Nevertheless, Wei *et al.* (2005) uncover that, although both techniques produce similar results, PCA outperforms ICA in the reconstruction of mutual funds in the Chinese financial market. On the other hand, Coli *et al.* (2005), in an application of ICA and PCA to a stocks portfolio of the Milan Stock Exchange, uncover that, although the principal components present a minimum reprojection error when they are used to reconstruct the data, the independent components make it easier to distinguish the trend and the cyclical components.

Finally, regarding to NNPCA, Weigang *et al.* (2007) compare NNPCA and PCA in terms of their dimensional reduction capability, with the objective of extracting the main feature explaining the trends of withdrawals from an employment time guarantee fund, thereby showing that NNPCA is more suitable than PCA for dimension reduction in this context[210]. Subsequently, the main contribution and objective of this chapter is to provide a theoretical and empirical comparative study among PCA, FA, ICA and NNPCA in the field of finance. First, the theoretical comparison will be made by way of a matrix parallelism among the four techniques and then, the empirical one will be performed by means of: a) the analysis of the reconstruction accuracy of the observed returns on equities, b) the statistical and graphical analysis of the components and betas estimated, c) the results of the econometric contrast using the different components or factors extracted through each technique, and finally, d) the schematic analysis of the loadings and interpretation given to each component in each technique.

[210] Neither other techniques to produce non-linear components nor other methods to obtain non-linear principal component analysis (NLPCA) different than NNPCA are in the scope of this research; nevertheless, the interested reader can find in literature some works where techniques such as the quantum-inspired evolutionary algorithm (QIA) to extract non-linear principal components, or kernel principal component analysis (KPCA) and curvilinear component analysis (CCA) are compared with some of the techniques used in this study.

The structure of this chapter is as follows: Section 7.2 presents the theoretical comparison via a matrix parallelism among the techniques used, where we explain the attributes of the factors extracted with each one of them. Section 7.3 describes the methodology and results of the empirical comparative study and section 7.4 draws some conclusions.

7.2. Theoretical comparison.

7.2.1. Matrix parallelism among PCA, FA, ICA and NNPCA.

The four techniques used in our study, PCA, FA, ICA and NNPCA[211], can be classified as latent variable analysis, dimension reduction or feature extraction techniques, whose main objective is to obtain some new underlying synthetic variables - from a set of observed data - capable of reproducing the behavior of the original data, in our context, returns on equities. Strictly speaking, we talk of latent variable analysis techniques, when we try to infer some unobservable artificial variables from a set of observable ones by using some mathematical models; we speak of dimension reduction techniques, when our objective is only to reduce the dimensionality of the problem by selecting a fewer number of new artificial variables created by the combination of the original ones, via some mathematical or geometric transformation of the observed variables; and, we refer to feature extraction techniques, when the new variables extracted represent the main or most relevant and meaningful components or factors resulting from specific combinations of the observed ones. Nevertheless, for our purposes, what we are prompt to obtain is a set of factors - hidden in the observed variables - to explain, in the best manner, why the returns on equities in our sample behave as they do.

The four classes of analysis include two different processes, the extraction of the underlying factors process and the generation of the original variables process.

[211] The explanation of each class of analysis is discussed in Chapters 4, 5 and 6; in this Chapter, we will focus only on the comparison among the four techniques.

In Table 7.1 we present a matrix parallelism among the extraction and generation processes employed in each technique and the main attributes of their extracted components or factors.

Table 7.1. *Matrix parallelism among techniques to extract the underlying factors of systematic risk.*

	Extraction Process.	**Generation Process.**	**Attributes of the extracted components or factors.**
Principal Component Analysis (PCA)	$\mathbf{Z} = \mathbf{XA}$	$\mathbf{X} = \mathbf{ZA}'$	1. Linearly uncorrelated components. 2. Minimum MSE reconstruction. 3. No ambiguity in the base that spans the space.
Factor Analysis (FA)	$\mathbf{F} = \mathbf{XC}$ (Bartlett's model) $\mathbf{C} = \mathbf{PQ}$ $\mathbf{P} = \mathbf{U}^{-1}\Lambda$ $\mathbf{Q} = \left(\Lambda'\mathbf{U}^{-1}\Lambda\right)^{-1}$	$\mathbf{X} = \mathbf{1}\boldsymbol{\mu} + \mathbf{F}\Lambda' + \mathbf{U}$	1. Linearly uncorrelated common factors. 2. Rotation ambiguity in the factors.
Independent Component Analysis (ICA)	$\mathbf{S} = \mathbf{WX}$	$\mathbf{X} = \mathbf{AS}$	1. Statistically independent components. 2. At most one component with Gaussian distribution.
Nonlinear Principal Component Analysis. (NLPCA)	$\mathbf{Z} = \mathbf{W}_2 g(\mathbf{W}_1 \mathbf{X})$	$\mathbf{X} = \mathbf{W}_4 g(\mathbf{W}_3 \mathbf{Z})$	1. Nonlinearly uncorrelated components.

Notes:

1. In PCA: **Z** = Matrix of principal components. **X** = Matrix of data. **A** = Matrix of loadings.
2. In FA: **F** = Matrix of common factors. **X** = Matrix of data. **Λ** = Matrix of loadings. **U** = Matrix of specificities or uniqueness. **μ** = vector of means.
3. In ICA: **S** = Matrix of independent components or original sources. **X** = Matrix of data. **W** = Demixing matrix. **A** = Mixing matrix.
4. In NLPCA: **Z** = Matrix of nonlinear principal components. **X** = Matrix of data. $\mathbf{W}_1$ = Matrix of weights from the first layer to the second layer. $\mathbf{W}_2$ = Matrix of weights from the second layer to the third layer. $\mathbf{W}_3$ = Matrix of weights from the third layer to the fourth layer. $\mathbf{W}_4$ = Matrix of weights from the third layer from the fifth layer. g = Transferring nonlinear function.

Although the assumptions, principles, philosophy, methodology and algorithms utilized are different in each technique, we can try to make a first attempt, not exempt of critique, of a matrix analogy among the extraction and generation process in the four kind of analysis that facilitate the comparison among them. For instance, the extraction and generation processes in NNPCA are equivalent to the demixing and mixing processes of ICA, where the combined effect of the matrices of weights ($\mathbf{W}_1$ and $\mathbf{W}_2$) and the nonlinear function in the extraction process would be equivalent to the effect of the demixing matrix (**W**) of ICA; the elements of the bottleneck layer (**Z**) would stand for the independent sources (**S**); and finally, the joint effect of the matrices of weights ($\mathbf{W}_3$ and $\mathbf{W}_4$) and the nonlinear function in the generation process would correspond to the effect of the mixing matrix (**A**).

The same kind of analogy can be made to include PCA and FA in the former parallelism as well, taking the matrices of weights in the extraction process (**A** and **C**), the matrices of the extracted components or factors (**Z** and **F**), and the factor loading matrices in the generation process (**A**' and **Λ**'), respectively. It is important to remark that, although there is a matrix parallelism among the elements of these techniques, in our context, the direct comparison of their values is not homogeneous among all of them, e.g., the generation processes in PCA, FA and ICA include only a linear mixing of the original data matrix and the demixing matrices; however, in NNPCA the process includes a non-linear combination of two matrices of weights and the original data matrix; thus, in this technique we do not have a single demixing matrix which, when multiplied directly by the data matrix, might produce the extracted factors. A similar situation occurs with the generation process, so we have to use other methods to compare the four techniques, such as the reconstruction accuracy of the observed variables.

On the other hand, strictly speaking, the FA should not be compared directly with the rest of these techniques since the FA includes an independent term corresponding to the specific factors (**U**), which is not considered in the rest of them[212]. Actually, the FA should be compared with the equivalent versions of the other techniques that consider an independent term in the model as well, e.g., the Noisy ICA (N-ICA) or Independent Factor Analysis (IFA) and the Non-linear Factor Analysis (NLFA). Nevertheless, PCA and FA have always been compared and in some cases even confused, since PCA is considered as a method of estimation within the FA, which is incorrect; thus, we decided to include FA results in this review, too. A next step in further research would be to compare FA with the equivalent versions of the independent and non-linear models.

From an interpretation standpoint of the extracted factors we could say that for PCA, FA and ICA, these factors may be interpreted as the coordinates of the observations in the space spanned by the demixing matrix of the table above. That is, first in PCA, the matrix **A** may be interpreted as a projection operator with directions that corresponds to the least error reconstruction. Secondly, in FA the matrix **C** may be interpreted as an operator that generates the variation around the mean value of the observations. Finally, in ICA the matrix **W**, represents a matrix that mixes unobservable factors using the criterion that the observable ones will have a maximum non-Gaussian distribution. On the other hand, although in NNPCA, we do not have a single demixing matrix, we could interpret the two matrices involved in the demixing process as stated in section 6.3.3 of Chapter 6. That is, matrix $\mathbf{W}_1$ may be interpreted as an operator that makes a non-linear transformation of data, which makes the function of the first layer of the network to be different from that of the other methods; while matrix $\mathbf{W}_2$ makes a dimensionality change of the representation given the output of the first layer.

[212] The complete factor analysis model specification includes the matrix of specific factors $\mathbf{U}$: $\mathbf{X} = \mathbf{1\mu} + \mathbf{F\Lambda}' + \mathbf{U}$, however we cannot use this matrix in the generation process because it represents the error in the reconstruction of the original variables, which we will know after the reproduction of the variables by: $\mathbf{U} = \mathbf{X} - (\mathbf{1\mu} + \mathbf{F\Lambda}')$.

In other words, considering that the matrices that generate the observations are obtained by way of different criteria and they look for finding different representation of data, they result not easily comparable in the sense that we are trying to compare objects with different dimensions. As an analogy, it is as if we would like to compare time and space units of measurement.

Finally, in our financial context, the most important differences among the four techniques are perhaps the attributes of the components or factors extracted, because we progress from only linearly uncorrelated components in PCA to linearly uncorrelated common factors in FA, then to statistically independent components in ICA, and lastly to non-linearly uncorrelated components in NNPCA. From a theoretical standpoint, the former statement would imply the uncovering of a more realistic latent systematic risk factor structure, as we advance to more sophisticated techniques. This nature of the components or factors extracted through each technique is given mainly for the following conditions: First, while the orthogonal components extracted by using PCA explain the total amount of variance in the observed variables, the orthogonal factors produced by FA explain only the amount of variance explained by common factors, i.e., the covariance among the variables. Nevertheless, both PCA and FA consider only the second moment absence of linear correlation; on the other hand, ICA considers higher moment absences of linear correlation, which produce not only linearly uncorrelated components but also statistically independent ones. Finally, while the three former techniques only consider a linear mixing in the extraction and generation processes, NNPCA includes a nonlinear transformation in both processes, which generates not only linearly uncorrelated components but also non-linearly uncorrelated ones.

7.3. Empirical comparison.

7.3.1. Accuracy in the reproduction of the observed returns.

According to the models in Table 7.1, we first made the extraction of the underlying factors by using Matlab® scripts[213], obtaining also the matrices of weights for the extraction process or demixing matrices and the matrices of loadings of the generation process or mixing matrices. For the estimation of the models, in PCA we used the classic linear version; in FA, the Maximum Likelihood method (MLFA); in ICA, the ICASSO software based on the FastICA algorithm; and in NNPCA, a hierarchical auto-associative neural network or autoencoder[214]. Secondly, we reconstructed the observed variables by means of the extracted factors and the mixing matrices.

We conducted our experiments for the four techniques, the four databases, and a test window ranging from two to nine extracted factors[215].

7.3.1.1. Graphical analysis.

The results obtained in the reconstruction of the observed returns using the four techniques individually were, from a visual standpoint, at first sight outstanding for all of them, making it difficult to determine which one is the best. For reasons of saving space these figures are included in the Appendix_2 of this dissertation from Figures 1 to 8 of Chapter 7,

[213] The PCA and FA scripts were of our own elaboration using the functions included in the software; ICA scripts were adapted from Himberg & Hyvärinen (2005); and NNPCA, from Scholz (2006b).
[214] For details about the estimation models, see Chapters 4, 5 and 6, respectively.
[215] Since there is not a definite widespread criterion to define the best number of components to extract in all the techniques, we have used nine different criteria usually accepted in PCA and FA literature. These criteria were: the eigenvalues arithmetic mean, the percentage of explained variance, the exclusion of the components or factors explaining a small amount of variance, the scree plot, the unretained eigenvalue contrast (Q statistic), the likelihood ratio contrast, Akaike's information criterion (AIC), the Bayesian information criterion (BIC), and the maximum number of components feasible to estimate in each technique. The comparable window across the four techniques indicated the results of the former criteria ranged from two to nine factors.

which present the observed *versus* the reconstructed returns produced by the four techniques, from all the stocks of the four databases when nine factors were extracted[216]. The line plots include all the observations, showing that in general all the techniques reproduce the real values successfully for the entire period; we can distinguish that FA and ICA apparently present greater errors in the reconstruction. Derived from the graphic analysis we can detect that, given the number of factors extracted, the four techniques fail to reproduce the highest and lowest peaks in the observations, but, if we increase the number of factors extracted from all the techniques, this problem disappears[217]. In addition, we can observe that in some cases the best reconstruction of each individual asset is not produced by the same technique, i.e., while some stocks are reconstructed better by one technique, other shares are better reproduced through another method. All the former results are similar for the entire cases of our experiments.

7.3.1.2. Measures of reconstruction accuracy.

In order to obtain a more objective measure of the accuracy of the reconstruction using the systematic risk factors obtained with each technique, we used some statistics widely employed to evaluate the accuracy of forecasting models in economy and finance, which in our context will represent measures of reconstruction accuracy. These measures taken from Pérez & Torra (2001) and Diebold & López (1996) are the following: mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), Theil's U statistic (U-Theil), confusion matrix (CM), confusion rate (CR), chi-squared contrast of independence, and Pesaran & Timmermann's directional accuracy statistic (DA).

[216] For the sake of saving space the results of the rest of experiments where eight, seven, six, five, four, three and two factors were extracted are not included in this document; nevertheless, the analysis and conclusions reported include the entire cases.

[217] The results of those additional experiments are not presented in this study, we only ran those experiments to test that the reproduction capacity of the techniques, considering all the factors feasible to compute in each one of them, was reliable.

The first four are measures of reconstruction accuracy, which represent different expressions to compute the error that we make in the reconstruction of the observed returns; these are their mathematical formulations:

$$MAE = \frac{1}{H}\sum_{h=1}^{H}\left|r_h - \hat{r}_h\right| , \tag{7.1}$$

$$MAPE = \frac{1}{H}\sum_{h}\left|(r_h - \hat{r}_h)/r_h\right| \times 100, \tag{7.2}$$

$$RMSE = \sqrt{\frac{1}{H}\sum_{h=1}^{H}(r_h - \hat{r}_h)^2} , \tag{7.3}$$

$$U-Theil = RMSE \Bigg/ \left[\sqrt{\frac{1}{H}\sum_{h=1}^{H} r_h^2} + \sqrt{\frac{1}{H}\sum_{h=1}^{H}\hat{r}_h^2}\right], \tag{7.4}$$

where H denotes the total number of observations; $h = 1, \ldots, H$; r_h are the observed returns and $\hat{r}_h$, the reconstructed returns.

The confusion matrix is a contingency table necessary to compute the contrasts for evaluating the direction-of-change reconstruction measures, namely, confusion rate and chi-squared contrast; it is constructed in this manner:

$$\begin{array}{ccc} & & r_h\_reconstructed & \\ & & \geq 0 & < 0 \\ & \geq 0 & n_{00} & n_{01} \\ r_h\_real & & & \\ & < 0 & n_{10} & n_{11} \end{array} , \tag{7.5}$$

where n_{ij} indicates the absolute frequency of occurrence of each condition.

The confusion rate shows the percentage of incorrect reconstructions and is calculated by:

$$CR = (n_{01} + n_{10})/H, \tag{7.6}$$

The chi-squared ($\hat{\chi}^2$) contrast assumes a null hypothesis of independence between the signs of the reconstruction and their real values; therefore, the rejection of the null hypothesis and the high values of the statistic imply a good performance based on the direction-of-change reconstruction; its formulation is like this[218]:

$$\hat{\chi}^2 = \sum_{i=0}^{1} \sum_{i=0}^{1} [n_{ij} - n_{i.}n_{.j}/H]^2 / [n_{i.}n_{.j}/H], \tag{7.7}$$

where $n_{i.}$ y $n_{.j}$ are the marginal frequencies.

Finally, the DA statistic is another directional accuracy reconstruction measure, with distribution N(0,1), which poses a null hypothesis of independence between the observed and the reconstructed values; its interpretation is similar to the former contrast and is built as follows:

$$DA = [\mathrm{var}(SR) - \mathrm{var}(SRI)]^{-0.5}(SR - SRI), \tag{7.8}$$

$$SR = H^{-1}\sum_{h=1}^{H} I_i[r_h \cdot \hat{r}_h > 0], \tag{7.9}$$

$$SRI = p\hat{p} + (1 - p)(1 - \hat{p}), \tag{7.10}$$

$$p = H^{-1}\sum_{h=1}^{H} I_i[y_h > 0], \tag{7.11}$$

$$\hat{p} = H^{-1}\sum_{h=1}^{H} I_i[\hat{y} > 0], \tag{7.12}$$

$$\mathrm{var}(SR) = H^{-1}[SRI(1 - SRI)], \tag{7.13}$$

$$\mathrm{var}(SRI) = H^{-2}\left[H(2\hat{p} - 1)^2 p(1 - p) + (2p - 1)^2 \hat{p}(1 - \hat{p}) + 4p\hat{p}(1 - p)(1 - \hat{p})\right], \tag{7.14}$$

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218 The degrees of freedom for this contrast are calculated by: $v = (r-1)(k-1)$, where *v* denotes the degrees of freedom; *r*, the number of rows of the confusion matrix; and *k*, the number of columns.

where *SR* denotes the success ratio; *SRI*, the success ratio in the case of independence between the observed and reconstructed values under the null hypothesis, and *I* is an indicative function denoting the occurrence of the condition imposed inside the square brackets[219].

We computed all the foregoing measures for each individual stock and proposed the arithmetic mean, median and standard deviation for the MAE, MAPE, RMSE, U-Theil and CR as synthetic global measures to evaluate the errors in reconstruction for all the assets. In addition, we analyzed the results of the directional accuracy statistics χ^2 and DA individually for each stock in order to test the null hypothesis of independence in the reconstruction process. We replicated all these calculations for the four extraction techniques, the four databases, and the entire window of testing.

For the sake of saving space in this Chapter, in Tables 7.2 and 7.3 we only present the the summary of the measures of the reconstruction accuracy corresponding to the databases of weekly returns and daily returns; nevertheless, in Tables 1 to 18 of Chapter 7 in Appendix_2, we include the results of the foregoing experiments applied on the four databases, when nine factors were extracted, for PCA, FA, ICA and NNPCA and a summary of the results for each database[220]. First of all, we have to remark that the results for all the techniques are outstanding and reflect a high quality reconstruction of the returns; however, in trying to find the best of these methods we can make the following distinctions.

Regarding the measures of reconstruction accuracy MAE, MAPE, RMSE and U-Theil, the smaller errors in the reconstruction - in terms of their arithmetic mean - points to PCA and NNPCA as the best ones. Strictly speaking, PCA scored better results in all the foregoing measures, but the difference between both techniques in the computed error is negligible. However, in many cases NNPCA and in some of them FA and ICA, presented a smaller

[219] If the condition is fulfilled, the indicator takes the value of 1.
[220] For reasons of saving space the results corresponding to the experiments when eight, seven, six, five, four, three and two factors were extracted are not included in this document; nevertheless the analysis and conclusions reported include the entire cases.

standard deviation of the former statistics, which means less sensitivity to the variations of mean values of the proposed synthetic measures. In addition, considering that the observed variables are not normally distributed and taking the median as a more suitable synthetic measure of the reconstruction accuracy in this case, the supremacy of PCA was not so evident, since in this case the four techniques were obtaining the best performance in different cases. Regarding the CR, the results are similar; PCA obtained the lowest percentage of incorrect reconstruction in terms of mean and median in all the cases, but in terms of standard deviation, the best results were for NNPCA and FA. Concerning the directional accuracy contrasts χ^2 and DA for each stock, our findings show that in almost all the cases we reject the null hypothesis of independence at 5% level of statistical significance in both tests; therefore, we can establish the association between the signs of the predictions and the real values of the returns[221].

In summary, considering the results of the rest of experiments, in almost all cases of our study[222], the results point to PCA as the best technique for the reconstruction in average terms of the measures of reconstruction used, when we retain a larger or medium number of factors; and to NNPCA, when we extract a smaller number of them, which would leads us to think that NNPCA performs better than the other techniques as a dimensional reduction or feature extraction technique, if the objective is to conserve the smaller number of components[223].

[221] We reject the null hypothesis of independence of the χ^2 and DA contrast in almost all cases; nevertheless, for some specific stocks, we could not reject it. We consider that the effect of these few cases does not significantly affect the overall results and conclusions derived from these statistics.

[222] The results of the experiments when eight, seven, six, five, four, three and two components were extracted are included in the electronic appendix of this dissertation; however the conclusion related to this analysis include all the cases.

[223] See Tables 7.4 and 7.5, where exceptionally and as an example, we present the summary of the measures of the reconstruction accuracy corresponding to the databases of weekly returns and daily returns when two factors were extracted, in order to provide evidence supporting these conclusions. We remark that in some cases ICA also performed better than the other techniques in small dimensions experiments, but in the most cases NNPCA was more accurate in those low dimensions.

However, if we can conserve a medium or larger number of them, the results would lead us to think that PCA is the better choice among the four techniques studied. Besides, in the daily databases the supremacy of PCA over the other techniques is not so clear as in the weekly databases, since in some dimensions and measures the best results were obtained mainly by NNPCA, and in some exceptional cases by ICA and FA.

Table 7.2. *Summary of measures of reconstruction accuracy. Database of weekly returns. Nine underlying factors.*

	PCA			FA			ICA			NNPCA		
	MEAN	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**
MAE	0.015	0.0183	0.006	0.017	0.018	0.006	0.021	0.021	0.006	0.017	0.019	0.004
MAPE	125.960	130.703	54.938	131.532	142.291	56.519	150.696	145.371	56.519	138.699	143.513	41.844
RMSE	0.020	0.024	0.008	0.023	0.024	0.007	0.027	0.028	0.007	0.023	0.026	0.005
U-Theil	0.267	0.287	0.140	0.277	0.297	0.161	0.367	0.328	0.161	0.295	0.320	0.109
CR	0.170	0.187	0.082	0.180	0.197	0.103	0.230	0.213	0.103	0.190	0.194	0.078

Notes:
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
RMSE: Root mean square error.
U-*Theil*: Theil's U statistic.
CR: Confusion rate
Marked cells represents the best results for each statistic across the four techniques.

Table 7.3. *Summary of measures of reconstruction accuracy. Database of daily returns. Nine underlying factors.*

	PCA			FA			ICA			NNPCA		
	MEAN	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**
MAE	0.007	0.009	0.002	0.008	0.008	0.003	0.009	0.009	0.002	0.008	0.009	0.003
MAPE	115.993	123.370	45.758	134.022	134.344	48.613	122.885	120.565	48.488	119.858	127.818	45.959
RMSE	0.010	0.011	0.003	0.011	0.010	0.005	0.0124	0.013	0.003	0.010	0.012	0.004
U-Theil	0.314	0.348	0.159	0.328	0.363	0.128	0.416	0.397	0.210	0.337	0.382	0.167
CR	0.210	0.224	0.082	0.215	0.235	0.074	0.250	0.243	0.091	0.220	0.248	0.085

Notes:
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
RMSE: Root mean square error.
U-*Theil*: Theil's U statistic.
CR: Confusion rate
Marked cells represents the best results for each statistic across the four techniques.

Table 7.4. *Summary of measures of reconstruction accuracy. Database of weekly returns. Two underlying factors.*

	PCA			FA			ICA			NNPCA		
	MEAN	MEDIAN	STD. DEV.	MEAN	MEDIAN	STD. DEV.	MEAN	MEDIAN	STD. DEV.	MEAN	MEDIAN	STD. DEV.
MAE	0.025	0.025	0.004	0.026	0.026	0.008	0.025	0.026	0.004	0.025	0.025	0.004
MAPE	159.118	160.532	33.076	160.591	169.752	40.795	159.913	162.722	33.955	160.609	165.707	33.324
RMSE	0.034	0.034	0.006	0.035	0.034	0.011	0.034	0.034	0.006	0.034	0.034	0.006
U-Theil	0.466	0.443	0.117	0.472	0.458	0.157	0.468	0.447	0.117	0.465	0.441	0.116
CR	0.273	0.264	0.058	0.273	0.276	0.081	0.273	0.268	0.059	0.270	0.266	0.062

Notes:
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
RMSE: Root mean square error.
U-*Theil*: Theil's U statistic.
CR: Confusion rate
Marked cells represents the best results for each statistic across the four techniques.

Table 7.5. *Summary of measures of reconstruction accuracy. Database of daily returns. Two underlying factors.*

	PCA			FA			ICA			NNPCA		
	MEAN	MEDIAN	STD. DEV.	MEAN	MEDIAN	STD. DEV.	MEAN	MEDIAN	STD. DEV.	MEAN	MEDIAN	STD. DEV.
MAE	0.0110	0.011	0.002	0.011	0.011	0.003	0.011	0.011	0.002	0.011	0.011	0.002
MAPE	138.764	138.488	33.172	139.837	139.159	41.594	140.248	139.286	34.827	139.736	139.540	33.065
RMSE	0.015	0.015	0.003	0.015	0.016	0.005	0.015	0.015	0.003	0.015	0.015	0.003
U-Theil	0.486	0.476	0.124	0.497	0.493	0.155	0.485	0.478	0.121	0.486	0.476	0.123
CR	0.293	0.300	0.059	0.290	0.296	0.082	0.292	0.297	0.060	0.293	0.299	0.059

Notes:
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
RMSE: Root mean square error.
U-*Theil*: Theil's U statistic.
CR: Confusion rate
Marked cells represents the best results for each statistic across the four techniques.

Additionally, in order to analyze the performance of each technique in the individual reproduction of the observed variables, we took as benchmark the results of the MAE, MAPE, RMSE, U-Theil and CR obtained in PCA, and then we confronted them with the results from the same measures obtained with the rest of the techniques by subtracting the former from the latter. For the sake of saving space, in this Chapter we only include the results related to the database of weekly returns when nine components were extracted, which are presented in Tables 7.6 to 7.8; nevertheless, in Appendix_2, Tables 19 to 27 of Chapter 7 present said results which refers to the four databases when nine components were extracted as well[224]. Our findings reveal that in terms of the individual reconstruction of the observed returns, in the database of weekly returns when we compare FA vs. PCA, more than the 50% of the stocks are better reproduced by FA than by PCA; when we compare ICA vs. PCA, is clearer the best performance of PCA in about 60% to 90% of the cases, and when we compare NNPCA vs. PCA, the latter surpass the former in around 65% to 90% of the quality of the stocks reproduction. Regarding the database of weekly excesses, the results are very similar to those of the weekly returns database. On the other hand, concerning the database of daily returns when we compare FA vs. PCA, FA produces better individual reproductions than PCA in around 45% to 64% of the cases, while PCA performs better than ICA and NNPCA in about 50% to 86%, and 64% to 82% of the stocks, respectively. With respect to the database of daily excesses the results were very similar to those of the daily returns database, as well.

[224] In line with the other empirical results reported, the results for the experiment when eight, seven, six, five, four, three and two factors where extracted are not included in this document; however, the analysis and conclusions reported include the entire cases.

In general, the foregoing results were similar in the totality of the cases and samples in our study, however, as in the average terms of the measures of reconstruction, in the models with a smaller number of components, the performance of NNPCA surpassed PCA but only in the weekly databases[225]. Interestingly, there was an exceptional case, in the experiment when seven factors were extracted, where a clear supremacy of ICA and NNPCA over PCA was detected. To the light of these results, we dare to point to NNPCA as a better technique for dimensionality reduction purposes, i.e., given a low dimension number of factors to extract, NNPCA performs a more accurate reconstruction.

Additionally and by way of illustration, derived from the previous benchmark analysis, we detected that in the particular cases of the five most volatile[226] stocks of the database of weekly returns, e.g., PEÑOLES*, GEOB, ELEKTRA*, TVAZTCPO and ALFAA; they were better reconstructed by PCA in all the cases, when nine factors were extracted and in almost all the cases, when two factors were estimated. Subsequently, to the light of this evidence, we dare to point to PCA as a better technique to reconstruct volatile stocks.

[225] See Tables 7.9 to 7.11, where exceptionally and as an example, we present the results corresponding to the databases of weekly returns when two factors were extracted, in order to provide evidence supporting these conclusions.
[226] We employed as a simple and quick measure of volatility for this purpose, the standard deviation of the returns.

Table 7.6. *Factor Analysis (FA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in FA minus measures of reconstruction accuracy obtained in PCA. Database of weekly returns. Nine underlying factors.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	FA > PCA		FA = PCA		FA < PCA	
																					Num.	%	Num.	%	Num.	%
MAE	0.04127	0.01187	-0.01801	-0.00351	0.01822	0.00630	0.00260	-0.00411	0.00063	-0.01968	0.01388	-0.00164	-0.01183	-0.00151	-0.01748	-0.00003	0.00166	-0.00046	0.02724	-0.00865	9	45%	0	0%	11	55%
MAPE	211.94391	62.23932	-121.75513	-45.45593	111.29801	64.23943	20.24966	-27.79782	15.33633	-127.51700	64.08102	-10.43843	-99.90991	-7.66938	-86.91512	4.70337	-5.15125	6.00872	202.63774	-118.68114	10	50%	0	0%	10	50%
RMSE	0.05323	0.01707	-0.02503	-0.00504	0.02466	0.00742	0.00282	-0.00524	0.00081	-0.02725	0.01770	-0.00152	-0.01488	-0.00221	-0.02298	-0.00011	0.00271	-0.00164	0.03675	-0.01102	9	45%	0	0%	11	55%
U-Theil	0.51260	0.28311	-0.51180	-0.09041	0.37192	0.05810	0.05407	-0.09055	0.01256	-0.34481	0.17809	-0.02907	-0.17982	-0.02873	-0.23030	-0.00973	0.04652	-0.02564	0.33985	-0.12230	9	45%	0	0%	11	55%
CR	0.36082	0.15120	-0.31615	-0.06186	0.17526	0.06186	0.00000	-0.03780	-0.01031	-0.20275	0.12027	-0.04467	-0.11684	0.00000	-0.12027	0.02062	0.05155	-0.01718	0.23024	-0.04811	8	40%	2	10%	10	50%

Notes:
FA > PCA: Cases where FA reproduce worse than PCA. i.e., FA's error in reproduction is greater than PCA's one. FA = PCA: Cases where FA reproduce just the same as PCA. i.e., FA's error in reproduction is equal to PCA's one. FA < PCA: Cases where FA reproduce better than PCA. i.e., FA's error in reproduction is less than PCA's one

Table 7.7. *Independent Component Analysis (ICA) vs. Principal Component Analysis (PCA).Measures of reconstruction accuracy obtained in ICA minus measures of reconstruction accuracy obtained in PCA. Database of weekly returns. Nine underlying factors.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	ICA > PCA		ICA = PCA		ICA< PCA	
																					Num.	%	Num.	%	Num.	%
MAE	0.00598	0.01693	0.00649	-0.00002	0.01191	0.01735	0.00709	0.00548	0.00785	0.00501	0.01020	0.00008	0.00216	0.00246	-0.00573	0.00150	0.00265	0.00173	0.00900	-0.00090	17	85%	0	0%	3	15%
MAPE	40.36378	147.07055	96.29655	-69.01105	120.11376	89.91737	33.54075	-23.96516	24.31992	16.35403	25.67545	8.06252	-17.11136	-9.10308	-22.91340	8.43151	41.91659	-22.19147	59.11461	-52.15880	13	65%	0	0%	7	35%
RMSE	0.00771	0.02217	0.00707	-0.00099	0.01616	0.02327	0.00896	0.00696	0.01078	0.00640	0.01310	-0.00020	0.00248	0.00444	-0.00783	0.00125	0.00432	0.00278	0.01199	-0.00071	16	80%	0	0%	4	20%
U-Theil	0.05943	0.29646	0.11368	0.00762	0.16097	0.23510	0.19689	0.19309	0.23770	0.14836	0.15507	-0.01572	0.05459	0.06349	-0.08635	0.01801	-0.02337	0.07039	0.10754	0.00420	17	85%	0	0%	3	15%
CR	0.05155	0.18557	0.13058	0.02405	0.08935	0.12027	0.09278	0.09278	0.14777	0.05498	0.05842	0.00000	0.04124	0.03780	-0.04811	0.02062	0.00687	0.01375	0.05842	0.01031	18	90%	1	5%	1	5%

Notes:
ICA > PCA: Cases where ICA reproduce worse than PCA. i.e., ICA's error in reproduction is greater than PCA's one. ICA = PCA: Cases where ICA reproduce just the same as PCA. i.e., ICA's error in reproduction is equal to PCA's one. ICA < PCA: Cases where ICA reproduce better than PCA. i.e., ICA's error in reproduction is less than PCA's one.

Table 7.8. *Neural Networks Principal Component Analysis (NNPCA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in NNPCA minus measures of reconstruction accuracy obtained in PCA. Database of weekly returns. Nine underlying factors.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	NNPCA > PCA		NNPCA = PCA		NNPCA < PCA	
																					Num.	%	Num.	%	Num.	%
MAE	0.00089	0.00110	0.00026	-0.00060	0.00863	0.00100	0.00104	0.00223	-0.00084	-0.00022	0.00446	0.00103	0.00233	0.00253	0.00120	-0.00014	0.00188	0.00219	0.00528	0.00201	16	80%	0	0%	4	20%
MAPE	4.56469	34.36170	7.26120	0.64995	70.19244	7.10988	2.71002	1.57038	2.27286	9.10447	21.79925	5.51696	3.57004	17.69130	5.88784	6.78867	-5.59263	25.75705	60.30772	-26.73023	18	90%	0	0%	2	10%
RMSE	0.00116	0.00160	0.00023	-0.00147	0.01161	0.00124	0.00091	0.00246	-0.00065	-0.00117	0.00632	0.00164	0.00296	0.00380	0.00113	-0.00031	0.00241	0.00284	0.00681	0.00292	16	80%	0	0%	4	20%
U-Theil	0.00861	0.02137	0.00432	-0.02946	0.14647	0.00997	0.01232	0.04548	-0.01270	-0.02177	0.06005	0.03062	0.03912	0.05162	0.01238	-0.00753	0.04152	0.04395	0.05548	0.03408	16	80%	0	0%	4	20%
CR	0.01031	-0.00687	0.00000	0.00344	0.08935	0.00000	-0.00344	0.01375	-0.02749	0.02062	0.01031	0.01031	0.03093	0.04124	0.01031	0.03780	0.04811	0.02062	-4.00000	-6.00000	13	65%	2	10%	5	25%

Notes:
NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one. NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one. NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

Table 7.9. *Factor Analysis (FA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in FA minus measures of reconstruction accuracy obtained in PCA. Database of weekly returns. Two underlying factors.*

																					FA > PCA		FA = PCA		FA < PCA	
	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	Num.	%	Num.	%	Num.	%
MAE	0.03452	0.00018	0.00007	-0.00012	0.00043	0.00309	0.00018	-0.00024	-0.00110	-0.00062	0.00081	-0.00561	-0.01788	-0.00064	-0.00073	0.00011	0.00008	-0.00078	0.00201	-0.00094	10	50%	0	0%	10	50%
MAPE	70.10854	14.16959	7.47549	12.12611	-1.01238	5.91353	3.34985	4.03498	-15.86795	-1.46500	-1.39449	-1.46028	-109.85861	11.87739	-0.63864	13.09233	5.79812	5.28762	3.15956	4.76344	13	65%	0	0%	7	35%
RMSE	0.04688	-0.00006	-0.00023	-0.00058	0.00035	0.00467	0.00089	-0.00040	-0.00110	-0.00105	0.00137	-0.00853	-0.02379	-0.00122	-0.00122	-0.00050	0.00015	-0.00054	0.00254	-0.00144	7	35%	0	0%	13	65%
U-Theil	0.67057	-0.00822	-0.01609	-0.01479	0.01097	0.06607	0.02230	-0.01283	-0.02197	-0.02477	0.01925	-0.18468	-0.33311	-0.01946	-0.01751	-0.01826	0.00116	-0.01216	0.03450	-0.02310	7	35%	0	0%	13	65%
CR	0.28866	0.01031	0.01031	0.01718	0.01718	0.01375	-0.01031	-0.00344	0.00000	-0.04467	0.00687	-0.08591	-0.20619	-0.03093	0.00687	-0.01031	-0.02405	-0.00687	0.04124	0.01031	10	50%	1	5%	9	45%

Notes:
NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one. NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one. NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

Table 7.10. *Independent Component Analysis (ICA) vs. Principal Component Analysis (PCA).Measures of reconstruction accuracy obtained in ICA minus measures of reconstruction accuracy obtained in PCA. Database of weekly returns. Two underlying factors.*

																					ICA > PCA		ICA = PCA		ICA< PCA	
	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	Num.	%	Num.	%	Num.	%
MAE	0.00096	0.00010	0.00001	-0.00005	0.00005	0.00085	0.00001	-0.00009	0.00013	0.00006	0.00012	0.00007	-0.00015	0.00018	0.00018	0.00041	-0.00001	-0.00005	-0.00009	0.00058	14	70%	0	0%	6	30%
MAPE	6.69144	-13.79041	12.52097	1.41330	3.46990	-12.31372	-3.01024	-9.87405	6.07827	4.31694	-10.64708	-1.87898	0.79124	14.06788	-6.40208	10.78043	-0.24593	-0.90092	5.67200	9.14653	11	55%	0	0%	9	45%
RMSE	0.00109	0.00015	-0.00001	-0.00014	-0.00001	0.00101	0.00007	0.00013	0.00005	0.00001	0.00067	0.00000	-0.00020	-0.00012	0.00040	0.00003	0.00002	-0.00004	-0.00019	0.00019	12	60%	0	0%	8	40%
U-Theil	0.00987	0.03545	-0.03250	-0.00771	-0.00509	0.03336	0.01183	0.01427	-0.01037	-0.01266	0.02324	0.00305	-0.00427	-0.01805	0.01934	-0.02141	-0.00243	0.00423	-0.00751	-0.00953	9	45%	0	0%	11	55%
CR	-0.00344	0.01031	0.00344	0.00000	-0.01031	0.04124	0.00000	-0.00344	0.00687	-0.02062	0.00344	-0.01031	-0.01375	-0.00687	0.00687	-0.01375	0.00344	-0.00344	0.00000	0.01375	8	40%	3	15%	9	45%

Notes:
NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one. NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one. NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

Table 7.11. *Neural Networks Principal Component Analysis (NNPCA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in NNPCA minus measures of reconstruction accuracy obtained in PCA. Database of weekly returns. Two underlying factors.*

																					NNPCA > PCA		NNPCA = PCA		NNPCA < PCA	
	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	Num.	%	Num.	%	Num.	%
MAE	0.00003	-0.00005	0.00006	0.00002	0.00001	-0.00019	0.00000	0.00008	-0.00008	0.00003	0.00000	-0.00002	-0.00003	-0.00009	0.00008	-0.00017	-0.00001	0.00001	0.00002	0.00008	11	55%	0	0%	9	45%
MAPE	-1.66542	9.15312	-0.21699	1.34230	0.91983	11.30110	7.36139	3.18513	-1.50095	0.81064	-0.29033	-0.33036	-2.68631	-1.56245	-3.46605	8.15575	1.63111	2.04339	0.99713	-5.37280	11	55%	0	0%	9	45%
RMSE	0.00004	-0.00005	-0.00002	0.00000	0.00000	-0.00015	-0.00011	-0.00004	-0.00003	0.00000	0.00000	0.00000	-0.00002	-0.00006	-0.00016	-0.00035	0.00000	-0.00004	0.00001	-0.00028	4	20%	0	0%	16	80%
U-Theil	0.00047	-0.00442	-0.00221	-0.00022	0.00002	-0.00369	-0.00587	-0.00167	-0.00001	0.00020	0.00041	0.00033	0.00010	-0.00026	-0.00116	-0.01048	-0.00023	-0.00103	0.00020	-0.00290	7	35%	0	0%	13	65%
CR	-0.01718	0.01031	-0.00344	-0.00344	-0.00687	0.00000	-0.01031	-0.01031	-0.01031	0.00000	0.00344	-0.00344	0.00344	-0.01375	-0.01718	0.00687	-0.00344	-0.01375	0.00000	-15.00000	4	20%	3	15%	13	65%

Notes:
NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one. NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one. NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

7.3.2. Underlying systematic risk structure.

The objective of this section is to continue the comparative study across the four techniques by means of the statistical and graphical analyses of both the underlying risk factors and their corresponding sensitivities (betas). We have said that the Arbitrage Pricing Theory is integrated by two main assumptions, the generative multifactor model of returns and the arbitrage absence principle or arbitrage principle; however, our study has been focused only on the first part, i.e., the improved estimation of the generative multifactor model of returns under a statistical approach. In that sense, the APT assumes the following generative multifactor model of returns[227]:

$$R_{it} = E(R_i) + \beta_{1i} \cdot F_{1t} + \beta_{2i} \cdot F_{2t} + ... + \beta_{ji} \cdot F_{jt} + \varepsilon_{it} \qquad (7.15)$$

In the four techniques used in our studies, we estimated this underlying structure of systematic risk, whose risk factors (*Fs*) and sensitivities to them (β) will be compared in this section. Therefore, we will continue the comparative study across the four techniques by means of the statistical and graphical analyses of both the underlying risk factors and their corresponding sensitivities (betas).

7.3.2.1. Statistical and graphical analysis.

In this section, we present the comparative study of both the underlying systematic risk factors extracted by PCA, FA, ICA and NNPCA, and the sensitivities to them (betas) estimated in the first stage of the econometric contrast. For the sake of saving space, in this Chapter we only present the results of the experiment when we extracted nine factors or components by way of the four techniques in the database of weekly returns using each technique; however, the conclusions derived are similar for all cases. Tables 7.12 to 7.15

[227] Where, β_{jig} represents the sensitivity of equity i to factor j, F_{jt} the value of the systematic risk factor j in time t common for all the stocks, and ε_i the idiosyncratic risk affecting only equity i.

show the descriptive statistics of the nine factors extracted by each technique[228]. As we can observe, although the scores of the underlying factors in all the techniques are not normalized, the mean of them in all the techniques is almost zero. The standard deviation of all the extracted factors within each technique is very similar; however, it is quite different across techniques. The skewness and kurtosis coefficients as well as the Jarque-Bera test indicate that in all cases, except the principal component number eight in the four databases, the underlying systematic risk factors are not univariate normally distributed.

As expected, given the theoretical construction of the four techniques, the underlying factors are uncorrelated with each other in almost all the cases in the four databases, as Tables 40 to 55 in the section corresponding to Chapter 7 of the Appendix_2 demonstrate[229]. In the most of the cases, the correlation is zero and we cannot reject the null hypothesis of non-correlation at a 5% of statistical significance, except in the case of the ninth non-linear component extracted using NNPCA in the four databases, where we reject the null hypothesis of non-autocorrelation; nevertheless the correlation value of this component with the rest of them was negligible[230].

Therefore, to the light of the foregoing analysis, we may state that from a statistical descriptive scope, the extracted factors via the four techniques have a similar behavior. Next, we will analyze if the shape of them are similar, in order to detect if the factors extracted by way of the four techniques may be similar from a morphological standpoint.

[228] The tables corresponding to the other three databases when nine factors were extracted are included in the Appendix_2, in Tables 28 to 39 of the section related to Chapter 7. For the same reason of saving space and in the line of all the empirical results reported in this dissertation, those corresponding to the experiments where eight, seven, six, five, four, three and two factors were extracted are not included in this document.

[229] In the same way, correlation matrices corresponding to the rest of experiments are not included in the present document.

[230] Nonetheless, we are aware of this fact could have affected the estimation of the betas and have conditioned the results in the econometric contrast of the APT.

Table 7.12. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of weekly returns.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Mean	-0.011147	0.005092	-0.004053	-0.001182	0.002419	0.002812	0.001521	-0.001205	0.001658
Median	-0.025207	0.005214	-0.002843	-0.001616	0.003391	0.004848	0.001526	-0.001049	0.001021
Maximum	0.622778	0.221954	0.198317	0.164228	0.194522	0.155387	0.210445	0.121947	0.132637
Minimum	-0.375429	-0.269590	-0.184985	-0.181771	-0.162721	-0.142336	-0.176655	-0.123509	-0.097858
Std. Dev.	0.128976	0.068302	0.053679	0.049616	0.046945	0.043626	0.041988	0.040538	0.038984
Skewness	0.921649	-0.044638	0.207094	0.199238	0.169339	0.028023	0.206886	-0.075126	0.216159
Kurtosis	5.568533	4.415327	4.220683	4.469012	4.864033	4.101746	6.211078	3.120087	3.753958
Jarque-Bera	121.1907	24.38485	20.14714	28.09094	43.52054	14.75594	127.0970	0.448584	9.158622
Probability	0.000000	0.000005	0.000042	0.000001	0.000000	0.000625	0.000000	0.799082	0.010262
Observations	291	291	291	291	291	291	291	291	291

Table 7.13. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of weekly returns.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
Mean	0.043786	0.044102	0.115499	-0.019651	-0.068016	0.176449	0.091415	-0.033200	0.113345
Median	0.058395	0.060544	0.163773	-0.009059	-0.007203	0.192711	0.061400	0.093805	0.059944
Maximum	3.271584	4.609701	3.383498	2.972203	3.317964	4.405352	7.147668	5.241201	6.544539
Minimum	-3.465415	-4.513370	-5.060657	-3.900273	-4.535080	-4.235792	-3.653112	-6.625135	-5.246489
Std. Dev.	1.001470	1.042931	1.166327	1.003150	1.004546	1.297407	1.413208	1.623710	1.716505
Skewness	-0.266661	-0.082358	-0.357369	-0.396239	-0.425664	0.075314	0.673684	-0.118020	0.262232
Kurtosis	4.412059	5.257861	4.314169	4.525154	5.251143	4.084084	5.594026	4.870430	4.797944
Jarque-Bera	27.62492	62.14144	27.13443	35.81864	70.23289	14.52487	103.6005	43.09496	42.53041
Probability	0.000001	0.000000	0.000001	0.000000	0.000000	0.000701	0.000000	0.000000	0.000000
Observations	291	291	291	291	291	291	291	291	291

Table 7.14. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of weekly returns.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
Mean	-0.011864	-0.001814	-0.001780	-0.003053	-0.007886	-0.002532	-0.004920	0.007014	0.008120
Median	-0.008407	-0.008019	-0.010114	-0.004324	-0.014678	-0.007545	-0.005665	0.008347	0.004961
Maximum	0.431340	0.914405	0.643291	0.558469	0.656328	0.408716	0.395152	0.579731	0.475467
Minimum	-0.538880	-0.270973	-0.442662	-0.366317	-0.384950	-0.476562	-0.669372	-0.369589	-0.370474
Std. Dev.	0.116841	0.117430	0.117431	0.117404	0.117178	0.117417	0.117341	0.117234	0.117162
Skewness	-0.284181	1.839358	0.981947	0.312745	0.779060	0.049481	-0.748905	0.570886	0.291023
Kurtosis	5.186298	15.23280	9.583743	4.807656	6.636865	4.571347	8.545598	5.680307	4.452942
Jarque-Bera	61.87307	1978.490	572.3309	44.36363	189.8111	30.05696	400.0897	102.9132	29.70403
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	291	291	291	291	291	291	291	291	291

Table 7.15. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of weekly returns.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Mean	0.008312	0.000706	0.001963	0.000203	0.000679	-0.000337	0.000294	-0.000552	0.008267
Median	-0.008041	-0.000902	0.002824	0.001347	0.001878	0.000155	0.000146	-0.000467	0.007234
Maximum	0.734043	0.329303	0.409686	0.134187	0.234243	0.073736	0.061220	0.063404	0.095442
Minimum	-0.398930	-0.376765	-0.441281	-0.139782	-0.176433	-0.098899	-0.127976	-0.040112	-0.040103
Std. Dev.	0.142438	0.097186	0.122639	0.038168	0.055045	0.030888	0.020717	0.017621	0.015609
Skewness	0.972586	0.077551	0.107231	-0.252996	0.341807	-0.219110	-0.755519	0.542766	0.868493
Kurtosis	5.869496	4.496825	4.203884	4.616058	4.567893	3.082000	7.721504	3.824014	6.467057
Jarque-Bera	145.7147	27.45755	18.13090	34.77048	35.47307	2.409976	297.9820	22.52074	182.3309
Probability	0.000000	0.000001	0.000116	0.000000	0.000000	0.299696	0.000000	0.000013	0.000000
Observations	291	291	291	291	291	291	291	291	291

Figures 7.1 to 7.4, plot the underlying systematic risk factors extracted by each technique in the database of weekly returns in the experiment where we estimated nine factors[231]. Regarding the morphology of the underlying factors seen as signals, we can observe two important aspects in those figures. First, that the signals are quite different within each technique and across the four techniques; second, that all the signals present a very high volatility.

In addition, we construct individual plots in order to compare the shape of each systematic risk factor extracted by each technique respecting the ranking produced by each one of them, which satisfies the criteria of the amount of variability explained. It is important to remark that this experiment represents only a first approach to detect whether the factors extracted by each technique might be the same or similar across techniques. For the sake of saving space, in this Chapter we only present the the plots of the first risk factor extracted by each technique in the databases of weekly and daily returns, which is presented in Figures 7.5 and 7.6, respectively[232]. As we can observe the factors estimated by PCA and NNPCA are very similar, which leads us to think that they could be almost the same systematic risk factors from a morphological standpoint. On the other hand, factors computed by FA and ICA in some periods of the observations present some similarities as well, but not at the same level as NNPCA and PCA; as a matter of fact, in points of high volatility they behave very differently. In addition, the volatility observed in the factors produced by FA and ICA is very high compared with that presented in PCA and NNPCA components. Finally, the values of the extracted factor by each technique vary as well; FA and ICA present higher values than those produced by PCA and NNPCA.

[231] The figures related to the other three databases are presented in the Section corresponding to the Chapter 7 in the Appendix_2 from Figures 9 to 20. The figures corresponding to the experiment when eight, seven, six, five, four, three and two factors were extracted are not included in this document.
[232] The plots containing all the ranked factors extracted in each database that correspond to the experiment when nine factors were extracted are included in the Appendix_2 from Figure 21 to Figure 56. The results of the rest of experiments are not included in this document.

Figure 7.1. *Plot of the underlying systematic risk factors extracted by Principal Component Analysis. Database of weekly returns. Nine components estimated.*

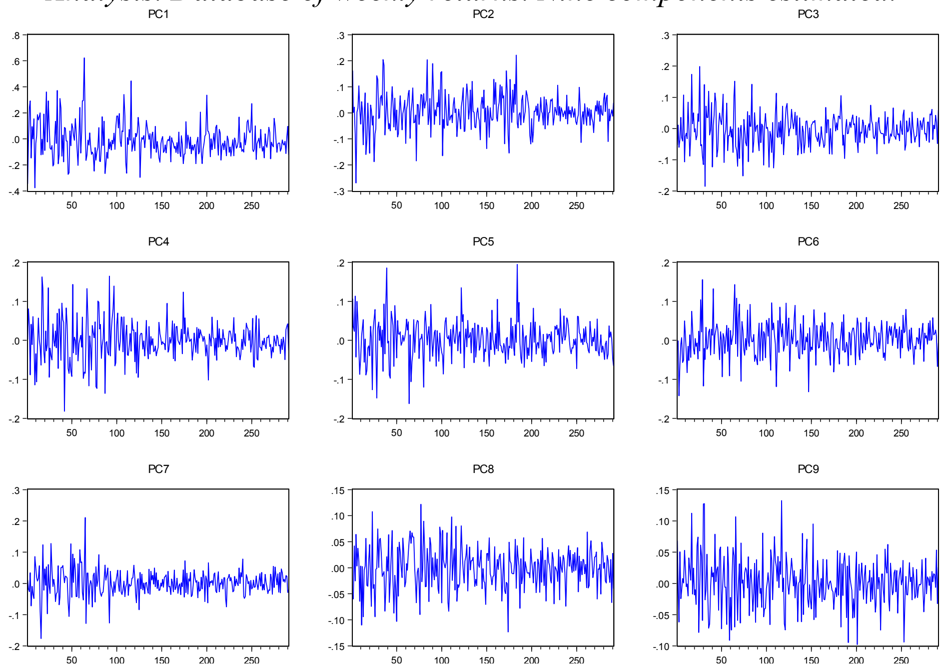


Figure 7.2. *Plot of the underlying systematic risk factors extracted by Factor Analysis. Database of weekly returns. Nine factors estimated.*

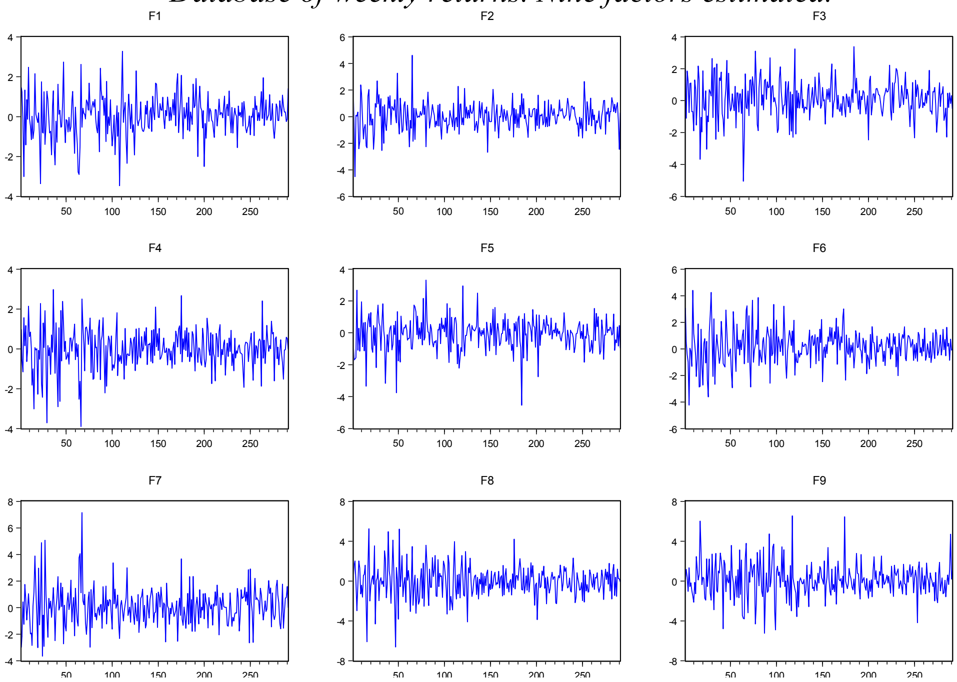


Figure 7.3. *Plot of the underlying systematic risk factors extracted by Independent Component Analysis. Database of weekly returns. Nine components estimated.*

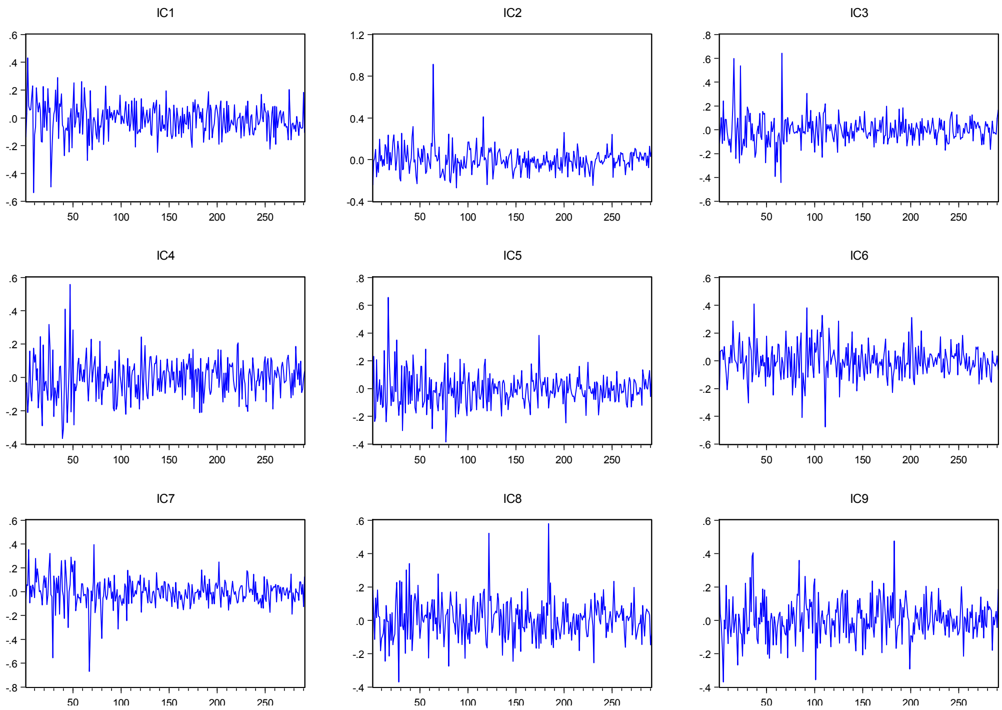


Figure 7.4. *Plot of the underlying systematic risk factors extracted by Neural Networks Principal Component Analysis. Database of weekly returns. Nine components estimated.*

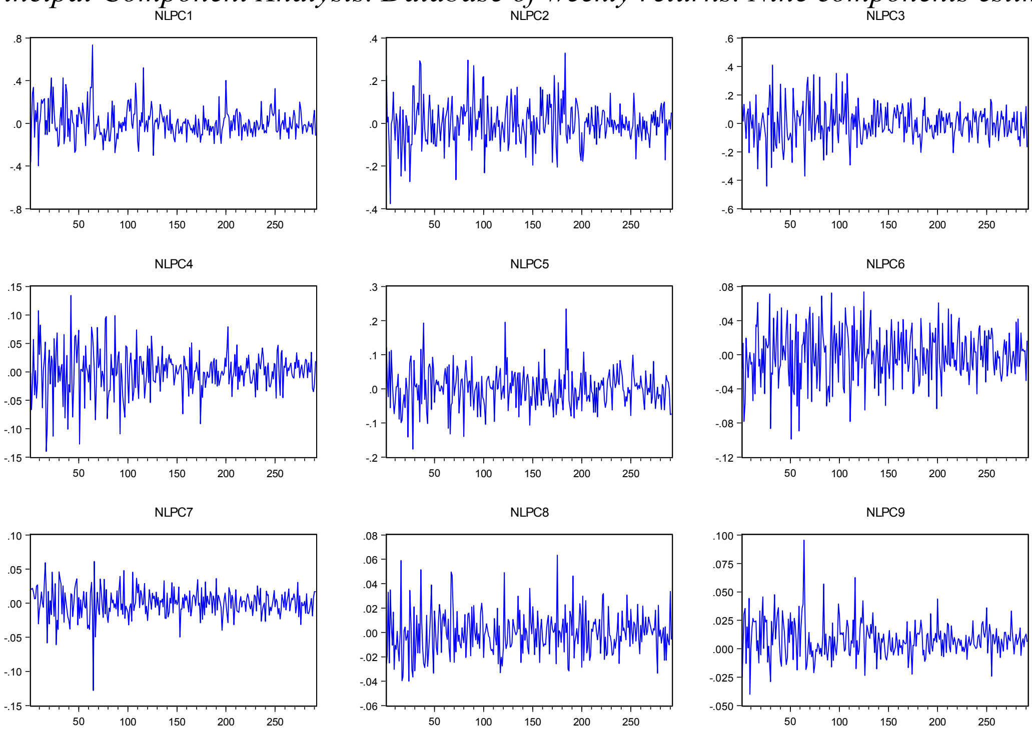


Figure 7.5. *First underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

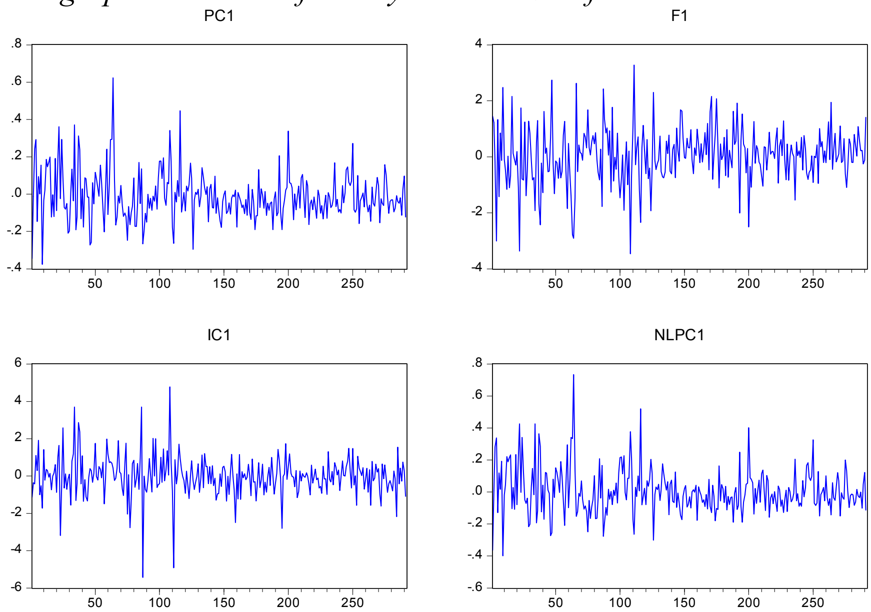
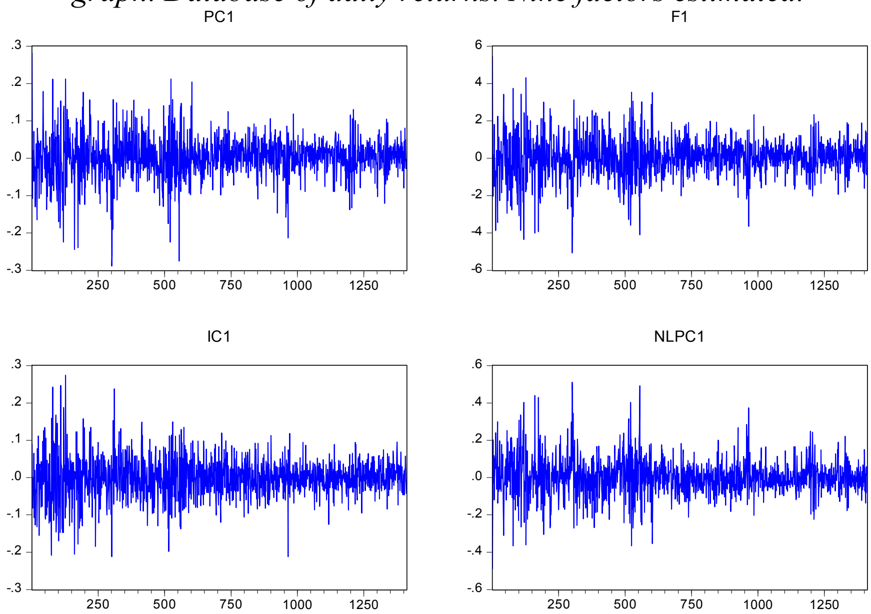


Figure 7.6. *First underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*



On the other hand, we made the same analysis of the matrix of sensitivities to the underlying systematic risk factors or betas, whose results are presented following the same structure of those corresponding to the risk factors. First, in line with the previously reported in this Chapter, in Tables 7.16 to 7.19 we present the descriptive statistics of the betas estimated in each technique for the database of weekly returns when nine components were extracted[233]. One of the main findings is that the mean of the values of the betas in general is very small, as they are practically zero in all cases, except in the case of the beta number nine extracted via NNPCA in the database of weekly returns, which presents very higher values with respect to all other cases. This beta reached a mean value of 3.642261, while the second larger absolute values ranged around 0.21 (PC1 in DBWR) and 0.54 (NLPC1 in DBWR); in general, the average higher values of the betas were produced by NNPCA. Another remarkable point is that in many cases the average sensitivities to some underlying systematic risk are negative, as in the case of the sensitivity to the first, fourth and sixth principal components; to the seventh factor of FA; to the first, second, sixth, seventh and ninth independent components; and to the first, seventh and eight principal nonlinear components.

Under a financial interpretation, the negative sensitivities implies that the reaction of the returns to the variation of those sensitivities to the related underlying factors would be inversely proportional, and that the changes in the returns on equities in relation to change in the value of these betas, would be very small in the most cases, except in the case mentioned above, where the value of the beta may be interpreted as a change in one unit of the factor number nine would change a variation of more than 3 points in the average returns of the stocks studied. In this case, according to the interpretation methodology used in the previous chapters. This factor correspond to the factor that combines the food products, beverages and construction sectors factor, in this case. The standard deviation of the betas is very similar

[233] The tables corresponding to the other three databases when nine factors were extracted are included in the Appendix_2, in Tables 56 to 67 of the section related to Chapter 7. For the same reason of saving space and in the line of all the empirical results reported in this dissertation, those corresponding to the experiments where eight, seven, six, five, four, three and two factors were extracted are not included in this document.

within the factors extracted by each technique but quite different across them. In most cases the skewness and kurtosis produce values closer to those corresponding to a normal univariate distribution, which is confirmed by the Jarque-Bera test, except in nine cases spread in PCA, FA and NNPCA. The correlation matrices show that the betas are uncorrelated as well, except in some cases of the betas estimated in NNPCA, as tables 68 to 83 in the section corresponding to Chapter 7 in Appendix_2 demonstrate[234].

Therefore, to the light of the foregoing analysis, we may state that from a statistical descriptive standpoint, the estimated betas related to the underlying risk factors by PCA, FA and NNPCA present a similar behavior; however, those computed in NNPCA differs significantly from the former ones. As we did for the underlying systematic risk factors extracted, next, we will analyze the shape of the betas, in order to detect if the betas computed for the four techniques could be similar from a morphological scope.

Table 7.16. *Descriptive Statistics. Matrix of Betas computed in Principal Component Analysis. Database of weekly returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.213564	0.018963	0.032341	-0.014160	0.012927	-0.003497	0.013722	0.002956	0.012851
Median	-0.213982	-0.057949	0.073170	-0.077437	-0.009958	0.059694	-0.017746	0.012146	-0.018488
Maximum	-0.097420	0.914852	0.318767	0.706323	0.446003	0.401071	0.586068	0.348935	0.659808
Minimum	-0.328798	-0.126960	-0.765574	-0.367746	-0.508578	-0.445564	-0.335898	-0.459268	-0.530716
Std. Dev.	0.067983	0.228589	0.227003	0.228955	0.229032	0.229388	0.228983	0.229396	0.229037
Skewness	0.028040	3.267882	-2.206947	1.621110	-0.533978	-0.426090	0.494909	-0.261884	0.536034
Kurtosis	2.000887	13.17860	8.740663	6.267261	3.420379	2.375802	3.073003	2.301176	5.509926
Jarque-Bera	0.834476	121.9334	43.69806	17.65582	1.097707	0.929862	0.820890	0.635574	6.207549
Probability	0.658864	0.000000	0.000000	0.000147	0.577612	0.628178	0.663355	0.727758	0.044879
Observations	20	20	20	20	20	20	20	20	20

[234] In the same sense, correlation matrices corresponding to the rest of experiments are not included in the present document.

Table 7.17. *Descriptive Statistics. Matrix of Betas computed in Factor Analysis. Database of weekly returns. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.022424	0.011371	0.007779	0.003715	0.002368	0.000885	-3.37E-05	0.001447	0.001073
Median	0.021531	0.010624	0.008320	0.004084	0.001276	7.57E-06	-0.000295	0.000127	-2.85E-05
Maximum	0.043241	0.035284	0.030054	0.023501	0.029489	0.029412	0.015460	0.013560	0.014523
Minimum	0.009629	-0.001596	-0.008214	-0.023029	-0.019347	-0.016698	-0.014130	-0.009402	-0.008015
Std. Dev.	0.008662	0.008500	0.008536	0.007928	0.008929	0.009544	0.006522	0.006521	0.006060
Skewness	0.476343	0.789956	0.504166	-1.225394	0.737083	1.266237	0.489035	0.207862	0.882806
Kurtosis	2.906572	4.413088	3.828497	9.337472	6.818580	5.495811	4.003653	2.368071	3.311818
Jarque-Bera	0.763615	3.744118	1.419285	38.47493	13.96227	10.53542	1.636617	0.476801	2.678846
Probability	0.682626	0.153807	0.491820	0.000000	0.000929	0.005155	0.441177	0.787887	0.261997
Observations	20	20	20	20	20	20	20	20	20

Table 7.18. *Descriptive Statistics. Matrix of Betas computed in Independent Component Analysis. Database of weekly returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.113065	-0.147400	0.058264	0.007181	0.024688	-0.116170	-0.018071	0.019129	0.034793
Median	-0.140755	-0.130808	0.093963	0.015549	0.016585	-0.106440	-0.010354	0.038931	-0.004120
Maximum	0.031415	-0.012336	0.153903	0.124484	0.157987	0.008243	0.171918	0.151297	0.516080
Minimum	-0.243882	-0.379684	-0.189827	-0.172986	-0.319361	-0.260805	-0.219870	-0.260815	-0.048224
Std. Dev.	0.084422	0.093804	0.086419	0.082817	0.098622	0.065597	0.092158	0.086939	0.118395
Skewness	0.196405	-0.723047	-1.230012	-0.580671	-1.983829	-0.107677	-0.227771	-1.937133	3.566360
Kurtosis	1.749982	3.031648	4.278765	2.505637	8.604731	2.893551	3.061689	7.032685	15.16361
Jarque-Bera	1.430704	1.743493	6.405795	1.327592	39.29610	0.048091	0.176103	26.06041	165.6909
Probability	0.489020	0.418220	0.040644	0.514893	0.000000	0.976241	0.915714	0.000002	0.000000
Observations	20	20	20	20	20	20	20	20	20

Table 7.19. *Descriptive Statistics. Matrix of Betas computed in Neural Networks Principal Component Analysis. Database of weekly returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.541890	-0.144045	0.182051	-0.199030	-0.082968	-0.050471	0.007347	-0.530388	3.642261
Median	-0.557320	-0.062540	0.141554	-0.303472	-0.169129	-0.061177	-0.047276	-0.654824	4.195968
Maximum	5.139106	2.362867	2.155201	3.055385	1.485774	0.588877	0.715768	8.626535	39.52712
Minimum	-3.890342	-1.713984	-3.117944	-2.288916	-1.123985	-1.087118	-1.111239	-5.831424	-55.41998
Std. Dev.	2.098866	0.957290	1.222231	1.277853	0.613240	0.402331	0.465539	3.185869	22.05250
Skewness	0.718213	0.541731	-0.728126	0.646054	0.611902	-0.801233	-0.425304	0.901666	-0.672855
Kurtosis	3.900535	3.582376	3.907497	3.292789	3.369601	3.736968	2.874113	4.588276	3.794487
Jarque-Bera	2.395237	1.260878	2.453517	1.462722	1.361916	2.592514	0.616151	4.812191	2.035122
Probability	0.301912	0.532358	0.293242	0.481254	0.506132	0.273554	0.734860	0.090167	0.361476
Observations	20	20	20	20	20	20	20	20	20

In Figures 7.7 to 7.10 we present the morphology of the betas treated as signals estimated in each technique for the database of weekly returns[235]. It can be seen that the form of the sensitivities to each factor is also very different and presents a high volatility as well. Additionally, as we did for the systematic risk factor, we plot the individual relationship of the betas to each factor in order to compare their shape and detect whether or not they are similar across the four techniques. The sensitivities to the first factor in the databases of weekly and daily returns when nine factors were computed are presented in Figures 7.11 and 7.12[236].

As we can observe, in general, the betas are different in the four techniques; nevertheless, in some exceptional cases the betas estimated for PCA, FA and ICA present similar shape but NNPCA behave differently. Moreover, the volatility observed in the betas from the first two techniques presents a higher level than that produced by these last techniques. As we have detected in the descriptive analysis, the highest values of the betas correspond to NNPCA, while the lowest correspond to FA. In addition, the former present the highest variability, and the latter the lowest.

Consequently, these results reveal that the sensitives to the underlying risk factors extracted by way of PCA, FA, ICA and NNPCA are different and change significantly for each stock studied.

[235] The figures related to the other three databases are presented in the Section corresponding to the Chapter 7 in the Appendix_2 from Figures 57 to 72. The figures corresponding to the experiment when eight, seven, six, five, four, three and two factors were extracted are not included in this document.
[236] The plots containing all the betas related to the ranked factors extracted in each database that correspond to the experiment when nine factors were extracted are included in the Appendix_2 from Figure 73 to Figure 108. The results of the rest of experiments are not included in this document.

Figure 7.7. *Plot of the Betas computed in Principal Component Analysis. Database of weekly returns. Nine components estimated.*

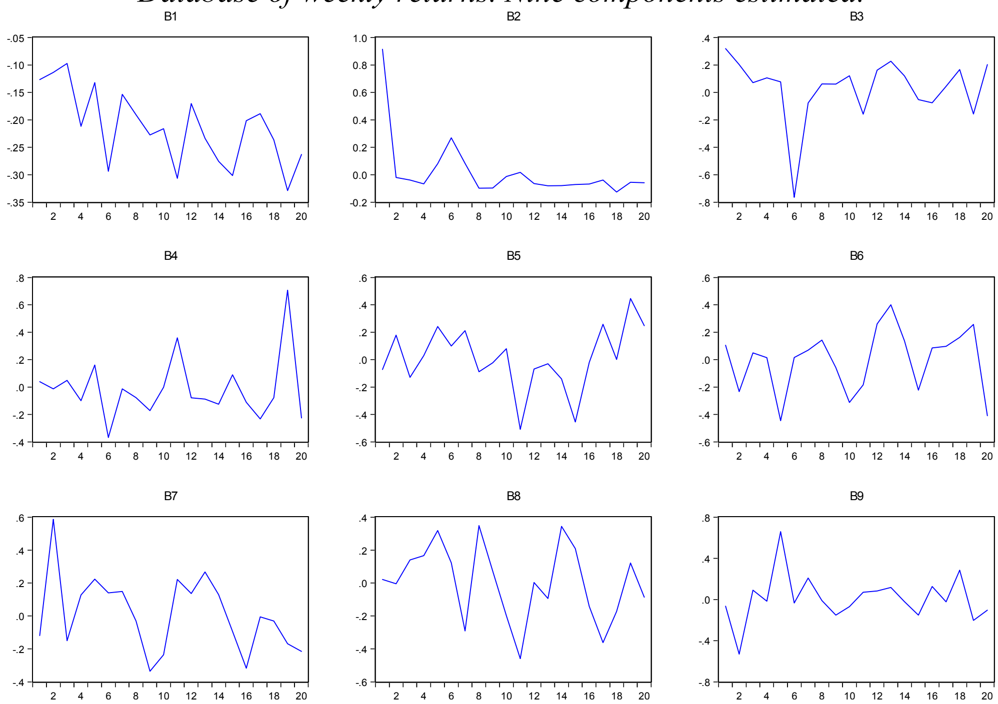


Figure 7.8. *Plot of the Betas computed in Factor Analysis. Database of weekly returns. Nine factors estimated.*

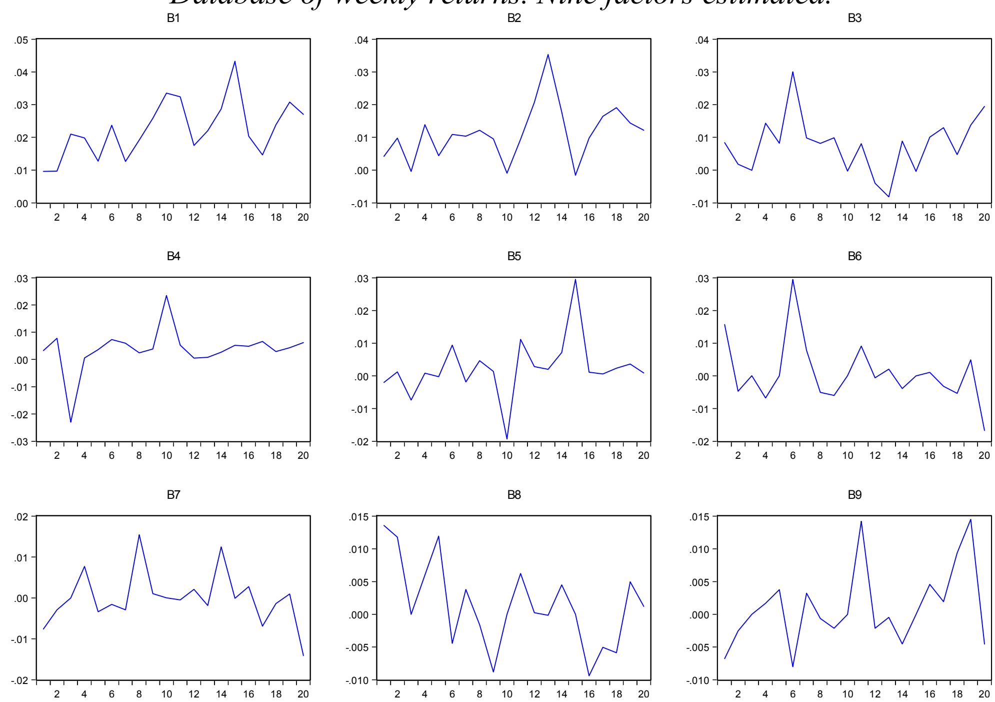


Figure 7.9. *Plot of the Betas computed in Independent Component Analysis. Database of weekly returns. Nine components estimated.*

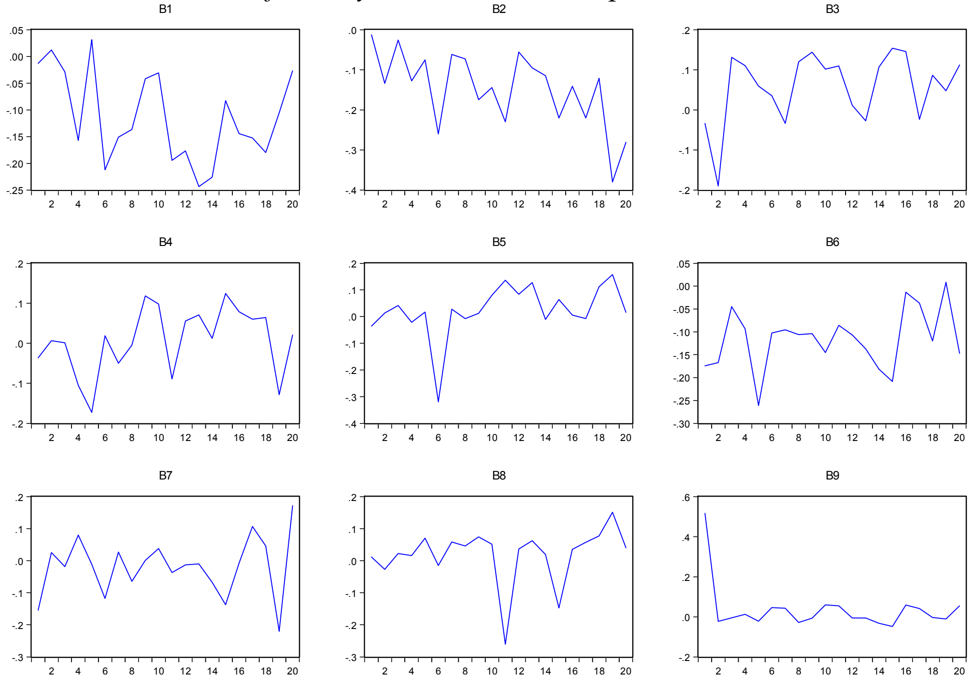


Figure 7.10. *Plot of the Betas computed in Neural Networks Principal Component Analysis. Database of weekly returns. Nine components estimated.*

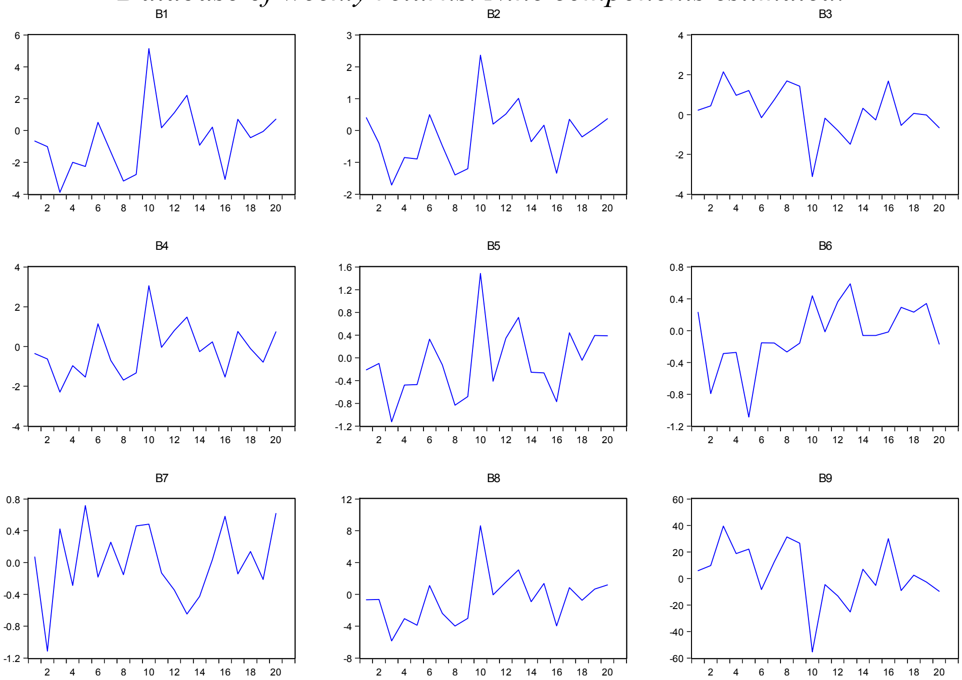


Figure 7.11. *Betas to the* ***first underlying*** *systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

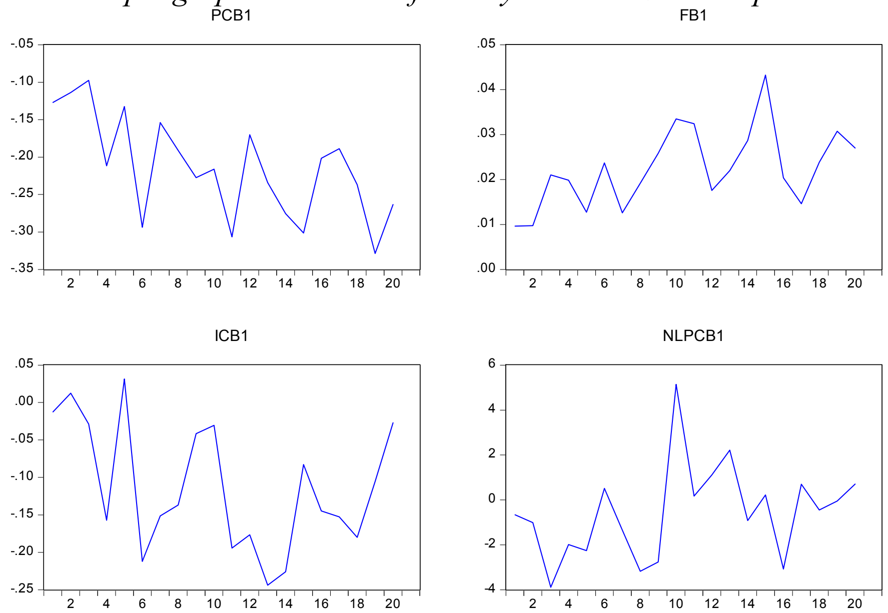
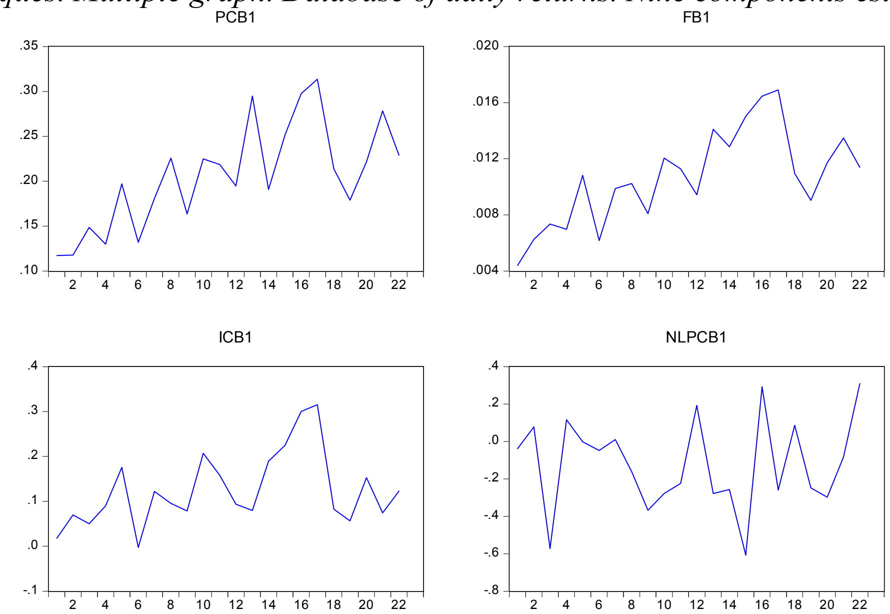


Figure 7.12. *Betas to the* ***first underlying*** *systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*



7.3.3. Results in the econometric contrast of the APT.

The objective of this section is to continue the comparative study across the four techniques by means of the results of the econometric contrast of the APT, when we utilized the systematic risk factors and betas computed in each technique.

As stated before, the Arbitrage Pricing Theory is integrated by two main assumptions, the generative multifactor model of returns and the arbitrage absence principle or arbitrage principle; however, our study has been focused mainly on the first part, i.e., the improved estimation of the generative multifactor model of returns under a statistical approach; the arbitrage principle is outside the scope of our research at this moment, although we recognize that some of the results obtained in the econometric contrast may have originated due to problems in this part of the pricing model; consequently the results in the econometric contrast should be seen under this light. Future lines of research will be focused on this aspect of the model.

In order to perform the econometric contrast of the underlying structure of systematic risk, under the framework of the statistical approach to the Arbitrage Pricing Theory, in the previous chapters we have followed a two-stage methodology which is described in Chapter 3.

For the sake of saving space we will not present in this Chapter the results in the econometric contrast obtained in each technique; however, the interested reader can consult the details in the previous Chapters that correspond to each technique used. In this paper we only present two tables that allow the comparison of the main results in the econometric contrast.

In table 7.20, we present the models that fulfill all the requirements in the econometric contrast of the APT, according to the criteria stablished in Chapter 3. As we can observe, in the econometric contrast PCA and FA were the techniques that produced the smallest number of models that fulfilled all the requirements in only three models. ICA and NNPCA were the techniques that generated the biggest number of them, with four. Interestingly, only the models expressed in returns produced completely accepted validation of the APT. In general, the models accepted in each technique were different; nevertheless, there are some models that were accepted in two and three techniques. Those models were: the one with eight factors that was accepted in both ICA and NNPCA, and with seven in PCA and NNPCA, in the database of weekly returns. Regarding the database of daily returns, those models were the one with three factors that was accepted in PCA, ICA and NNPCA; and with nine, in PCA and FA. This findings may indicate some relevance of these specifications; however a deeper analysis will be necessary on this matter.

Table 7.20. *Models that fulfill all the requirements in the econometric contrast of the APT.*

	PCA	FA	ICA	NNPCA
Database of weekly returns.				
Model with 5 betas		○		
Model with 6 betas			○	
Model with 7 betas	○			○
Model with 8 betas			○	○
Database of daily returns.				
Model with 3 betas	○		○	○
Model with 5 betas			○	
Model with 8 betas		○		
Model with 9 betas	○	○		

Notes:
PCA: Principal component Analysis.
FA: Factor Analysis.
ICA: Independent Component Analysis.
NNPCA: Neural Networks Principal Component Analysis.
○= Model which fulfill all the requirements of the econometric contrast.

Although only the models presented in Table 7.20 were the ones that fulfilled all the requirements of the econometric contrast of the APT, there were some other specifications of the model where we found partial evidence supporting the multifactor structure of the underlying systematic risks; i.e., models where betas different from β_0 were statistically significant but where β_0 was not equal to its theoretic value. In order to compare these results across techniques, in Tables 7.21 and 7.22, we show the value of the estimated lambdas (risk premiums) corresponding to the betas that were statistically significant in all the models. Models considering only two factors obtained the worst results; the rest of the specifications showed a relatively similar performance considering the number of statistically significant factors. The sensitivity to the underlying systematic risk factor that was statistically significant in most of the models was the β_3 followed by β_2, and then by β_5 and β_6, which may point to them as interesting factors to be analyzed more deeply.

Moreover, the general values of the risk premiums produced in all models and across the four techniques are really low, in all the cases the produced values were smaller than one; additionally, many of them presented a negative sign.

Finally, we made an additional statistical analysis of the estimated risk premiums presented in Tables 7.21 and 7.22, where we could detect the following interesting findings:

a) FA detects the 38% of the total statistical significant risk premiums, but its values are those with the greatest dispersion in the weekly databases. Conversely, for daily data FA only contributes with the 28% of the relevant risk premiums at the same level that ICA; which could be explained because the higher moments of daily data are more relevant than those related to weekly data, since in the latter there is less noise. In addition, there is a clearly higher dispersion in the FA values than in the other techniques as well.

b) Regarding the behavior of the relevant risk premiums in function of the dimension of the model to contrast (number of betas), we observe that for the weekly databases, the higher the dimension of the model, the greater the grade of outliers in the risk premiums values; which becomes the models with the highest number of betas (8 and 9) those with the greatest dispersion of their values. In opposition, the dispersion in the daily does not change depending on the dimension, and it is not so evident the increase of atypical risk premiums as the number of betas considered in the model grows. If we make a segmentation among techniques, FA always presents the major variability in the relevant risk premiums.

c) Concerning the ranking of the lambdas associated to the systematic risk factors, we can see that in both the weekly and daily frequencies, FA and ICA reveal a bigger number of relevant latent factors than PCA and NNPCA.

Table 7.21. *Betas statistically significant.*

		DATABASE OF WEEKLY RETURNS					DATABASE OF WEEKLY EXCESSES					DATABASE OF DAILY RETURNS					DATABASE OF DAILY EXCESSES				
		PCA	FA	ICA	NNPCA		PCA	FA	ICA	NNPCA		PCA	FA	ICA	NNPCA		PCA	FA	ICA	NNPCA	Total
Model with 2 betas	λ_1					λ_1					λ_1					λ_1					0
	λ_2					λ_2					λ_2	-0.00049	-0.04908			λ_2	-0.00052	-0.04878		0.00046	5
Model with 3 betas	λ_1					λ_1					λ_1		-0.03853			λ_1					1
	λ_2	0.00296			0.01034	λ_2	0.00298			-0.00195	λ_2	-0.00057	0.02121	-0.00302	0.00113	λ_2	-0.00061			0.00085	10
	λ_3	-0.00770	0.12722	0.01665	0.02173	λ_3	-0.00769	0.12758	0.01662	-0.02129	λ_3	-0.00137	0.01201		-0.00104	λ_3	-0.00141		0.00318	0.00162	**14**
Model with 4 betas	λ_1					λ_1					λ_1		0.00113			λ_1					1
	λ_2	0.00292		-0.01492	0.00193	λ_2	0.00294	-0.05436	-0.01774	-0.00237	λ_2		0.02701	0.00286	0.00090	λ_2				-0.00043	11
	λ_3	-0.00777		-0.01220	0.01002	λ_3	-0.00776	-0.00193	0.00891	-0.00481	λ_3	-0.00129	0.05664	-0.00262	-0.00184	λ_3	-0.00132		0.00245	-0.00140	**14**
	λ_4		0.13780			λ_4		0.02853			λ_4		0.06924			λ_4					3
Model with 5 betas	λ_1		-0.07078			λ_1		-0.07021			λ_1					λ_1					2
	λ_2	0.00300		-0.01771	-0.00892	λ_2	0.00303			-0.00505	λ_2					λ_2			-0.00289	-0.00080	7
	λ_3	-0.00762			0.02423	λ_3	-0.00761			-0.03206	λ_3	-0.00130		-0.00254	-0.00229	λ_3	-0.00133			-0.00174	**9**
	λ_4					λ_4					λ_4		0.10101			λ_4		0.10455			2
	λ_5		0.21077		0.00348	λ_5		0.20969			λ_5					λ_5					3
Model with 6 betas	λ_1		-0.09734			λ_1		-0.09697			λ_1					λ_1					3
	λ_2	0.00292		-0.01899	0.00378	λ_2	0.00295			-0.00404	λ_2					λ_2					6
	λ_3	-0.00775			-0.00997	λ_3	-0.00775			-0.00882	λ_3	-0.00130			0.00401	λ_3	-0.00133			0.00402	**8**
	λ_4					λ_4					λ_4					λ_4			0.00309		2
	λ_5		0.20782			λ_5		0.20709		0.00147	λ_5			0.00291		λ_5					5
	λ_6		-0.13978			λ_6			0.01717		λ_6		0.05257	-0.00162		λ_6					5

Notes:
PCA: Principal Component Analysis.
FA: Factor Analysis.
ICA: Independent Component Analysis.
NNPCA: Neural Networks Principal Component Analysis.
Numbers represent the risk premium of betas that were statistically significant at 5 % of error.
Total: Number of times that the betas was statistically significant.

Table 7.22. *Betas statistically significant. (Cont.)*

		DATABASE OF WEEKLY RETURNS					DATABASE OF WEEKLY EXCESSES					DATABASE OF DAILY RETURNS					DATABASE OF DAILY EXCESSES				
		PCA	FA	ICA	NNPCA		PCA	FA	ICA	NNPCA		PCA	FA	ICA	NNPCA		PCA	FA	ICA	NNPCA	Total
Model with 7 betas	λ_1					λ_1					λ_1		-0.05676			λ_1		-0.05971			2
	λ_2	0.00292		0.02036	0.00362	λ_2	0.00294			0.00218	λ_2					λ_2			0.00222		6
	λ_3	-0.00776			-0.01168	λ_3	-0.00776			-0.00650	λ_3	-0.00130			0.00211	λ_3	-0.00130			0.00146	**8**
	λ_4		-0.15198			λ_4		-0.15182			λ_4		-0.12533	0.00288		λ_4		-0.13575			5
	λ_5		-0.06563			λ_5		-0.06446		0.00168	λ_5		0.07379			λ_5				-0.00065	5
	λ_6		0.07245			λ_6	0.00322		0.01431		λ_6			0.00119		λ_6		0.06580	-0.00287		6
	λ_7					λ_7			-0.00500		λ_7		0.05998			λ_7		0.07526			3
Model with 8 betas	λ_1		-0.10643			λ_1		-0.10598			λ_1			0.00244		λ_1		-0.05614	-0.00197		5
	λ_2	0.00288	-0.05528	0.01043	0.00303	λ_2	0.00290	-0.05599		0.00439	λ_2			0.00329		λ_2					8
	λ_3	-0.00783	-0.06844	-0.01765	-0.02117	λ_3	-0.00782	-0.06776		-0.02272	λ_3	-0.00131			-0.00163	λ_3	-0.00134			-0.00284	**11**
	λ_4		0.12686			λ_4		0.12691			λ_4			0.00281		λ_4		0.06366	0.00096		5
	λ_5		-0.08073			λ_5		-0.08090			λ_5		0.05464			λ_5				-0.00069	4
	λ_6		0.09068			λ_6		0.08932			λ_6		-0.14354			λ_6		-0.14532	0.00283		5
	λ_7		0.07573			λ_7		0.07557			λ_7					λ_7		0.03899		0.00028	4
	λ_8		0.17361			λ_8		0.17512	-0.01046		λ_8			0.00267		λ_8					4
Model with 9 betas	λ_1		-0.14932			λ_1		-0.14882			λ_1					λ_1			0.00300		3
	λ_2	0.00290				λ_2	0.00292		-0.01257	0.00613	λ_2	-0.00050				λ_2	-0.00052		-0.00183	0.00281	8
	λ_3	-0.00780			0.02016	λ_3	-0.00780	0.04280		-0.02391	λ_3	-0.00136		-0.00353	-0.00361	λ_3	-0.00139		0.00250		**10**
	λ_4		0.05005			λ_4		0.04998			λ_4	-0.00051	-0.10860			λ_4	-0.00055	-0.10328			6
	λ_5			-0.01158		λ_5			0.01050		λ_5	0.00041		0.00288		λ_5	0.00041		-0.00076		6
	λ_6		0.16900			λ_6		0.16767			λ_6				0.00058	λ_6					3
	λ_7		0.09160			λ_7		0.09366	0.01247		λ_7					λ_7		0.09296			4
	λ_8		-0.11678			λ_8		-0.11721	-0.01057		λ_8					λ_8		-0.07264	0.00274		5
	λ_9		0.10175			λ_9		0.10273	0.00941	-0.00040	λ_9	-0.00094	0.10590	0.00100		λ_9	0.00097		0.00109		9

Notes:
PCA: Principal Component Analysis.
FA: Factor Analysis.
ICA: Independent Component Analysis.
NNPCA: Neural Networks Principal Component Analysis.
Numbers represent the risk premium of betas that were statistically significant at 5 % of error.
Total: Number of times that the betas was statistically significant.

7.3.4. Interpretation of the underlying risk factors.

In order to compare if the meanings of each factor, in the four databases may be similar across the four techniques, under the scope of the methodology of interpretation used in the previous chapters, in this section we will compare the interpretation given to the extracted factors across techniques.

In Figures 7.13 to 7.20 we present a schematic representation of the loading matrices that we used for the interpretation under an economic sector approach; i.e., the contribution of each stock in the formation of each extracted factor. These figures, displays in green lines the positive loadings, and in red lines the negative ones. The wider the line the greater the contribution of each stock in the related factor. Circles next to the stock name filled in yellow color point the stocks with the higher frequency of contributions to different factors in each database. In line with all the reported results, in this Chapter we only present the figures that correspond to the experiment where nine factors were extracted in the database of weekly returns[237].

We can observe that, as expected in theory, in PCA and FA we clearly can identify the first component or factor to the market one; however, in ICA and NNPCA we cannot do the same. Making a particular analysis by database we can state the following.

In the database of weekly returns, when we use PCA, the stocks with the highest loadings in the components to which they contribute were: PEÑOLES*, BIMBOA, CONTAL*, GEOB, ELEKTRA* and ALFAA. On the other hand, the previous stocks are those with the highest frequency in their contribution to the formation of factors in addition to: WALMEXV, COMERUBC, TELECOA1, TELEVICPO, TVAZTCPO, GFINBURO and

[237] The plots concerning the other three databases when we extracted nine factors are included in Figures 109 to 116 of the section referred to Chapter 7 in Appendix_2. The results corresponding to the rest of the experiments are not included in this document.

CIEB. Concerning FA, the highest loadings corresponded to PEÑOLES*, GMODELOC, GEOB, WALMEXV, COMERUBC, ELEKTRA*, TELECOA1, TVAZTCPO and ALFAA; while all the stocks except FEMSAUBD and ARA* contributed in two or more factors. Concerning ICA, the highest loadings corresponded to PEÑOLES*, BIMBOA, CONTAL*, GEOB, ELEKTRA*, TELEVICPO, GFINBURO and ALFAA; while the highest frequency was related to CONTAL*, TVAZTECPO, GFINBURO, ALFAA and CIEB. Finally, in NNPCA the highest loadings were related to PEÑOLES*, BIMBOA, CONTAL*, GEOB, ELEKTRA* and ALFAA; while the highest frequency matches with the previous stocks plus TVAZTECPO.

In the database of weekly excesses, when we use PCA, the results were the same that in the case of the database of weekly returns. Concerning FA, the results were almost the same as well with the exception of GMODELO in this case did not have a high loading. Concerning ICA, the results are similar in the most of the cases, however, there are some little differences, in this case the highest loadings correspond to PEÑOLES*, BIMBOA, CONTAL*, GEOB, COMERUBC, ELEKTRA*, GFINBURO, ALFAA and CIEB; while the highest frequency was related to PEÑOLES, GEO, ALFAA and CIEB. Finally, in NNPCA the results are almost the same, with the exception that in this case, GFINBURO substitutes ALFAA in the group of stocks with the highest loadings; while the highest frequency includes the same group of stocks, in addition to ARA*, WALMEXV, SORIANA B, TVAZTECPO, and ALFAA.

In the database of daily returns when we use PCA, the stocks with the highest loadings in the components to which they contribute were: PEÑOLES*, CONTAL*, GEOB, ELEKTRA*, ALFAA and CIEB, which differs lightly to those from the databases of weekly returns and excesses. On the other hand, the foregoing stocks are those with the highest frequency in their contribution to the formation of factors in addition to: BIMBOA, ARA*, WALMEXV, TELEVICPO, TVAZTCPO, GFNORTEO and GFINBURO, which also coincide with many of the stocks considered in the previous databases. Concerning FA, the highest loadings corresponded to PEÑOLES*, FEMSAUBD, ARA*, WALMEXV, TELMEXL, TVAZTCPO, GFNORTE and ALFAA; while all the stocks except KIMBERA, SORIANAB, TELECOA1, GINBURO, and GCARSOA1 contributed in two or more factors. Concerning ICA, the highest loadings corresponded to PEÑOLES*, BIMBOA, CONTAL*, GEOB, ELEKTRA*, TELEVICPO, GFINBURO and ALFAA; while the highest frequency was related to these same stocks in addition to ARA*, WALMEXV, TLEVICPO and CIEB. Finally, in NNPCA the highest loadings were related to PEÑOLES*, CONTAL*, GEOB, COMERUBC, TVAZTECPO and ALFAA; while the highest frequency matches with the previous stocks in addition to ELEKTRA* and GFINBURO.

In the database of daily excesses, when we use PCA, the results were the same that in the case of the database of daily return. Interestingly, in FA the results presents certain parallelism to those obtained in the database of daily returns; however, in many cases where there were two or more stocks belonging the same economic sector, in the database of daily returns the stock with the higher loading was one of them, and in the database of daily excesses was the another. Concerning ICA, the results are similar in the most of the cases, however, there are some little differences, in this case the highest loadings correspond to PEÑOLES*, CONTAL*, GEOB, COMERUBC, ELEKTRA*, TLEVICPO, ALFAA and CIEB; while the highest frequency was related to PEÑOLES, CONTAL, GEOB, COMERUBC, ELEKTRA*, TELMEXL, TLEVICPO, TVAZTCPO, CIEB.

Finally, in NNPCA the results are almost the same, with the exception that in this case COMERUBC and CIEB do not present high loadings, but ELEKTRA* does it; while the highest frequency includes the same group of stocks, but replacing COMERUBC and GFINBURO by GFNORTE and CIEB.

Figure 7.13. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Principal Component Analysis.
Database of weekly returns. Nine components.

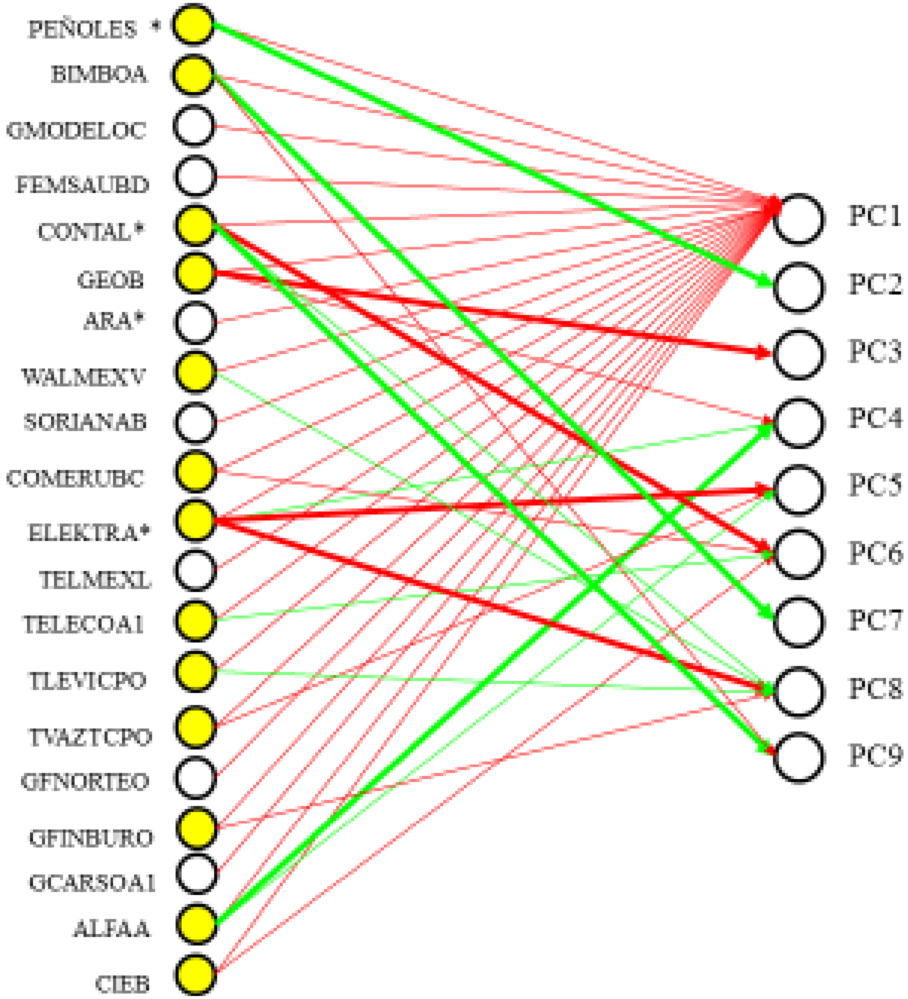


Figure 7.14. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Factor Analysis.
Database of weekly returns. Nine components.

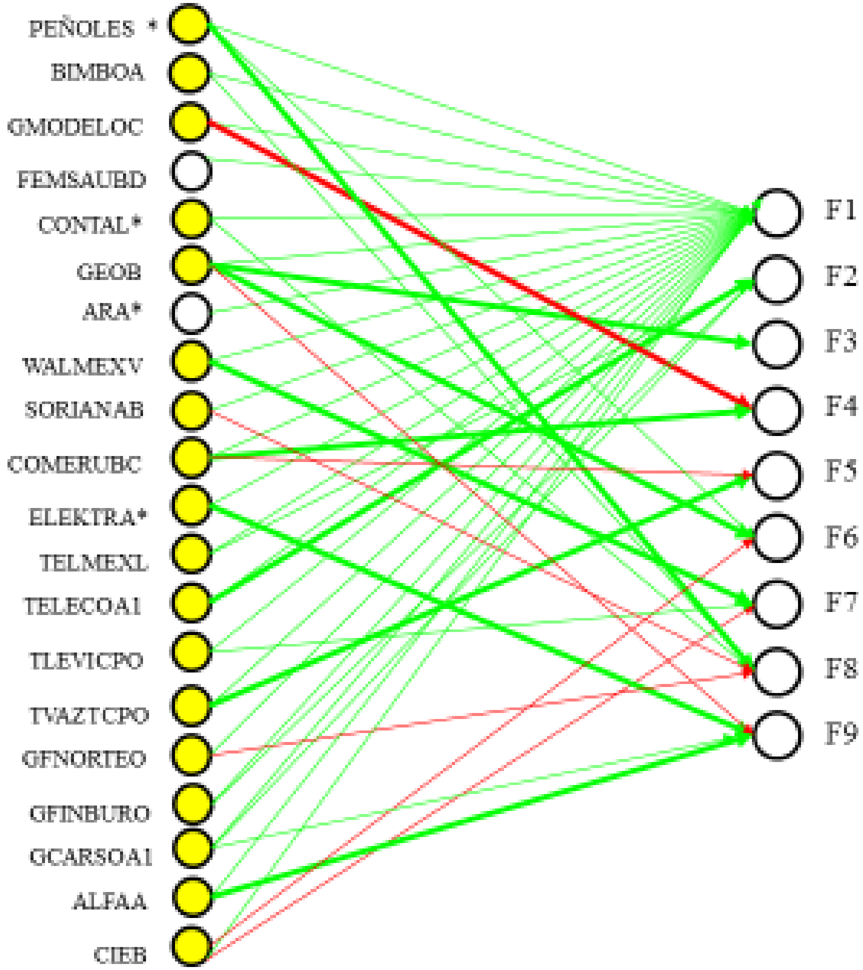


Figure 7.15. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Independent Component Analysis.
Database of weekly returns. Nine components.

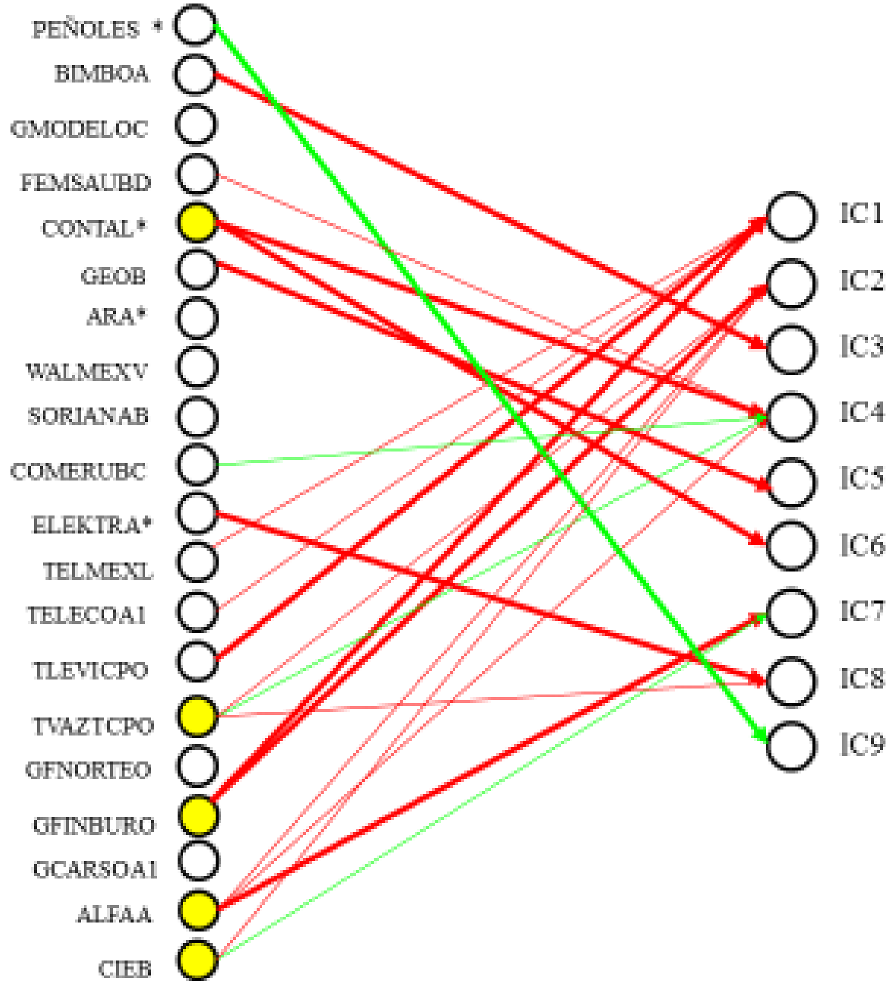


Figure 7.16. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Neural Networks Principal Component Analysis.
Database of weekly returns. Nine components.

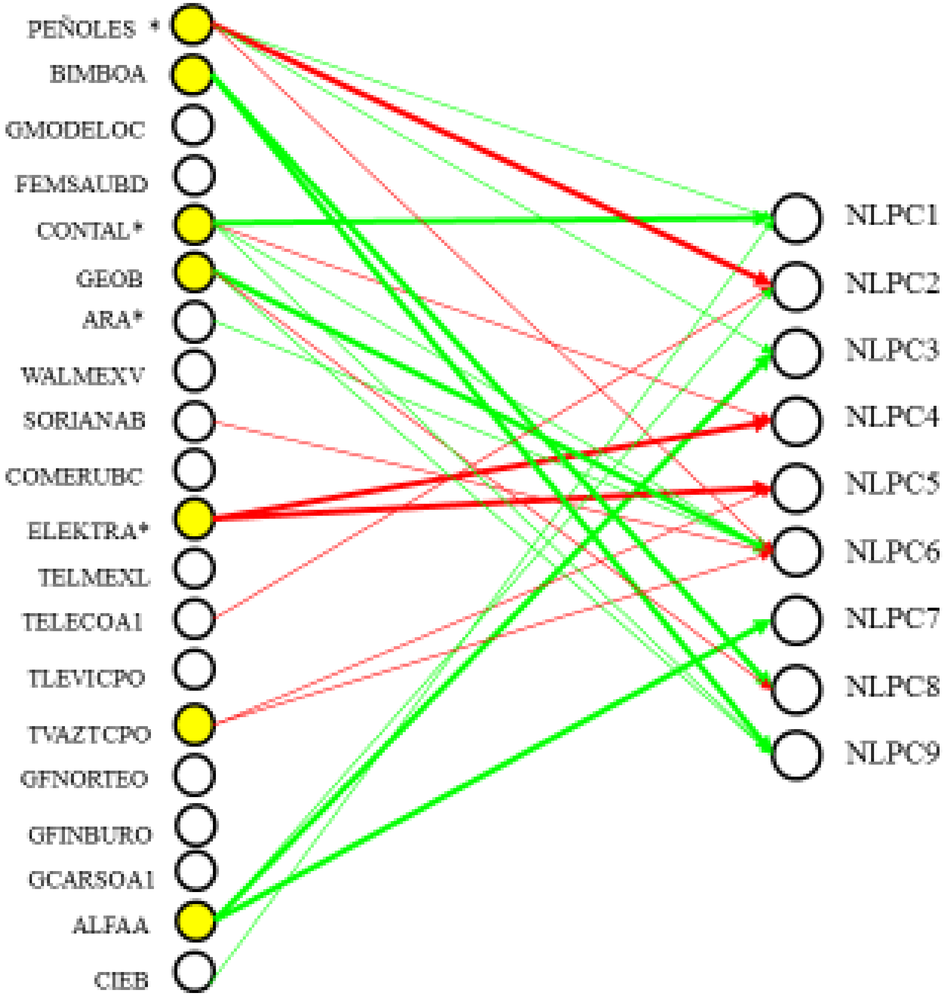


Figure 7.17. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Principal Component Analysis.
Database of daily returns. Nine components.

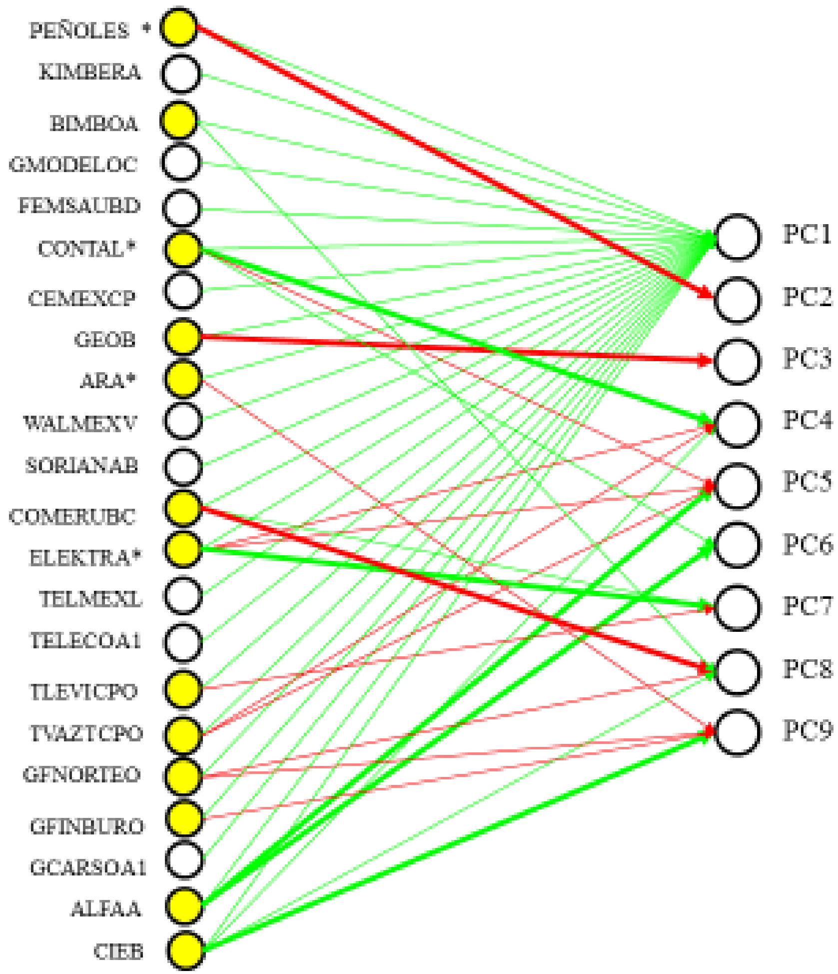


Figure 7.18. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Factor Analysis.
Database of daily returns. Nine components.

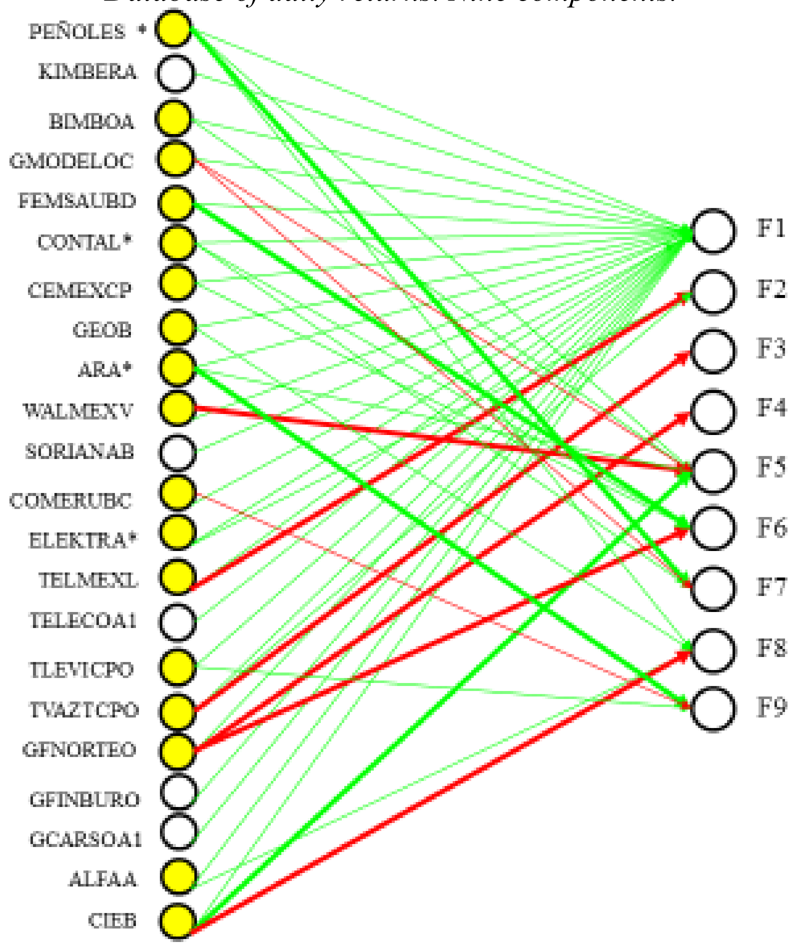


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Figure 7.19. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Independent Component Analysis.
Database of daily returns. Nine components.

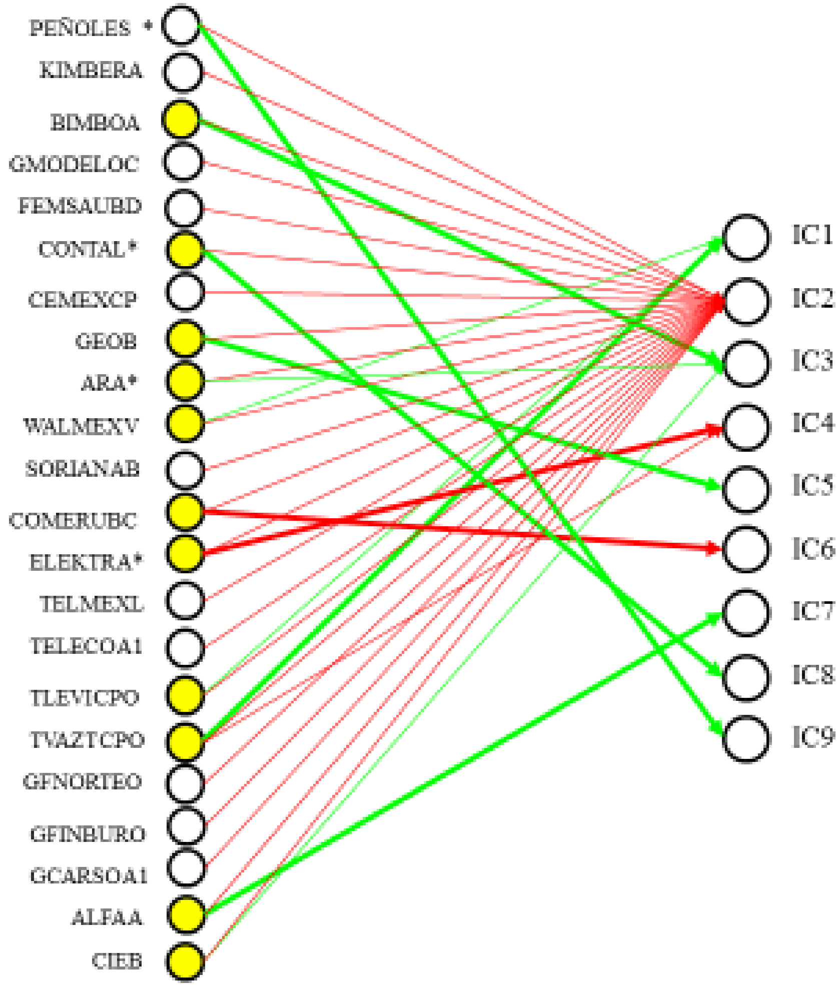
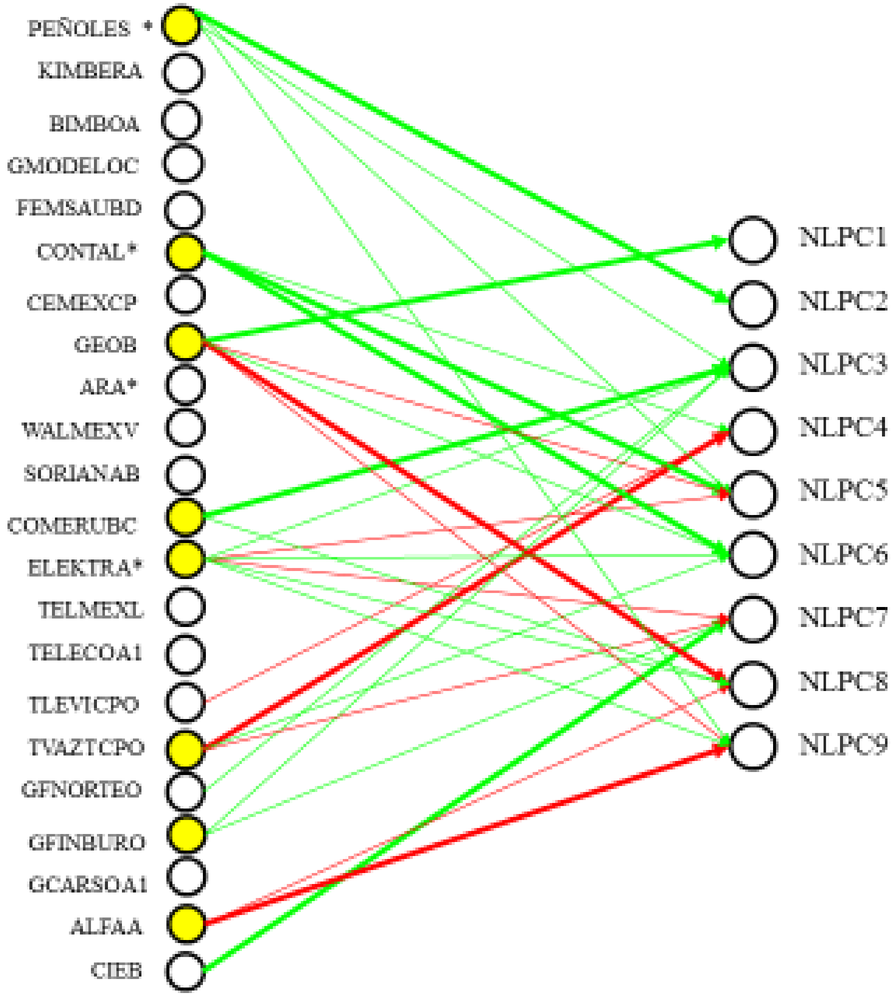


Figure 7.20. *Loadings matrices.*
Diagram for interpretation of extracted factors.
Neural Networks Principal Component Analysis.
Database of daily returns. Nine components.



Additionally, we present a set of comparative tables about the interpretation of each ranked factor extracted by PCA, FA, ICA and NNPCA for each database. Tables 7.23 to 7.26 present the results regarding the experiment when nine factors were extracted[238].

We can observe that in general the interpretation of the same factor across the four techniques is no clearly identified. In the best cases the same interpretation could be given in up to three techniques; as in the case of the market factor identified with factor number one for PCA, FA and ICA, in the database of daily excesses. In addition market factor was clearly identified in the four databases with the first factor when we used PCA and FA. Moreover in database of weekly returns, the factor number three in PCA and FA, and factor number five in PCA and NNPCA, were related to the construction and to the Salinas Group factors, respectively. In database of weekly excesses, we also find the same interpretation for the factor number three in PCA and FA. In database of daily returns, we can also identify the factor number two with the mining sector in PCA and NNPCA. Finally, in the database of daily excesses, we cannot clearly identify another additional factor with the same interpretation across techniques. On the other hand, there are many factors with the same meaning but in different order across the four techniques and the four databases. Moreover, there are many common sectors that contribute to many factors, such as: the food, beverage, holdings, consumer staples, specialty retail, telecommunication and communication media sectors factors, and evidently, the Slim and Salinas Groups factors.

Lastly, there are two findings that call our attention. First, the fact that using NNPCA neither the market factor nor the Slim Group factor are clearly identified with any of the extracted factors. Secondly, the constant contribution of PEÑOLES in the formation and interpretation of many of factors across the four techniques, databases and window of test of the experiments.

[238] The results corresponding to the rest of experiments are not included in this document for reasons of saving space.

Table 7.23. *Comparative interpretation of the underlying systematic risk factors. Database of weekly returns. Nine components estimated.*

PCA		FA		ICA		NNPCA	
PC1	Market factor	**F1**	Market factor	**IC1**	Slim Group plus Televisa factor	**NLPC1**	Beverages and Leisure / Mining sectors factor.
PC2	Mining sector factor (Peñoles factor)	**F2**	Slim Group factor	**IC2**	Financial service, Holdings, Leisure and Communication media sectors factor.	**NLPC2**	Mining and Telecommunications / Holdings sectors factor.
PC3	Construction sector factor	**F3**	Construction sector factor	**IC3**	Food products sector factor (Bimbo factor)	**NLPC3**	Holdings / Mining sectors factor.
PC4	Capital goods consume sector factor	**F4**	Ordinary consume sector factor	**IC4**	Consume sector plus communication media sectors factor.	**NLPC4**	Home Furnishing and Beverages sectors factor.
PC5	Salinas Group sector factor	**F5**	Communication / commercial sectors factor	**IC5**	Construction sector factor (Geo factor)	**NLPC5**	Salinas Group Factor.
PC6	Ordinary consume sector factor	**F6**	Infrastructure / Mining sectors factor	**IC6**	Beverage sector factor (Contal factor)	**NLPC6**	House building and Beverages / Consumer staples, Communication media and Mining sectors factors.
PC7	Food sector factor (Bimbo factor)	**F7**	Ordinary consume / entertainment sectors factor	**IC7**	Holdings / Leisure sectors factor	**NLPC7**	Holdings / Food products sectors factors.
PC8	Miscellaneous sectors factor	**F8**	Miscellaneous sectors factor	**IC8**	Salinas Group factor	**NLPC8**	Food products / Construction sectors factors.
PC9	Beverages and food sector factor	**F9**	Capital goods consume / holdings sectors factor	**IC9**	Mining sector factor (Peñoles factor)	**NLPC9**	Food products, Beverages and Construction sectors factors.

Table 7.24. *Comparative interpretation of the underlying systematic risk factors. Database of weekly excesses. Nine components estimated.*

PCA		FA		ICA		NNPCA	
PC1	Market factor	**F1**	Market factor	**IC1**	Construction sector factor (GEO factor)	**NLPC1**	Mining / Food products and beverages, Consumer staples and Communication media sectors factor.
PC2	Mining sector factor (Peñoles factor)	**F2**	Slim Group factor	**IC2**	Home furnishing, Holdings and Brewers / Construction sectors factor.	**NLPC2**	Mining / House building sectors factor.
PC3	Construction sector factor	**F3**	Construction sector factor	**IC3**	Consumer staples / Leisure sectors factor.	**NLPC3**	House building, Mining and Holdings sectors factor.
PC4	Capital goods consume sector factor	**F4**	Ordinary consume sector factor	**IC4**	Food products, Communication media and Telecommunications / Leisure sector factors.	**NLPC4**	Beverages, Leisure and Home furnishing sectors factor.
PC5	Salinas Group sector factor	**F5**	Communication / commercial sectors factor	**IC5**	Mining / Consumer staples sector factor	**NLPC5**	Consume sector factor
PC6	Ordinary consume sector factor	**F6**	Infrastructure / Mining sectors factor	**IC6**	Holdings sector factor (Alfa factor)	**NLPC6**	Construction sector factor (Geo Factor).
PC7	Food sector factor (Bimbo factor)	**F7**	Ordinary consume / entertainment sectors factor	**IC7**	Beverage / Financial services sector factor	**NLPC7**	Financial and House building /Consumer staples sectors factors.
PC8	Miscellaneous sectors factor	**F8**	Miscellaneous sectors factor	**IC8**	Mining sector factor (Peñoles factor)	**NLPC8**	Food and beverages sector factor.
PC9	Beverages and food sector factor	**F9**	Capital goods consume / holdings sectors factor	**IC9**	Financial services and Leisure / House building, Holdings and Communication media sectors factor	**NLPC9**	House building, communication media and consumer staples sector factor.

Table 7.25. *Comparative interpretation of the underlying systematic risk factors. Database of daily returns. Nine components estimated.*

PCA		FA		ICA		NNPCA	
PC1	Market factor	**F1**	Market factor	**IC1**	Communication media plus consumer staples sectors factor.	**NLPC1**	Construction sector factor (Geo factor)
PC2	Mining sector factor (Peñoles factor)	**F2**	Communication / commercial sector factor	**IC2**	Market factor	**NLPC2**	Mining sector factor (Peñoles factor)
PC3	Construction sector factor	**F3**	Radio and television sector factor (Azteca factor)	**IC3**	Food products, Leisure and House building sector factor	**NLPC3**	Consumer staples, Financial services, Home furnishing and Mining sectors factors.
PC4	Entertainment consume sector factor.	**F4**	Financial sector factor (GF Norte Factor)	**IC4**	Salinas Group factor	**NLPC4**	Communication media and Beverage sectors factor
PC5	Holdings / Beverage / Salinas group factor.	**F5**	Miscellaneous sectors factor	**IC5**	Construction sector factor (Geo factor)	**NLPC5**	Beverages and mining / Home furnishing and house building sectors factor.
PC6	Holdings / Food and beverage sector factor	**F6**	Beverage / construction / financial sectors factor	**IC6**	Ordinary consume sector factor (Comercial Mexicana factor)	**NLPC6**	Beverages, Communication media, House building and Home furnishing sectors factor.
PC7	Ordinary consume sector factor	**F7**	Mining / beverage sectors factor	**IC7**	Holdings sector factor (Alfa factor)	**NLPC7**	Leisure and Financial services sectors / Salinas Group factor.
PC8	Miscellaneous sectors factor	**F8**	Holdings / Mining / construction sectors factor	**IC8**	Beverage sector factor (Contal factor)	**NLPC8**	House building and Holdings / Home furnishing and Consumers staples sectors factor.
PC9	Infrastructure / Financial sector factor	**F9**	Construction / communication / commercial sectors factor	**IC9**	Mining sector factor (Peñoles factor)	**NLPC9**	Holdings and House building / Mining and Home furnishing sectors factors.

Table 7.26. *Comparative interpretation of the underlying systematic risk factors. Database of daily excesses. Nine components estimated.*

PCA		FA		ICA		NNPCA	
PC1	Market factor	**F1**	Market factor	**IC1**	Market factor	**NLPC1**	Salinas Group / Mining sector factor.
PC2	Mining sector factor (Peñoles factor)	**F2**	Communication / commercial sectors factor	**IC2**	Communication media and telecommunication sector factor.	**NLPC2**	Beverages / Home furnishing and Financial services sectors factor.
PC3	Construction sector factor	**F3**	Radio and television sector factor (Azteca factor)	**IC3**	Leisure sector factor	**NLPC3**	Salinas Group, Holdings and Mining / Leisure sectors factor.
PC4	Entertainment consume sector factor.	**F4**	Financial sector factor (GF Norte Factor)	**IC4**	Salinas Group factor	**NLPC4**	Holdings / Leisure sectors factors.
PC5	Holdings / Beverage / Salinas group factor.	**F5**	Miscellaneous sectors factor	**IC5**	Holdings sector factor (Alfa factor)	**NLPC5**	Beverages and House building / Mining sectors factors.
PC6	Holdings / Food and beverage sector factor	**F6**	Beverage / construction / financial sectors factor	**IC6**	Ordinary consume sector factor (Comercial Mexicana factor)	**NLPC6**	House building and Holdings / Leisure sectors factor.
PC7	Ordinary consume sector factor	**F7**	Mining sector factor (Peñoles factor).	**IC7**	Beverage sector factor (Contal factor)	**NLPC7**	Communication media / Financial services sectors factor.
PC8	Miscellaneous sectors factor	**F8**	Financial / brewers / cellulose sectors factor	**IC8**	Construction sector factor (Geo factor)	**NLPC8**	Mining sector factor (Peñoles factor)
PC9	Infrastructure / Financial sector factor	**F9**	Construction sector factor	**IC9**	Mining sector factor (Peñoles factor)	**NLPC9**	Mining and Beverages sectors factor.

7.4. Conclusions.

From the theoretic standpoint, we could said that NNPCA would be the technique, which produce the underlying factors with the more desirable statistical attributes in the context of a statistical approach to the APT[239]; they are nonlinearly uncorrelated, warranting not only linearly uncorrelated systematic risk factors for the Arbitrage Pricing Theory (APT) model but also nonlinearly uncorrelated ones.

Our findings in the empirical study do not demonstrate a clear hegemony of one technique over the others, since all the techniques were capable to reproduce the observed returns. Nevertheless, based on its theoretical statistical attribute and the evidence uncovered, we dare to point out the NNPCA as the best technique to reduce dimensionality, in other words, it was the technique with the best performance in the reconstruction of the observed returns when we considered a low number of dimensions. On the other hand, to the light of our results we would point to PCA as the best technique to reconstruct the observed returns, when we consider the average results of the measures of reconstruction considering a high number of dimensions and also to reproduce the returns of the most volatile stocks, in almost all the cases. Moreover, FA was the best technique regarding the number of accurate reconstructed individual stocks, according the statistical measures used in this study. Lastly, ICA was the technique with the worst performance in the reconstruction[240].

According to the attributes of the components or factors produced by each technique, we could expect that the results in the reconstruction should be better as we move from basic techniques such as PCA and FA to advanced methods like ICA and NNPCA; however, in general, the ICA reconstruction was worse than the PCA in average terms of the first four measures of reconstruction accuracy in almost all cases. Furthermore, we must not forget the

[239] In the APT we look for systematic risk factors as different as possible in order to catch the effect of different sources of risk that explain the returns on equities. The more uncorrelated and independent the factors, the better their theoretical attributes in this context.

[240] It is important to point that the results in the reconstruction obtained by ICA were suitable; simply the results of the others techniques were better. In addition, we remark that from a theoretical standpoint the factors extracted via ICA are statistically independent, which imply also absent of linear correlation, and would suppose a better behavior among them, specially considering the non-Gaussian nature of our data.

clarification stated in the section on matrix parallelism about the direct comparison of FA with the other types of analysis used in this study. A future step in research will be to compare FA to its equivalent versions for the independent and non-linear models.

Accordingly, some natural expansions of this part of our research would be the search for some other measures to evaluate the accuracy of the reproduction – both in univariate and in multivariate terms – and some other methodologies to compare the results of the four techniques, a deeper study regarding the univariate and multivariate statistics and the morphology of the components and factors extracted, and the interpretation of the underlying factors of systematic risk, namely, the risk attribution process.

Regarding the comparative analysis of the latent extracted factors and betas by way of the four techniques presented, under a statistical and graphical focus, the empirical results obtained will lead us to conclude that in general, PCA, FA and ICA produce similar systematic risk factors and sensitivities to them (betas) from an statistical and morphological standpoint, but NNPCA present a very different performance.

Concerning the comparison of the results of the econometric contrast, the results may suggest that NNPCA could produce a better performance in the econometric contrast, since the first stage of it, i.e., the simultaneously estimation of the betas by means of the SUR, theoretically should surpass the WLS estimation used in the other three techniques, because of the reliability of the betas estimation. Nevertheless, the results of the average cross section contrast of the APT show that NNPCA and ICA were the techniques that produced the smallest number of models accepted. In this arena, PCA and FA were the techniques with the worst performance.

As we stated before, the methodology used in the econometric contrast represents only a first approach to this issue, and our results should be seen under this light. Many other methodologies for contrasting the APT and multifactor models should be tested in future researches.

With respect to the comparative of the interpretation across the four techniques we can conclude that in addition to the market factor that was clearly identified as the first factor in PCA and FA, there is not a constant interpretation of the same factor across the four techniques. We remark that the interpretation methodology here used represents a first approach to give some meaning to the extracted factors but it is not definitive. In the same sense, the findings concerning the sensitivities that placed β_3, β_2, β_5, and β_6 as those that were the most common in the majority of the models across the four techniques, should be investigated more deeply in the risk attribution stage, using other methodologies of interpretation according to the statistical approach of the underlying systematic risk factor analysis.

Finally, as reported in other comparative studies regarding some of the techniques used in this study and to the light of the evidence found, we could say that depending on the characteristics of the data and the purpose of the research, one specific kind of analysis is more suitable than the others. In our particular case, we can warrant that the extraction of risk factors is very sensitive to the technique used for this purpose, which could condition the results of the APT.

Chapter 8

Conclusions.

This dissertation have focused on the estimation of the underlying multifactor model driving the returns on equities of the Mexican Stock Exchange by means of different dimension reduction and feature extraction techniques in an Arbitrage Pricing Theory framework under a statistical approach. Under this conceptualization, both the latent systematic risk factors and the sensitivities to those factors (betas) can be computed from the observed returns on equities by way of statistical and computational techniques. There are two differentiated stages under this statistical scope regarding the systematic risk factors, namely, the risk extraction and the risk attribution processes; our empirical studies have focused mainly on the former.

In Chapter 4 we estimated the underlying structure of systematic risk by using Principal Component Analysis and Factor Analysis; it included the testing of our models in two versions: returns and returns in excess of the riskless interest rate for weekly and daily databases, and a two-stage methodology for the econometric contrast. First, we extracted the underlying systematic risk factors by means of both the standard linear version of the Principal Component Analysis and the maximum likelihood Factor Analysis estimation, and we were able to reconstruct the observed returns with our generative multifactor model estimated in all cases. Then, for the purpose of estimating the betas simultaneously for all the systems of equations, we simultaneously estimated the sensitivities to the systematic risk factors (betas) by Weighted Least Squares (WLS). Finally, we tested the pricing model by using an average cross-section methodology via Ordinary Least Squares (OLS), corrected by a heteroscedasticity and autocorrelation consistent (HAC) estimation of covariance. Our results showed that the APT is very sensitive to the extraction technique utilized and to the number of components or factors retained, which suggests that APT explains partially the variations in average returns on the selected stocks of the Mexican Market for the periods considered. Nevertheless, we found certain evidence supporting the APT according to the methodology presented.

In Chapter 5 we tried to uncover a more realistic[241] latent systematic risk factor structure by means of the Independent Component Analysis, in order to find out whether the statistical approach of the Arbitrage Pricing Theory performs better on the Mexican Stock Exchange, using the systematic risk factors and betas extracted via this technique, which is more appropriate for non-Gaussian financial time series. In order to ensure the correct performance of ICA and to demonstrate that the extraction of betas by classic multivariate may not be very reliable, we first tested the univariate and multivariate non-Gaussianity of the data by means of the Jarque-Bera test for univariate normality and the Mardia and Henze-Zirkler tests for multivariate normality. In addition, to homogenize the criteria of ranking in the four techniques, we sorted out the independent component extracted by using the criteria proposed by Garcia-Ferrer *et al.* (2008). Moreover, we tested the statistical independence of the estimated factors, by way of the HSIC test (Groover *et al.*, 2008) which warranted the statistically independence and consequently the linear uncorrelation of our risk factors. The estimated generative multifactor model of returns reproduced the observed returns in all cases. The evidence we found in the econometric contrast showed mixed results for the acceptance of the APT; on one hand we found several model with statistically significant factors, but on the other hand, only a few models fulfilled all the requirements to accept the validity of the APT.

In Chapter 6 we used the Nonlinear Principal Component Analysis (NLPCA) as an extension of the standard Principal Component Analysis (PCA) that overcomes the limitation of the PCA's assumption about the linearity of the model. NLPCA belongs to the family of nonlinear versions of dimension reduction or underlying features extraction techniques, including nonlinear factor analysis and nonlinear independent component analysis, where the principal components obtained are non-linear. NLPCA can be achieved via an artificial neural network specification where the PCA classic model is generalized to a nonlinear mode, namely, Neural Networks Principal Component Analysis (NNPCA). We used an auto-associative multilayer perceptron neural network or autoencoder, where the 'bottleneck' layer represents the principal nonlinear components, or in our context, the scores of the underlying factors of systematic risk. This neural network represents an alternative technique capable of

[241] More realistic, in the sense that the generative multifactor model of returns estimated was computed by means of a technique which deals with the real non-gaussian nature of the data.

performing a nonlinear transformation of the observed variables into the principal nonlinear components, and to execute a nonlinear mapping that reproduces the original variables. The evidence found showed that the generative multifactor model of returns estimated via NLPCA was capable to reproduce the observed returns in all cases; nevertheless, the results in an econometric contrast led us to a partial acceptance of the APT in the samples and periods studied.

In the four techniques we proposed a first attempt to give an interpretation to the risk factors extracted, under an economic sector approach, by means of the loading matrices that contribute in the formation of the extracted factors in each technique. In general the interpretation of the extracted factors varied across techniques, although some factors share the same interpretation in particular cases. These common interpretation pointed to the market factor, the Slim and Salinas Groups factors, the mining, construction, consumer staples, specialty retail, leisure, telecommunication and communication media sectors factors as the most persistent and clearly identified systematic factors across the four techniques. In addition, there were many factors that did not produce a completely clear interpretation, since they mixed or contrasted the effect of diverse economic sectors.

In addition, an important conclusion related to this issue is that the market factor, identified as a similar loadings values for all the stocks, was clearly detected in PCA and FA which was related to the first factor that represents the one with more importance from the explained risk standpoint in both cases. Conversely, for the alternative techniques this fact does not happen; we could give that interpretation only in the case when two factors are extracted via ICA in the daily databases.

Finally, in Chapter 7 we made a first attempt to compare the four techniques. From a theoretical standpoint, the estimated factors should be superior as we advance from classical techniques, i.e., Principal Component Analysis and Factor Analysis, to more sophisticated techniques, i.e., Independent Component Analysis and Neural Networks Principal Component Analysis[242]; however, their own internal assumptions, procedures and algorithms, make the

[242] Given that we consider that the presence of relevant higher-order moments and non-linear components, respectively, would suppose that ICA and NNPCA would have had a better performance.

direct comparison among either the extracted factors or the factor loadings, produced by each one of them, problematic. This fact led us to compare the former techniques in such a way that they could be measured homogeneously. In order to present an objective and homogeneous comparative study concerning techniques, we carried on our research according to two different perspectives. First, we evaluated them from a theoretical and matrix scope, making a parallelism among their particular mixing and demixing processes, as well as the attributes of the systematic risk factors extracted by each method. Secondly, we carried on an empirical study in order to measure the level of accuracy in the reconstruction of the original variables, reproduced by the multifactor generative model of returns, when we employed the underlying systematic risk factors estimated by means of each extraction technique. Our results showed that the reproduction capacity of the four techniques is very good[243]; however, PCA is the one that presents the lowest level of error in reconstruction in almost all the cases and experiments, followed by NNPCA, FA and ICA. Third, we continued the empirical comparative study across the four techniques on one hand, by means of the statistical and graphic analyses of both the underlying risk factors and their corresponding sensitivities (betas); and, on the other hand, by means of the comparative analysis of the results obtained in the econometric contrast of the APT, when we utilized the systematic risk factors and betas computed in each technique. The results pointed to NNPCA and ICA as the techniques with the higher number of models completely accepted and PCA and FA, as those with the lower number[244]. In addition, we could detect that the betas that were statistically significant more times in the different expressions and frequencies of the models contrasted across the four techniques were: the factor number three followed by factor number two, and then by factor number five and factor number six, which may point to them as interesting factors to be analyzed more deeply. Finally, we also compared the interpretation given to the factors extracted by the four techniques by way of the analysis of the stocks that contributed in the formation of each factor in each database across the four techniques and the comparison of the

[243] We are aware of the good results showed in the statistics could be suitable due to we are working on the own databases studied; nevertheless, as we have stated along this dissertation, we are only studying the explanatory capacity of the four techniques; i.e., the forecasting properties of them are out scope of this research and it will be a future line of research derived from this work.

[244] It is important to remark that the four techniques produced very similar results both in the reproduction of the observed returns and in the econometric contrast. Actually, regarding the reproduction of the observed variables, the four techniques achieved a very good reconstruction in terms of the statistical measures used, i.e., any of them reproduced the observed variables in a very suitable way. Concerning the econometric contrast, the same situation occurred, the difference in the number of completely accepted models across the techniques was minimum.

meaning proposed to each factor extracted. The results pointed to the following stocks as those with the highest loadings in the formation of risk factors: PEÑOLES*, BIMBOA, CONTAL*, GEOB, ELEKTRA*, ALFAA, TELEVICPO, GFINBURO, COMERUBC, CIEB, FEMSAUBD, ARA*, WALMEXV, TELMEXL, TVAZTCPO and GFNORTE. Regarding the interpretation given to the extracted factors, in general, the interpretation of the same factor across the four techniques is no clearly identified. Nevertheless, to the light of the found evidence, there are some factors that share the same interpretation in two or more techniques, therefore, we dare to point in some cases to factor number one as the market factor, factor number three as the construction sector factor, factor number five as the Salinas Group factor, and factor number two as the mining sector factor[245]. In that sense we could identify the former factors as interesting sectors to consider for the risk management in the construction of portfolios in context of the Mexican Stock Exchange.

Summarizing the results of the comparative study, we can conclude that the four techniques were capable to reproduce the observed returns; nevertheless, the hegemony of one of them over the others is not clear and is very sensitive to the number of components or factors retained, the expression of the model, and the specific asset analyzed; which may condition the empirical contrast of the APT later. Consequently, we might state that the selection of one or another technique will depend mainly on the number of dimensions to retain, the specific stock object of study, and the purpose of the research. That is, to the light of the evidence found we could say that if our objective is to reduce the dimensionality until the smallest number of factors (2-4), NNPCA will produce the best reconstructions in average; nevertheless, if we can handle a bigger number of factors (5-9), PCA will generate the best reproduction of the observed variables in average as well. In addition, PCA would be the best choice to reproduce volatile stocks individually. On the other hand, if the objective is to reproduce individual stocks or to find the maximum number of priced factors, FA would be the technique that produce the higher figures. Furthermore, if our objective is to warrant some statistical attributes of the extracted factors such as: statistical independence or nonlinear uncorrelation, ICA and NNPCA would be the suitable techniques, respectively. Additionally, if our interest is to find the best results in the econometric contrast of the APT, these two last

[245] We remark that the market factor was only clearly identified in PCA, FA and in the case of daily databases in ICA. In NNPCA was not possible to identify clearly this factor using the loading matrix considered for the interpretation of factors in this study.

techniques would extract the factors that generates more totally accepted models in the validation of the APT as an asset pricing model as well[246].

According to the above stated and the empirical evidence obtained in this study we can make the following statements regarding the hypothesis posed in the introduction of this study.

Regarding the **hypothesis number one**: The generative multifactor model of returns is sensitive to the typology of the extraction technique used to extract the latent systematic risk factors. We can conclude that, to the light of the evidence found, this hypothesis is fulfilled since each technique produced different generative multifactor models of returns as we showed along this dissertation, but specially as demonstrated in Chapter 7 via the comparative study of the four techniques. Nevertheless, under the scope of the quality of reconstruction of the observed returns by way of our generative models estimated, the four techniques produced a very suitable generative multifactor model of returns, in the four databases studied across all the window of test used in this study. This evidence was proved via the graphical analysis of the observed and reconstructed variables and the construction of a set of statistical measures used to test the quality of the reconstruction. Evidently, the greater the number of extracted factors the higher the level of the reconstruction; however, if we increase the dimension the improvement in the reconstruction does not improve significantly. Therefore, derived from the results obtained, we dare to point that PCA produces better results than the other techniques for a higher number of components extracted, while NNPCA does it when a smaller number of factors is estimated. In that sense, the practical application of the techniques used in this study, that allow to create non-observable systematic risk factors in the portfolio risk management industry, is to facilitate the control of the risk portfolio with a number of factors smaller than the number of observed assets.

With respect to the **hypothesis number two**: The average cross-section econometric contrast methodology of the Arbitrage Pricing Theory is conditioned to the extraction

[246] We remark that these results correspond to the experiment when we use a topology of the neural network in NNPCA of the type [20-9-9-9-20] for the weekly databases, as an example. In our previous experiments not reported in this dissertation, when we used a topology of the type [20-20-9-20-20] in the same example, NNPCA surpassed to all the techniques in basically all the aspects.

technique chosen, the frequency of the data and the expression of the model (returns or excesses). The obtained results showed that this hypothesis is fulfilled as well. NNPCA and ICA produced the higher number of completely accepted models, however, the difference with the number of completely accepted models in FA and PCA was negligible. Regarding the frequency of the data, the daily databases produced more statistically significant factors than weekly databases across the four techniques and the entire test window about the number of extracted factors (137 versus 111). Finally, concerning the expression of the models, only those expressed in returns produced models that were completely accepted. Therefore, the obtained results showed partial evidence in favor of the APT as an asset pricing model using the underlying systematic risk factor extracted via the four techniques. In each technique we only obtained from three to four models, from a total number of 32 contrasted models, that were completely accepted according to all the conditions established in Chapter 3 to validate the APT[247]. However, all the techniques generated statistical significant risk factors that ranged from one to eight across the different specifications of the models, which produced 113 models with priced factors from a total number of 128 contrasted models in the four techniques, which gives some evidence in favor of the APT. In general, in all the models that were not completely accepted but that produced statistical significant risk factors across the techniques, the only condition not fulfilled was the equality of the independent term to the theoretical value required in the APT, however they fulfilled the rest of the conditions, which provide certain evidence in favor of the APT as well. As we have stated along this dissertation, the APT consider on one hand a generative multifactor of returns, and an arbitrage principle. This study have focused only in the first part of this model, i.e. in trying to obtain the best generative multifactor model of returns under a statistical scope to the systematic risk factors used in a multifactor asset pricing model such as the APT. Nonetheless, our results in the econometric contrast of the APT using the underlying factors extracted by the techniques proposed could be affected also by the not fulfilment of the arbitrage absence principle considered by the APT, which was out of the scope of this dissertation. Further research will be needed about this issue as well as the testing of other methodologies of contrast of the APT.

[247] Our results are in line with those reported in other studies where the APT has been tested in different markets which have found both evidence in favor or against the APT as an asset pricing model. See references cited in the introduction of Chapter 2.

Concerning the **hypothesis number three**: It exists stability in the interpretation of the latent risk factors according to the methodology used. We can conclude that under the methodology used in this study to give some meaning to the factors extracted in each technique there was not a clear and homogenous interpretation across the techniques. However, to the light of the results of this research PCA and FA, perhaps would be the techniques that produced clearer interpretation of the factors associated, first to the market factor, and secondly to some economic sectors. In addition there were some factors that we dare to point as important in the Mexican stock market, given their persistent across the four techniques, the four databases and the entire test of window, namely: the market factor, the Slim Group factor, the Salinas Group factor, and the mining, construction, specialty retail, communication media, telecommunication, leisure and holdings sectors factors.

On the other hand, another interesting conclusion to the light of the evidence found was that the nonlinear technique namely, NNPCA had a better performance in the reconstruction of the observed returns when we retained a smaller number of factors; i.e., this technique produced better reconstruction with a smaller number of factors than the rest of the techniques used in this study. Yet, with a bigger number of extracted factors PCA was the technique that produced the best reconstructions. To the light of these results we could state that under the methodology applied in this dissertation and the stocks and periods included in this study, it would appears that in our case, the no iterative technique which does not assume any model for its estimation and that in fact only represents a factorization method was superior to those iterative techniques.

Revisiting the contributions posed in the introduction of this dissertation, we can summarize them as follows:

1. This dissertation contributed, from a statistical standpoint and in the context of an emerging market, with the analysis of different extraction techniques of non-observable systematic risk factors, in order to explain the returns on equities generated in the Mexican stock market.

2. In that sense, we have carried on classic extraction techniques such as: Principal Component Analysis and Factor Analysis, and alternative techniques such as: Independent Component Analysis and Neural Networks Principal Component Analysis.

3. Consequently, we have tested the reproduction power of these four different techniques that allowed the reduction of the dimensionality of the problem to analyze; and

4. We have tested the risk premiums associated to those latent systematic risk factors, in the context of the Arbitrage Pricing Theory, following one of the possibilities of its econometric contrast, by way of a two-stage returns-average cross-section methodology.

According to the above stated and to the light of the evidence found we can affirm that the purpose of this dissertation stated in the introduction, namely: to carry on different extraction techniques of latent risk factors in order to test the explanatory power of the generative multifactor model of returns on equities in the context of the Mexican stock market, and to test the presence of relevant risk premiums associated with those underlying risk factors in the context of a statistical approach of the asset pricing model APT, was fulfilled. Nevertheless, derived from the findings of this study and the limitations and scope of this dissertation, we can propose the following:

Future lines of research.

1. Regarding the expression of the returns used in this study, one possible extension could be to include the dividends and application rights to calculate the return on equities in addition to price variation, if the information is available to us.

2. In general, forthcoming researches could be centered on the risk attribution process of the statistical approach as well as on the test of the arbitrage principle of the APT.

3. Regarding the risk attribution other methods could be carried on such as: the correlation or association of the underlying risk factors with macroeconomic or fundamental factors or the application of alternative techniques for this purpose for example genetic algorithms. In addition, we remark that the interpretation of the meaning of the factors proposed represented only a first basic approach, since the main objective of this research was the risk extraction and not the risk attribution under the statistical approach to the underlying multifactor risk analysis.

4. Regarding to the econometric contrast of the APT using the underlying risk factors extracted by way of PCA, FA, ICA and NNPCA, we remark that in this study we have focused only on the returns generating process of the APT; as Reinganum (1981) stresses, many of the problems in the APT empirical contrast may be attributed also to violations of the absence arbitrage principle and not only to the misspecification of the returns generating model. Nonetheless, we leave all the aspects concerning the arbitrage conditions, as well as a deeper analysis of the different APT econometric contrast methodologies, to further investigations. Consequently, for now, we could attribute the unsatisfactory results of the econometric contrast to two possible reasons: a) The methodology used for the contrast might not be the most suitable for a statistical approach to the APT, and perhaps it would be necessary to use time series moving regressions to estimate the sensitivities to the risk factors or betas (Nieto, 2001; Roll & Ross, 1980), or mimicking portfolios as proxies of the underlying factors (Marin & Rubio, 2001; Zivot & Wang, 2003). b) The origin of the problem might not be in the first assumption of the APT, i.e., the generative multifactor model of returns,

but in the second, that is, the arbitrage absence principle (Khan & Sun, 2003); aspect that we have not investigated yet. c) The relation among the risk factors and the returns on equities might be non-linear. Further research would be needed concerning these two possible causes of the results in the econometric contrast.

5. In the same sense, regarding the econometric contrast, other methodologies and variations of the one used in this study can be tested in order to improve the estimation. For example to use a GARCH modelling for the simultaneously estimation of the betas, or to use mimicking portfolios in the econometric contrast of the APT, or in general to carry on other econometric contrast methodologies like those used in other studies.

6. Moreover, the obtained results may be explained by a non-linear specification of the APT, which was out of the scope of this study but represents a natural future line of research as a continuation of the present work as well.

7. Derived from the exhaustive amount of information obtained in all the experiments carried as a result to have applied four different techniques of extraction (PCA, FA, ICA, NNPCA), to two different periodicities of the databases (weekly and excesses), to two different expression of the models (returns and excesses), and a test window ranging from two to nine factors, we consider that a deeper analysis of the dynamic sensitivity of the results obtained could be another research line for future studies.

8. Extension of the techniques already used such as in FA, the Independent Factor Analysis, where the hidden factors are independent and non-Gaussian instead of uncorrelated and Gaussian.

9. Or in the case of ICA: the noisy ICA, the non-linear ICA, etc. That is, regarding ICA, the expression used in this study represents the most basic definition of the ICA model; some generalizations and modifications in them, such as the addition of a noise term, the case when the number of observed mixtures and the number of sources are different, or the mixing process is not linear, could be explored in future researches.

10. Also related to ICA, a deeper investigation on the estimated ICs derived from the results of the *Iq* as a criterion to sort the ICs estimated by the ICASSO methodology would be interesting, or a ranking according other criteria such as, the similarity of the estimations that could be used as another criterion to sort the independent components, and might represent possible lines of interpretation of them.

11. Moreover, although theoretically the ICASSO methodology used produces better results for said model, other estimation algorithms should be tested in further research.

12. Regarding NNPCA, another interesting line of research would be to carry on another methodology to get an equivalent to the loading matrix of the other techniques, in order to test if by using that loading matrix we could avoid the trade-off produced with the methodology used in this study, between on one hand, the accuracy in the reproduction and the results of the econometric contrast, and on the other hand, the capability to give meaning to those extracted factors. A possible methodology could be the one propose by Scholz, *et al.* (2007) where it is necessary to compute a loading in each point of the curve according to its direction.

13. In addition, some natural expansions of this work would be the search for some other measures to evaluate the accuracy of the reproduction – both in univariate and in multivariate terms – and some other methodologies to compare the results of the four techniques, a deeper study regarding the univariate and multivariate statistics and the morphology of the components and factors extracted, and the interpretation of the underlying factors of systematic risk, namely, the risk attribution process.

14. Another natural extension according to the predictive nature of the four techniques, would be the testing of the forecasting power of the estimated models by way of the four techniques in subsequent periods not included in this study, the comparison of the results in the crisis and post-crisis periods, and in other six-year Presidential terms of office in Mexico.

15. Derived of the previous points, the study with a more recent sample and other stocks would allow to compare also the results of this dissertation in an out of sample context and in a different window test regarding the stocks studied; evidently if the information is available.

16. In the same line, extensions to other emergent and developed markets would be of interest as well, in order to compare the generative multifactor model of returns produced by PCA, FA, ICA and NNPCA in different countries.

17. Further research about the financial implications of the results would be needed too. For instance, concerning the fact that there were stocks that were relevant in all the techniques such as: GEO, COMERCI, PEÑOLES and ALFA, which were some of the companies most affected in the last financial crisis. A deeper study about this issue would be interesting specially if we carry on this study in the financial crisis period. In some way, these techniques revealed the importance of these stocks and they might be used as a prevention mechanism in portfolios that may overweight these stocks in their construction. In other words, these techniques pointed those stocks as assets that we should follow and watch closely when we build portfolios, given their possible implications in crisis periods in order to avoid an over exposition to them.

18. Finally, considering the wide range of dimension reduction or feature extraction technique that have been developed through the years in different fields of science, another possible extension to this research would be the application of other linear and non-linear techniques to perform the extraction of risk factors under a statistical approach to the equity risk factors.

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Table 1. *Principal Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of weekly returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000186	0.000181	1.030785	0.3027
C(2)	-0.126897	0.001382	-91.82221	0.0000
C(3)	0.914852	0.002610	350.5703	0.0000
C(4)	0.318767	0.003321	95.99847	0.0000
C(5)	0.038830	0.003592	10.80879	0.0000
C(6)	-0.072420	0.003797	-19.07375	0.0000
C(7)	0.105669	0.004086	25.86311	0.0000
C(8)	-0.119725	0.004245	-28.20310	0.0000
C(9)	0.020960	0.004397	4.767006	0.0000
C(10)	-0.064335	0.004572	-14.07097	0.0000
C(11)	0.003000	0.000913	3.284130	0.0010
C(12)	-0.113679	0.006990	-16.26311	0.0000
C(13)	-0.020017	0.013199	-1.516561	0.1294
C(14)	0.201671	0.016795	12.00769	0.0000
C(15)	-0.012999	0.018170	-0.715376	0.4744
C(16)	0.179627	0.019204	9.353546	0.0000
C(17)	-0.232653	0.020665	-11.25822	0.0000
C(18)	0.586068	0.021471	27.29525	0.0000
C(19)	-0.005175	0.022239	-0.232714	0.8160
C(20)	-0.530716	0.023126	-22.94896	0.0000
C(21)	0.001739	0.001597	1.089242	0.2761
C(22)	-0.097420	0.012217	-7.974038	0.0000
C(23)	-0.038412	0.023070	-1.665034	0.0960
C(24)	0.070841	0.029355	2.413270	0.0158
C(25)	0.047867	0.031758	1.507229	0.1318
C(26)	-0.128884	0.033565	-3.839798	0.0001
C(27)	0.049686	0.036119	1.375619	0.1690
C(28)	-0.150310	0.037528	-4.005260	0.0001
C(29)	0.140175	0.038870	3.606206	0.0003
C(30)	0.089890	0.040420	2.223908	0.0262
C(31)	0.000573	0.001775	0.322811	0.7469
C(32)	-0.211808	0.013585	-15.59170	0.0000
C(33)	-0.067626	0.025652	-2.636296	0.0084
C(34)	0.105197	0.032640	3.222891	0.0013
C(35)	-0.099098	0.035313	-2.806253	0.0050
C(36)	0.030042	0.037322	0.804933	0.4209
C(37)	0.013647	0.040162	0.339794	0.7340
C(38)	0.127503	0.041729	3.055521	0.0023
C(39)	0.166489	0.043221	3.852024	0.0001
C(40)	-0.016027	0.044944	-0.356590	0.7214
C(41)	0.000267	0.000584	0.457110	0.6476
C(42)	-0.132309	0.004471	-29.58967	0.0000
C(43)	0.080728	0.008444	9.560995	0.0000
C(44)	0.075499	0.010744	7.027242	0.0000
C(45)	0.160585	0.011623	13.81552	0.0000
C(46)	0.241953	0.012285	19.69525	0.0000
C(47)	-0.445564	0.013219	-33.70522	0.0000
C(48)	0.223491	0.013735	16.27143	0.0000

C(49)	0.318993	0.014226	22.42247	0.0000
C(50)	0.659808	0.014794	44.60097	0.0000
C(51)	-0.000282	0.000514	-0.548713	0.5832
C(52)	-0.293667	0.003934	-74.64564	0.0000
C(53)	0.269049	0.007429	36.21650	0.0000
C(54)	-0.765574	0.009453	-80.98964	0.0000
C(55)	-0.367746	0.010227	-35.95921	0.0000
C(56)	0.099028	0.010809	9.161937	0.0000
C(57)	0.015674	0.011631	1.347626	0.1778
C(58)	0.139301	0.012085	11.52705	0.0000
C(59)	0.122664	0.012517	9.799822	0.0000
C(60)	-0.033579	0.013016	-2.579841	0.0099
C(61)	0.000810	0.001737	0.466164	0.6411
C(62)	-0.153875	0.013288	-11.57992	0.0000
C(63)	0.081291	0.025092	3.239740	0.0012
C(64)	-0.077583	0.031928	-2.429967	0.0151
C(65)	-0.012444	0.034542	-0.360267	0.7187
C(66)	0.211205	0.036507	5.785271	0.0000
C(67)	0.069702	0.039285	1.774273	0.0761
C(68)	0.149491	0.040817	3.662432	0.0003
C(69)	-0.290541	0.042277	-6.872236	0.0000
C(70)	0.208249	0.043963	4.736936	0.0000
C(71)	0.002158	0.001516	1.423512	0.1546
C(72)	-0.191070	0.011598	-16.47378	0.0000
C(73)	-0.098287	0.021901	-4.487712	0.0000
C(74)	0.061952	0.027868	2.223064	0.0263
C(75)	-0.077264	0.030150	-2.562656	0.0104
C(76)	-0.087542	0.031865	-2.747235	0.0060
C(77)	0.142707	0.034290	4.161818	0.0000
C(78)	-0.030179	0.035627	-0.847078	0.3970
C(79)	0.348935	0.036902	9.455801	0.0000
C(80)	-0.009896	0.038373	-0.257902	0.7965
C(81)	-0.000183	0.001551	-0.117929	0.9061
C(82)	-0.227527	0.011869	-19.17027	0.0000
C(83)	-0.096796	0.022412	-4.318974	0.0000
C(84)	0.060851	0.028518	2.133802	0.0329
C(85)	-0.172514	0.030853	-5.591541	0.0000
C(86)	-0.023314	0.032608	-0.714967	0.4747
C(87)	-0.058331	0.035089	-1.662368	0.0965
C(88)	-0.335898	0.036458	-9.213350	0.0000
C(89)	0.072029	0.037762	1.907459	0.0565
C(90)	-0.152850	0.039267	-3.892581	0.0001
C(91)	0.001322	0.001754	0.753721	0.4510
C(92)	-0.216157	0.013424	-16.10213	0.0000
C(93)	-0.012800	0.025349	-0.504973	0.6136
C(94)	0.121731	0.032255	3.774071	0.0002
C(95)	-0.001803	0.034896	-0.051656	0.9588
C(96)	0.079592	0.036881	2.158053	0.0310
C(97)	-0.311785	0.039687	-7.856073	0.0000
C(98)	-0.236521	0.041235	-5.735883	0.0000
C(99)	-0.197895	0.042710	-4.633429	0.0000
C(100)	-0.068402	0.044413	-1.540147	0.1236
C(101)	-0.000330	0.000849	-0.388065	0.6980
C(102)	-0.306461	0.006498	-47.16135	0.0000
C(103)	0.016709	0.012270	1.361691	0.1734
C(104)	-0.160190	0.015613	-10.25983	0.0000
C(105)	0.358791	0.016892	21.24052	0.0000
C(106)	-0.508578	0.017853	-28.48712	0.0000

C(107)	-0.184630	0.019211	-9.610604	0.0000
C(108)	0.221530	0.019961	11.09839	0.0000
C(109)	-0.459268	0.020675	-22.21415	0.0000
C(110)	0.070003	0.021499	3.256141	0.0011
C(111)	-0.000715	0.001102	-0.648828	0.5165
C(112)	-0.170229	0.008429	-20.19633	0.0000
C(113)	-0.064603	0.015916	-4.058963	0.0000
C(114)	0.161386	0.020252	7.968863	0.0000
C(115)	-0.077970	0.021910	-3.558599	0.0004
C(116)	-0.068125	0.023157	-2.941880	0.0033
C(117)	0.260308	0.024919	10.44629	0.0000
C(118)	0.136312	0.025891	5.264871	0.0000
C(119)	0.003331	0.026817	0.124226	0.9011
C(120)	0.081760	0.027886	2.931956	0.0034
C(121)	-0.001827	0.001182	-1.544924	0.1224
C(122)	-0.233999	0.009048	-25.86103	0.0000
C(123)	-0.081362	0.017086	-4.761897	0.0000
C(124)	0.226844	0.021741	10.43406	0.0000
C(125)	-0.088706	0.023521	-3.771381	0.0002
C(126)	-0.029744	0.024859	-1.196487	0.2316
C(127)	0.401071	0.026750	14.99305	0.0000
C(128)	0.267766	0.027794	9.633903	0.0000
C(129)	-0.093510	0.028788	-3.248183	0.0012
C(130)	0.115624	0.029936	3.862412	0.0001
C(131)	-0.001214	0.001428	-0.850691	0.3950
C(132)	-0.275543	0.010924	-25.22447	0.0000
C(133)	-0.080797	0.020627	-3.917011	0.0001
C(134)	0.119662	0.026247	4.559128	0.0000
C(135)	-0.125244	0.028396	-4.410645	0.0000
C(136)	-0.140376	0.030011	-4.677398	0.0000
C(137)	0.136611	0.032295	4.230149	0.0000
C(138)	0.128401	0.033555	3.826631	0.0001
C(139)	0.344072	0.034755	9.899976	0.0000
C(140)	-0.020949	0.036140	-0.579663	0.5622
C(141)	-0.001064	0.001388	-0.766353	0.4435
C(142)	-0.301458	0.010624	-28.37573	0.0000
C(143)	-0.071828	0.020061	-3.580504	0.0003
C(144)	-0.053150	0.025526	-2.082169	0.0374
C(145)	0.088748	0.027616	3.213598	0.0013
C(146)	-0.454739	0.029188	-15.57985	0.0000
C(147)	-0.222687	0.031408	-7.090091	0.0000
C(148)	-0.094510	0.032634	-2.896115	0.0038
C(149)	0.208810	0.033801	6.177673	0.0000
C(150)	-0.152757	0.035148	-4.346097	0.0000
C(151)	0.004436	0.001791	2.476968	0.0133
C(152)	-0.201459	0.013703	-14.70137	0.0000
C(153)	-0.069185	0.025876	-2.673682	0.0075
C(154)	-0.075840	0.032926	-2.303352	0.0213
C(155)	-0.110932	0.035622	-3.114146	0.0019
C(156)	-0.021209	0.037649	-0.563339	0.5732
C(157)	0.085079	0.040513	2.100050	0.0358
C(158)	-0.318333	0.042093	-7.562538	0.0000
C(159)	-0.141737	0.043599	-3.250929	0.0012
C(160)	0.126113	0.045337	2.781681	0.0054
C(161)	-0.000833	0.001565	-0.532221	0.5946
C(162)	-0.188846	0.011976	-15.76911	0.0000
C(163)	-0.038797	0.022614	-1.715626	0.0863
C(164)	0.043815	0.028774	1.522694	0.1279

C(165)	-0.233515	0.031131	-7.501143	0.0000
C(166)	0.257862	0.032902	7.837312	0.0000
C(167)	0.096592	0.035405	2.728201	0.0064
C(168)	-0.005313	0.036786	-0.144428	0.8852
C(169)	-0.361445	0.038102	-9.486237	0.0000
C(170)	-0.023839	0.039621	-0.601687	0.5474
C(171)	0.000908	0.001518	0.598365	0.5496
C(172)	-0.236767	0.011615	-20.38468	0.0000
C(173)	-0.126960	0.021933	-5.788629	0.0000
C(174)	0.166017	0.027908	5.948764	0.0000
C(175)	-0.077609	0.030193	-2.570445	0.0102
C(176)	0.001292	0.031911	0.040500	0.9677
C(177)	0.162087	0.034339	4.720266	0.0000
C(178)	-0.030264	0.035678	-0.848261	0.3963
C(179)	-0.173170	0.036954	-4.686062	0.0000
C(180)	0.284472	0.038427	7.402828	0.0000
C(181)	-0.000680	0.000239	-2.852476	0.0044
C(182)	-0.328798	0.001825	-180.1166	0.0000
C(183)	-0.056609	0.003447	-16.42241	0.0000
C(184)	-0.157671	0.004386	-35.94758	0.0000
C(185)	0.706323	0.004745	148.8471	0.0000
C(186)	0.446003	0.005015	88.92865	0.0000
C(187)	0.256539	0.005397	47.53497	0.0000
C(188)	-0.169384	0.005607	-30.20721	0.0000
C(189)	0.122174	0.005808	21.03558	0.0000
C(190)	-0.203166	0.006039	-33.63974	0.0000
C(191)	-0.003081	0.001423	-2.164775	0.0304
C(192)	-0.263305	0.010889	-24.18050	0.0000
C(193)	-0.059289	0.020562	-2.883416	0.0039
C(194)	0.202602	0.026164	7.743598	0.0000
C(195)	-0.226510	0.028306	-8.002124	0.0000
C(196)	0.246870	0.029917	8.251902	0.0000
C(197)	-0.409671	0.032193	-12.72557	0.0000
C(198)	-0.214977	0.033449	-6.427060	0.0000
C(199)	-0.086764	0.034645	-2.504379	0.0123
C(200)	-0.102380	0.036026	-2.841824	0.0045

Equation: PE_OLES_01=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9

Observations: 291

R-squared	0.997965	Mean dependent vary	0.004729
Adjusted R-squared	0.997900	S.D. dependent var	0.067404
S.E. of regression	0.003089	Sum squared resid	0.002681
Durbin-Watson stat	2.095523		

Equation: BIMBOA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)*PC4
+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9

Observations: 291

R-squared	0.867030	Mean dependent var	0.003161
Adjusted R-squared	0.862771	S.D. dependent var	0.042175
S.E. of regression	0.015623	Sum squared resid	0.068590
Durbin-Watson stat	2.029709		

Equation: GMODELOC=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)
*PC4+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 291

R-squared	0.300619	Mean dependent var	0.001865
Adjusted R-squared	0.278219	S.D. dependent var	0.032142
S.E. of regression	0.027307	Sum squared resid	0.209533
Durbin-Watson stat	2.298799		

Equation: FEMSAUBD=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 291

R-squared	0.502035	Mean dependent var	0.002358
Adjusted R-squared	0.486086	S.D. dependent var	0.042355
S.E. of regression	0.030363	Sum squared resid	0.259065
Durbin-Watson stat	2.316138		

Equation: CONTAL_01=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 291

R-squared	0.949645	Mean dependent var	0.002039
Adjusted R-squared	0.948032	S.D. dependent var	0.043841
S.E. of regression	0.009994	Sum squared resid	0.028068
Durbin-Watson stat	2.126282		

Equation: GEOB=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)*PC4
+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 291

R-squared	0.981040	Mean dependent var	0.008191
Adjusted R-squared	0.980433	S.D. dependent var	0.062862
S.E. of regression	0.008793	Sum squared resid	0.021728
Durbin-Watson stat	2.218143		

Equation: ARA_01=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)*PC4
+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 291

R-squared	0.481581	Mean dependent var	0.004898
Adjusted R-squared	0.464977	S.D. dependent var	0.040605
S.E. of regression	0.029700	Sum squared resid	0.247875
Durbin-Watson stat	2.154514		

Equation: WALMEXV=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)
*PC4+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 291

R-squared	0.589620	Mean dependent var	0.003334
Adjusted R-squared	0.576476	S.D. dependent var	0.039835
S.E. of regression	0.025924	Sum squared resid	0.188846
Durbin-Watson stat	2.409036		

Equation: SORIANAB=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)
*PC4+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 291

R-squared	0.645088	Mean dependent var	0.000746
Adjusted R-squared	0.633721	S.D. dependent var	0.043833
S.E. of regression	0.026528	Sum squared resid	0.197752
Durbin-Watson stat	2.292097		

Equation: COMERUBC=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 291

R-squared	0.576971	Mean dependent var	0.002256
Adjusted R-squared	0.563422	S.D. dependent var	0.045411
S.E. of regression	0.030005	Sum squared resid	0.252977
Durbin-Watson stat	2.220469		

Equation: ELEKTRA_01=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 291

R-squared	0.936802	Mean dependent var	0.002654
Adjusted R-squared	0.934778	S.D. dependent var	0.056871
S.E. of regression	0.014524	Sum squared resid	0.059277
Durbin-Watson stat	2.072088		

Equation: TELMEXL=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 291

R-squared	0.692273	Mean dependent var	0.001198
Adjusted R-squared	0.682417	S.D. dependent var	0.033430
S.E. of regression	0.018839	Sum squared resid	0.099732
Durbin-Watson stat	2.185971		

Equation: TELECOA1=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 291

R-squared	0.799319	Mean dependent var	0.001320
Adjusted R-squared	0.792892	S.D. dependent var	0.044440
S.E. of regression	0.020224	Sum squared resid	0.114933
Durbin-Watson stat	2.262191		

Equation: TLEVICPO=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 291

R-squared	0.743752	Mean dependent var	0.000899
Adjusted R-squared	0.735544	S.D. dependent var	0.047478
S.E. of regression	0.024416	Sum squared resid	0.167512
Durbin-Watson stat	2.130634		

Equation: TVAZTCPO=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 291

R-squared	0.803658	Mean dependent var	-0.000334
Adjusted R-squared	0.797369	S.D. dependent var	0.052751
S.E. of regression	0.023745	Sum squared resid	0.158441
Durbin-Watson stat	1.999357		

Equation: GFNORTEO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 291

R-squared	0.522566	Mean dependent var	0.006851
Adjusted R-squared	0.507274	S.D. dependent var	0.043634
S.E. of regression	0.030629	Sum squared resid	0.263614
Durbin-Watson stat	2.166391		

Equation: GFINBURO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 291

R-squared	0.617323	Mean dependent var	0.002456
Adjusted R-squared	0.605066	S.D. dependent var	0.042593
S.E. of regression	0.026767	Sum squared resid	0.201331
Durbin-Watson stat	2.076564		

Equation: GCARSOA1=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 291

R-squared	0.669994	Mean dependent var	0.003413
Adjusted R-squared	0.659424	S.D. dependent var	0.044485
S.E. of regression	0.025961	Sum squared resid	0.189385
Durbin-Watson stat	2.143658		

Equation: ALFAA=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3+C(185)
*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8+C(190)
*PC9
Observations: 291

R-squared	0.995789	Mean dependent var	0.003559
Adjusted R-squared	0.995654	S.D. dependent var	0.061893
S.E. of regression	0.004080	Sum squared resid	0.004678
Durbin-Watson stat	2.073691		

Equation: CIEB=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3+C(195)
*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8+C(200)
*PC9
Observations: 291

R-squared	0.775063	Mean dependent var	-0.001948
Adjusted R-squared	0.767859	S.D. dependent var	0.050515
S.E. of regression	0.024339	Sum squared resid	0.166456
Durbin-Watson stat	2.084575		

Table 2. *Principal Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of weekly excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000198	0.000181	1.094890	0.2736
C(2)	-0.128621	0.001383	-93.03156	0.0000
C(3)	0.914825	0.002620	349.1881	0.0000
C(4)	0.318410	0.003336	95.43473	0.0000
C(5)	0.038227	0.003608	10.59520	0.0000
C(6)	-0.072042	0.003813	-18.89247	0.0000
C(7)	0.105108	0.004103	25.61607	0.0000
C(8)	-0.119753	0.004264	-28.08716	0.0000
C(9)	0.020881	0.004416	4.728943	0.0000
C(10)	-0.064310	0.004594	-13.99936	0.0000
C(11)	0.002478	0.000907	2.730768	0.0063
C(12)	-0.114174	0.006938	-16.45520	0.0000
C(13)	-0.019511	0.013148	-1.483941	0.1379
C(14)	0.201153	0.016744	12.01337	0.0000
C(15)	-0.013230	0.018107	-0.730692	0.4650
C(16)	0.179744	0.019137	9.392393	0.0000
C(17)	-0.231994	0.020592	-11.26601	0.0000
C(18)	0.588670	0.021397	27.51125	0.0000
C(19)	-0.004762	0.022160	-0.214901	0.8299
C(20)	-0.529515	0.023054	-22.96809	0.0000
C(21)	0.000700	0.001591	0.439715	0.6602
C(22)	-0.097772	0.012167	-8.036113	0.0000
C(23)	-0.038033	0.023055	-1.649664	0.0991
C(24)	0.070472	0.029361	2.400222	0.0164
C(25)	0.047743	0.031750	1.503713	0.1327
C(26)	-0.129052	0.033557	-3.845757	0.0001
C(27)	0.050038	0.036109	1.385767	0.1659
C(28)	-0.151242	0.037520	-4.030937	0.0001
C(29)	0.140286	0.038858	3.610253	0.0003
C(30)	0.087455	0.040426	2.163360	0.0306
C(31)	0.000613	0.001770	0.346543	0.7289
C(32)	-0.211574	0.013536	-15.63033	0.0000
C(33)	-0.067898	0.025650	-2.647067	0.0081
C(34)	0.104672	0.032666	3.204351	0.0014
C(35)	-0.099130	0.035324	-2.806323	0.0050
C(36)	0.030077	0.037334	0.805602	0.4205
C(37)	0.013791	0.040173	0.343277	0.7314
C(38)	0.127362	0.041744	3.051041	0.0023
C(39)	0.166301	0.043232	3.846749	0.0001
C(40)	-0.015360	0.044976	-0.341509	0.7327
C(41)	0.000198	0.000583	0.340265	0.7337
C(42)	-0.132138	0.004455	-29.66207	0.0000
C(43)	0.080704	0.008442	9.560359	0.0000
C(44)	0.073680	0.010750	6.853748	0.0000
C(45)	0.161726	0.011625	13.91166	0.0000
C(46)	0.240403	0.012287	19.56598	0.0000
C(47)	-0.444461	0.013221	-33.61765	0.0000
C(48)	0.222137	0.013738	16.16958	0.0000
C(49)	0.318488	0.014228	22.38528	0.0000
C(50)	0.661647	0.014802	44.70052	0.0000
C(51)	-0.000243	0.000513	-0.474545	0.6351
C(52)	-0.294405	0.003921	-75.09143	0.0000

C(53)	0.268035	0.007429	36.07779	0.0000
C(54)	-0.766692	0.009461	-81.03408	0.0000
C(55)	-0.365744	0.010231	-35.74758	0.0000
C(56)	0.098299	0.010814	9.090351	0.0000
C(57)	0.016143	0.011636	1.387348	0.1654
C(58)	0.139059	0.012091	11.50127	0.0000
C(59)	0.122631	0.012522	9.793534	0.0000
C(60)	-0.033239	0.013027	-2.551555	0.0108
C(61)	0.000426	0.001732	0.246081	0.8056
C(62)	-0.154042	0.013244	-11.63107	0.0000
C(63)	0.081230	0.025097	3.236675	0.0012
C(64)	-0.078866	0.031961	-2.467602	0.0136
C(65)	-0.011561	0.034562	-0.334508	0.7380
C(66)	0.210551	0.036529	5.764023	0.0000
C(67)	0.070341	0.039306	1.789567	0.0736
C(68)	0.148204	0.040843	3.628629	0.0003
C(69)	-0.290667	0.042299	-6.871785	0.0000
C(70)	0.206675	0.044006	4.696559	0.0000
C(71)	0.001849	0.001510	1.224743	0.2207
C(72)	-0.190599	0.011548	-16.50451	0.0000
C(73)	-0.098560	0.021883	-4.503860	0.0000
C(74)	0.061326	0.027869	2.200528	0.0278
C(75)	-0.077239	0.030137	-2.562961	0.0104
C(76)	-0.087619	0.031852	-2.750835	0.0060
C(77)	0.142942	0.034274	4.170599	0.0000
C(78)	-0.031129	0.035614	-0.874063	0.3821
C(79)	0.348821	0.036883	9.457544	0.0000
C(80)	-0.011707	0.038371	-0.305110	0.7603
C(81)	-0.000371	0.001547	-0.240111	0.8103
C(82)	-0.227958	0.011828	-19.27354	0.0000
C(83)	-0.096911	0.022412	-4.323971	0.0000
C(84)	0.061563	0.028542	2.156899	0.0311
C(85)	-0.173264	0.030865	-5.613589	0.0000
C(86)	-0.022293	0.032622	-0.683385	0.4944
C(87)	-0.059432	0.035102	-1.693116	0.0905
C(88)	-0.334488	0.036475	-9.170424	0.0000
C(89)	0.072405	0.037775	1.916768	0.0553
C(90)	-0.153292	0.039299	-3.900644	0.0001
C(91)	0.001230	0.001748	0.703641	0.4817
C(92)	-0.216331	0.013371	-16.17912	0.0000
C(93)	-0.012994	0.025337	-0.512822	0.6081
C(94)	0.121894	0.032267	3.777645	0.0002
C(95)	-0.002108	0.034893	-0.060413	0.9518
C(96)	0.079854	0.036879	2.165316	0.0304
C(97)	-0.312504	0.039683	-7.874984	0.0000
C(98)	-0.235258	0.041235	-5.705358	0.0000
C(99)	-0.197525	0.042704	-4.625437	0.0000
C(100)	-0.070837	0.044428	-1.594445	0.1109
C(101)	-0.000255	0.000846	-0.301637	0.7629
C(102)	-0.306127	0.006470	-47.31276	0.0000
C(103)	0.015574	0.012261	1.270239	0.2041
C(104)	-0.159193	0.015614	-10.19538	0.0000
C(105)	0.359006	0.016885	21.26195	0.0000
C(106)	-0.509815	0.017846	-28.56775	0.0000
C(107)	-0.183407	0.019203	-9.551055	0.0000
C(108)	0.220635	0.019954	11.05742	0.0000
C(109)	-0.459446	0.020665	-22.23334	0.0000
C(110)	0.069949	0.021499	3.253628	0.0011

C(111)	-0.000962	0.001098	-0.876275	0.3809
C(112)	-0.170090	0.008394	-20.26228	0.0000
C(113)	-0.064637	0.015907	-4.063471	0.0000
C(114)	0.161012	0.020258	7.948239	0.0000
C(115)	-0.078322	0.021906	-3.575367	0.0004
C(116)	-0.067872	0.023153	-2.931504	0.0034
C(117)	0.260675	0.024913	10.46327	0.0000
C(118)	0.135428	0.025887	5.231456	0.0000
C(119)	0.003209	0.026810	0.119697	0.9047
C(120)	0.081848	0.027892	2.934466	0.0034
C(121)	-0.001477	0.001178	-1.254419	0.2097
C(122)	-0.233816	0.009007	-25.96000	0.0000
C(123)	-0.081624	0.017067	-4.782485	0.0000
C(124)	0.226978	0.021735	10.44279	0.0000
C(125)	-0.089406	0.023504	-3.803838	0.0001
C(126)	-0.029093	0.024842	-1.171116	0.2416
C(127)	0.401360	0.026731	15.01489	0.0000
C(128)	0.267023	0.027776	9.613510	0.0000
C(129)	-0.093712	0.028766	-3.257745	0.0011
C(130)	0.117564	0.029927	3.928414	0.0001
C(131)	-0.000767	0.001422	-0.539424	0.5896
C(132)	-0.275457	0.010878	-25.32250	0.0000
C(133)	-0.081309	0.020613	-3.944538	0.0001
C(134)	0.120165	0.026251	4.577545	0.0000
C(135)	-0.125915	0.028387	-4.435636	0.0000
C(136)	-0.139772	0.030003	-4.658636	0.0000
C(137)	0.136608	0.032284	4.231436	0.0000
C(138)	0.128621	0.033546	3.834124	0.0001
C(139)	0.343970	0.034742	9.900733	0.0000
C(140)	-0.019275	0.036144	-0.533272	0.5939
C(141)	-0.000995	0.001385	-0.718388	0.4725
C(142)	-0.301306	0.010589	-28.45553	0.0000
C(143)	-0.072680	0.020065	-3.622261	0.0003
C(144)	-0.051863	0.025553	-2.029643	0.0424
C(145)	0.088200	0.027632	3.191917	0.0014
C(146)	-0.454759	0.029205	-15.57138	0.0000
C(147)	-0.222681	0.031426	-7.085992	0.0000
C(148)	-0.093589	0.032654	-2.866082	0.0042
C(149)	0.208999	0.033818	6.180124	0.0000
C(150)	-0.152320	0.035183	-4.329392	0.0000
C(151)	0.004002	0.001784	2.242972	0.0249
C(152)	-0.201024	0.013646	-14.73165	0.0000
C(153)	-0.069594	0.025858	-2.691405	0.0071
C(154)	-0.076854	0.032930	-2.333854	0.0196
C(155)	-0.110365	0.035610	-3.099278	0.0019
C(156)	-0.021605	0.037636	-0.574043	0.5660
C(157)	0.084983	0.040498	2.098441	0.0359
C(158)	-0.320213	0.042082	-7.609335	0.0000
C(159)	-0.141859	0.043581	-3.255021	0.0011
C(160)	0.120912	0.045340	2.666764	0.0077
C(161)	-0.000973	0.001560	-0.624040	0.5326
C(162)	-0.188711	0.011930	-15.81840	0.0000
C(163)	-0.038977	0.022606	-1.724183	0.0847
C(164)	0.042821	0.028789	1.487393	0.1370
C(165)	-0.233256	0.031132	-7.492442	0.0000
C(166)	0.258189	0.032904	7.846781	0.0000
C(167)	0.096026	0.035406	2.712160	0.0067
C(168)	-0.005264	0.036790	-0.143073	0.8862

C(169)	-0.361612	0.038101	-9.490797	0.0000
C(170)	-0.022350	0.039639	-0.563843	0.5729
C(171)	0.001149	0.001511	0.760208	0.4472
C(172)	-0.236775	0.011555	-20.49163	0.0000
C(173)	-0.127194	0.021896	-5.809115	0.0000
C(174)	0.166393	0.027884	5.967328	0.0000
C(175)	-0.078233	0.030153	-2.594516	0.0095
C(176)	0.001903	0.031869	0.059702	0.9524
C(177)	0.161825	0.034293	4.718961	0.0000
C(178)	-0.030778	0.035633	-0.863751	0.3878
C(179)	-0.173324	0.036903	-4.696724	0.0000
C(180)	0.286234	0.038393	7.455461	0.0000
C(181)	-0.000546	0.000241	-2.259712	0.0239
C(182)	-0.328755	0.001847	-178.0201	0.0000
C(183)	-0.057635	0.003499	-16.46973	0.0000
C(184)	-0.155695	0.004457	-34.93608	0.0000
C(185)	0.706754	0.004819	146.6527	0.0000
C(186)	0.445655	0.005094	87.49488	0.0000
C(187)	0.255859	0.005481	46.68275	0.0000
C(188)	-0.169158	0.005695	-29.70239	0.0000
C(189)	0.122277	0.005898	20.73174	0.0000
C(190)	-0.203508	0.006136	-33.16577	0.0000
C(191)	-0.002573	0.001420	-1.812450	0.0700
C(192)	-0.262681	0.010857	-24.19473	0.0000
C(193)	-0.059909	0.020573	-2.911966	0.0036
C(194)	0.201921	0.026200	7.706832	0.0000
C(195)	-0.226608	0.028332	-7.998212	0.0000
C(196)	0.247301	0.029945	8.258571	0.0000
C(197)	-0.411142	0.032222	-12.75976	0.0000
C(198)	-0.213159	0.033481	-6.366463	0.0000
C(199)	-0.086897	0.034675	-2.506074	0.0122
C(200)	-0.099466	0.036074	-2.757266	0.0058

Equation: PE_OLES_01=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 291

R-squared	0.997952	Mean dependent var	0.003041
Adjusted R-squared	0.997887	S.D. dependent var	0.067481
S.E. of regression	0.003102	Sum squared resid	0.002704
Durbin-Watson stat	2.098103		

Equation: BIMBOA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)*PC4
+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 291

R-squared	0.868231	Mean dependent var	0.001472
Adjusted R-squared	0.864011	S.D. dependent var	0.042216
S.E. of regression	0.015568	Sum squared resid	0.068103
Durbin-Watson stat	2.031260		

Equation: GMODELOC=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)
*PC4+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 291

R-squared	0.302151	Mean dependent var	0.000176
Adjusted R-squared	0.279800	S.D. dependent var	0.032167
S.E. of regression	0.027298	Sum squared resid	0.209399
Durbin-Watson stat	2.299519		

Equation: FEMSAUBD=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 291

R-squared	0.502944	Mean dependent var	0.000669
Adjusted R-squared	0.487024	S.D. dependent var	0.042404
S.E. of regression	0.030371	Sum squared resid	0.259193
Durbin-Watson stat	2.316372		

Equation: CONTAL_01=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 291

R-squared	0.949623	Mean dependent var	0.000350
Adjusted R-squared	0.948009	S.D. dependent var	0.043836
S.E. of regression	0.009995	Sum squared resid	0.028073
Durbin-Watson stat	2.125635		

Equation: GEOB=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)*PC4
+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 291

R-squared	0.981098	Mean dependent var	0.006502
Adjusted R-squared	0.980492	S.D. dependent var	0.062982
S.E. of regression	0.008797	Sum squared resid	0.021744
Durbin-Watson stat	2.218890		

Equation: ARA_01=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)*PC4
+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 291

R-squared	0.482051	Mean dependent var	0.003209
Adjusted R-squared	0.465462	S.D. dependent var	0.040644
S.E. of regression	0.029716	Sum squared resid	0.248127
Durbin-Watson stat	2.154826		

Equation: WALMEXV=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)
*PC4+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 291

R-squared	0.590347	Mean dependent var	0.001645
Adjusted R-squared	0.577227	S.D. dependent var	0.039850
S.E. of regression	0.025911	Sum squared resid	0.188657
Durbin-Watson stat	2.411701		

Equation: SORIANAB=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)
*PC4+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 291

R-squared	0.646695	Mean dependent var	-0.000943
Adjusted R-squared	0.635379	S.D. dependent var	0.043948
S.E. of regression	0.026537	Sum squared resid	0.197890
Durbin-Watson stat	2.292816		

Equation: COMERUBC=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 291

R-squared	0.578562	Mean dependent var	0.000568
Adjusted R-squared	0.565064	S.D. dependent var	0.045490
S.E. of regression	0.030001	Sum squared resid	0.252909
Durbin-Watson stat	2.220610		

Equation: ELEKTRA_01=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 291

R-squared	0.937035	Mean dependent var	0.000965
Adjusted R-squared	0.935019	S.D. dependent var	0.056950
S.E. of regression	0.014517	Sum squared resid	0.059222
Durbin-Watson stat	2.072070		

Equation: TELMEXL=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 291

R-squared	0.693069	Mean dependent var	-0.000491
Adjusted R-squared	0.683239	S.D. dependent var	0.033465
S.E. of regression	0.018835	Sum squared resid	0.099682
Durbin-Watson stat	2.187132		

Equation: TELECOA1=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 291

R-squared	0.800219	Mean dependent var	-0.000369
Adjusted R-squared	0.793821	S.D. dependent var	0.044505
S.E. of regression	0.020209	Sum squared resid	0.114756
Durbin-Watson stat	2.264464		

Equation: TLEVICPO=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 291

R-squared	0.744968	Mean dependent var	-0.000790
Adjusted R-squared	0.736800	S.D. dependent var	0.047574
S.E. of regression	0.024407	Sum squared resid	0.167390
Durbin-Watson stat	2.132377		

Equation: TVAZTCPO=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 291

R-squared	0.804169	Mean dependent var	-0.002023
Adjusted R-squared	0.797897	S.D. dependent var	0.052847
S.E. of regression	0.023758	Sum squared resid	0.158605
Durbin-Watson stat	1.999622		

Equation: GFNORTEO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 291

R-squared	0.523466	Mean dependent var	0.005163
Adjusted R-squared	0.508203	S.D. dependent var	0.043658
S.E. of regression	0.030617	Sum squared resid	0.263407
Durbin-Watson stat	2.169587		

Equation: GFINBURO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 291

R-squared	0.618053	Mean dependent var	0.000767
Adjusted R-squared	0.605819	S.D. dependent var	0.042633
S.E. of regression	0.026767	Sum squared resid	0.201328
Durbin-Watson stat	2.077508		

Equation: GCARSOA1=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 291

R-squared	0.672170	Mean dependent var	0.001724
Adjusted R-squared	0.661670	S.D. dependent var	0.044571
S.E. of regression	0.025925	Sum squared resid	0.188866
Durbin-Watson stat	2.144110		

Equation: ALFAA=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3+C(185)
*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8+C(190)
*PC9

Observations: 291

R-squared	0.995671	Mean dependent var	0.001871
Adjusted R-squared	0.995533	S.D. dependent var	0.061994
S.E. of regression	0.004144	Sum squared resid	0.004824
Durbin-Watson stat	2.077114		

Equation: CIEB=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3+C(195)
*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8+C(200)
*PC9

Observations: 291

R-squared	0.775057	Mean dependent var	-0.003637
Adjusted R-squared	0.767852	S.D. dependent var	0.050558
S.E. of regression	0.024360	Sum squared resid	0.166744
Durbin-Watson stat	2.084044		

Table 3. *Principal Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of daily returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.52E-05	2.31E-05	-0.656807	0.5113
C(2)	0.117277	0.000413	284.0886	0.0000
C(3)	-0.973511	0.000788	-1236.012	0.0000
C(4)	0.096652	0.001040	92.91131	0.0000
C(5)	-0.100518	0.001096	-91.72998	0.0000
C(6)	0.085719	0.001147	74.75726	0.0000
C(7)	-0.086521	0.001164	-74.35263	0.0000
C(8)	0.000798	0.001220	0.654285	0.5129
C(9)	0.012306	0.001274	9.656538	0.0000
C(10)	-0.029220	0.001333	-21.92088	0.0000
C(11)	5.24E-05	0.000345	0.151695	0.8794
C(12)	0.117706	0.006155	19.12253	0.0000
C(13)	-0.004097	0.011744	-0.348888	0.7272
C(14)	0.009729	0.015511	0.627213	0.5305
C(15)	0.181604	0.016339	11.11481	0.0000
C(16)	0.033397	0.017097	1.953430	0.0508
C(17)	-0.042078	0.017351	-2.425144	0.0153
C(18)	0.012899	0.018186	0.709281	0.4782
C(19)	0.010925	0.019001	0.574953	0.5653
C(20)	0.113274	0.019875	5.699194	0.0000
C(21)	0.000492	0.000378	1.300405	0.1935
C(22)	0.148436	0.006744	22.00902	0.0000
C(23)	-0.036119	0.012868	-2.806999	0.0050
C(24)	-0.015305	0.016995	-0.900583	0.3678
C(25)	0.231567	0.017902	12.93496	0.0000
C(26)	-0.008874	0.018733	-0.473721	0.6357
C(27)	0.152692	0.019011	8.031767	0.0000
C(28)	0.107816	0.019926	5.410741	0.0000
C(29)	0.334676	0.020819	16.07516	0.0000
C(30)	0.138036	0.021777	6.338535	0.0000
C(31)	0.000131	0.000358	0.365989	0.7144
C(32)	0.129918	0.006377	20.37181	0.0000
C(33)	-0.006767	0.012167	-0.556181	0.5781
C(34)	0.095008	0.016070	5.912076	0.0000
C(35)	0.080014	0.016928	4.726648	0.0000
C(36)	0.021540	0.017713	1.216039	0.2240
C(37)	0.001719	0.017976	0.095599	0.9238
C(38)	-0.062749	0.018842	-3.330282	0.0009
C(39)	-0.171372	0.019687	-8.705039	0.0000
C(40)	0.003197	0.020592	0.155253	0.8766
C(41)	0.000230	0.000349	0.659640	0.5095
C(42)	0.197091	0.006225	31.66077	0.0000
C(43)	0.047015	0.011877	3.958500	0.0001
C(44)	0.044271	0.015687	2.822226	0.0048
C(45)	0.039223	0.016524	2.373686	0.0176
C(46)	0.018307	0.017290	1.058782	0.2897
C(47)	-0.120970	0.017547	-6.893981	0.0000
C(48)	-0.089376	0.018392	-4.859456	0.0000
C(49)	-0.050793	0.019216	-2.643184	0.0082
C(50)	0.075617	0.020101	3.761917	0.0002
C(51)	-9.63E-05	9.93E-05	-0.969381	0.3324

C(52)	0.132065	0.001772	74.53834	0.0000
C(53)	-0.115742	0.003380	-34.23930	0.0000
C(54)	0.034728	0.004465	7.778296	0.0000
C(55)	0.510560	0.004703	108.5591	0.0000
C(56)	-0.510300	0.004921	-103.6939	0.0000
C(57)	0.536398	0.004994	107.4021	0.0000
C(58)	-0.203487	0.005235	-38.87219	0.0000
C(59)	-0.156846	0.005469	-28.67711	0.0000
C(60)	-0.186973	0.005721	-32.68173	0.0000
C(61)	0.000280	0.000332	0.845019	0.3981
C(62)	0.180871	0.005919	30.55964	0.0000
C(63)	0.022931	0.011292	2.030680	0.0423
C(64)	0.014058	0.014914	0.942565	0.3459
C(65)	0.036934	0.015711	2.350911	0.0187
C(66)	-0.006984	0.016439	-0.424831	0.6710
C(67)	-0.026538	0.016683	-1.590653	0.1117
C(68)	-0.041823	0.017487	-2.391719	0.0168
C(69)	-0.072307	0.018270	-3.957569	0.0001
C(70)	-0.081715	0.019111	-4.275814	0.0000
C(71)	6.40E-06	0.000102	0.062851	0.9499
C(72)	0.225849	0.001815	124.4428	0.0000
C(73)	-0.059157	0.003463	-17.08451	0.0000
C(74)	-0.891996	0.004573	-195.0436	0.0000
C(75)	-0.168168	0.004817	-34.90780	0.0000
C(76)	-0.112279	0.005041	-22.27346	0.0000
C(77)	0.010028	0.005116	1.960284	0.0500
C(78)	-0.202801	0.005362	-37.82103	0.0000
C(79)	0.006027	0.005602	1.075852	0.2820
C(80)	0.116431	0.005860	19.86809	0.0000
C(81)	5.39E-06	0.000375	0.014365	0.9885
C(82)	0.163555	0.006687	24.45981	0.0000
C(83)	-0.001398	0.012758	-0.109586	0.9127
C(84)	-0.198275	0.016850	-11.76728	0.0000
C(85)	0.075148	0.017749	4.233841	0.0000
C(86)	0.025236	0.018573	1.358797	0.1742
C(87)	-0.058643	0.018848	-3.111319	0.0019
C(88)	0.037707	0.019756	1.908636	0.0563
C(89)	0.190285	0.020641	9.218625	0.0000
C(90)	-0.385155	0.021591	-17.83867	0.0000
C(91)	0.000189	0.000349	0.542248	0.5877
C(92)	0.224860	0.006232	36.08428	0.0000
C(93)	0.027891	0.011889	2.345889	0.0190
C(94)	0.066353	0.015703	4.225540	0.0000
C(95)	0.061221	0.016541	3.701169	0.0002
C(96)	0.064257	0.017308	3.712484	0.0002
C(97)	-0.107477	0.017565	-6.118647	0.0000
C(98)	-0.162189	0.018411	-8.809266	0.0000
C(99)	-0.101101	0.019236	-5.255717	0.0000
C(100)	-0.027224	0.020121	-1.352977	0.1761
C(101)	-0.000126	0.000351	-0.357612	0.7206
C(102)	0.218567	0.006266	34.88057	0.0000
C(103)	0.013687	0.011955	1.144873	0.2523
C(104)	0.024749	0.015790	1.567398	0.1170
C(105)	0.088093	0.016633	5.296223	0.0000
C(106)	0.033299	0.017405	1.913214	0.0557
C(107)	-0.113927	0.017663	-6.449983	0.0000
C(108)	-0.018807	0.018514	-1.015825	0.3097
C(109)	-0.107152	0.019343	-5.539502	0.0000

C(110)	0.198334	0.020233	9.802416	0.0000
C(111)	-0.000160	0.000240	-0.667304	0.5046
C(112)	0.194787	0.004286	45.44628	0.0000
C(113)	-0.004795	0.008177	-0.586310	0.5577
C(114)	-0.047340	0.010801	-4.383151	0.0000
C(115)	0.106974	0.011377	9.402583	0.0000
C(116)	0.089717	0.011905	7.536190	0.0000
C(117)	0.088346	0.012082	7.312418	0.0000
C(118)	0.375847	0.012663	29.67981	0.0000
C(119)	-0.638845	0.013231	-48.28408	0.0000
C(120)	0.281432	0.013840	20.33522	0.0000
C(121)	-5.06E-05	0.000192	-0.264082	0.7917
C(122)	0.294896	0.003417	86.30378	0.0000
C(123)	0.032482	0.006519	4.982443	0.0000
C(124)	0.089370	0.008610	10.37941	0.0000
C(125)	-0.417701	0.009070	-46.05273	0.0000
C(126)	-0.409545	0.009491	-43.15185	0.0000
C(127)	0.135759	0.009632	14.09500	0.0000
C(128)	0.551258	0.010095	54.60444	0.0000
C(129)	0.116898	0.010548	11.08249	0.0000
C(130)	-0.161634	0.011033	-14.64976	0.0000
C(131)	-0.000145	0.000266	-0.544594	0.5860
C(132)	0.190876	0.004742	40.24855	0.0000
C(133)	0.040909	0.009048	4.521291	0.0000
C(134)	0.088137	0.011950	7.375187	0.0000
C(135)	0.034310	0.012588	2.725546	0.0064
C(136)	0.074800	0.013172	5.678560	0.0000
C(137)	-0.121430	0.013368	-9.083658	0.0000
C(138)	-0.213092	0.014012	-15.20815	0.0000
C(139)	-0.029400	0.014640	-2.008212	0.0446
C(140)	-0.082459	0.015313	-5.384827	0.0000
C(141)	-0.000286	0.000318	-0.900363	0.3679
C(142)	0.251475	0.005665	44.39309	0.0000
C(143)	0.045548	0.010808	4.214373	0.0000
C(144)	0.098991	0.014275	6.934843	0.0000
C(145)	0.076606	0.015037	5.094615	0.0000
C(146)	0.171658	0.015734	10.90993	0.0000
C(147)	-0.132722	0.015968	-8.311868	0.0000
C(148)	-0.192538	0.016737	-11.50401	0.0000
C(149)	0.006824	0.017487	0.390236	0.6964
C(150)	-0.106576	0.018291	-5.826643	0.0000
C(151)	-0.000240	0.000310	-0.776181	0.4376
C(152)	0.297633	0.005525	53.87240	0.0000
C(153)	0.085528	0.010541	8.113976	0.0000
C(154)	0.110027	0.013922	7.903200	0.0000
C(155)	-0.112249	0.014665	-7.654109	0.0000
C(156)	-0.109032	0.015345	-7.105213	0.0000
C(157)	-0.174872	0.015573	-11.22898	0.0000
C(158)	-0.322397	0.016323	-19.75096	0.0000
C(159)	-0.024119	0.017055	-1.414238	0.1573
C(160)	-0.076632	0.017839	-4.295675	0.0000
C(161)	0.000103	0.000286	0.358488	0.7200
C(162)	0.313603	0.005105	61.43316	0.0000
C(163)	0.080714	0.009739	8.287274	0.0000
C(164)	0.258394	0.012864	20.08734	0.0000
C(165)	-0.360452	0.013550	-26.60109	0.0000
C(166)	-0.351377	0.014179	-24.78185	0.0000
C(167)	-0.082768	0.014389	-5.752037	0.0000

C(168)	-0.200247	0.015082	-13.27705	0.0000
C(169)	0.048858	0.015758	3.100491	0.0019
C(170)	0.211246	0.016483	12.81585	0.0000
C(171)	0.000198	0.000323	0.613529	0.5395
C(172)	0.213796	0.005764	37.09261	0.0000
C(173)	0.060403	0.010997	5.492755	0.0000
C(174)	-0.123404	0.014524	-8.496415	0.0000
C(175)	0.044131	0.015300	2.884403	0.0039
C(176)	0.148043	0.016009	9.247234	0.0000
C(177)	-0.203432	0.016247	-12.52107	0.0000
C(178)	0.279897	0.017029	16.43606	0.0000
C(179)	-0.312871	0.017793	-17.58422	0.0000
C(180)	-0.348748	0.018611	-18.73851	0.0000
C(181)	-0.000272	0.000334	-0.814287	0.4155
C(182)	0.178957	0.005962	30.01385	0.0000
C(183)	0.053846	0.011376	4.733357	0.0000
C(184)	-0.011782	0.015025	-0.784148	0.4330
C(185)	0.209839	0.015827	13.25834	0.0000
C(186)	0.137777	0.016561	8.319285	0.0000
C(187)	-0.065131	0.016807	-3.875238	0.0001
C(188)	0.199550	0.017616	11.32758	0.0000
C(189)	0.284825	0.018406	15.47470	0.0000
C(190)	-0.399761	0.019253	-20.76399	0.0000
C(191)	0.000334	0.000369	0.903670	0.3662
C(192)	0.221710	0.006590	33.64427	0.0000
C(193)	0.035970	0.012573	2.860974	0.0042
C(194)	0.107254	0.016606	6.458871	0.0000
C(195)	0.140309	0.017492	8.021212	0.0000
C(196)	0.136466	0.018304	7.455675	0.0000
C(197)	-0.071374	0.018575	-3.842386	0.0001
C(198)	0.011392	0.019470	0.585093	0.5585
C(199)	0.051382	0.020342	2.525838	0.0115
C(200)	-0.010589	0.021278	-0.497629	0.6187
C(201)	-6.35E-05	9.60E-05	-0.661640	0.5082
C(202)	0.278485	0.001712	162.6742	0.0000
C(203)	0.061667	0.003266	18.88038	0.0000
C(204)	0.055725	0.004314	12.91768	0.0000
C(205)	-0.271528	0.004544	-59.75304	0.0000
C(206)	0.553027	0.004755	116.3056	0.0000
C(207)	0.682432	0.004826	141.4203	0.0000
C(208)	-0.081255	0.005058	-16.06489	0.0000
C(209)	0.103866	0.005285	19.65449	0.0000
C(210)	0.061710	0.005528	11.16369	0.0000
C(211)	-0.000263	0.000242	-1.084743	0.2780
C(212)	0.228982	0.004318	53.02707	0.0000
C(213)	0.003136	0.008239	0.380669	0.7035
C(214)	-0.036193	0.010881	-3.326125	0.0009
C(215)	0.336151	0.011462	29.32645	0.0000
C(216)	-0.013054	0.011994	-1.088349	0.2764
C(217)	-0.154383	0.012172	-12.68323	0.0000
C(218)	0.259536	0.012758	20.34255	0.0000
C(219)	0.387151	0.013330	29.04336	0.0000
C(220)	0.508508	0.013943	36.46953	0.0000

Equation: PE_OLES_01=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4 +C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 1410

R-squared	0.999139	Mean dependent var	0.001028
Adjusted R-squared	0.999134	S.D. dependent var	0.029462
S.E. of regression	0.000867	Sum squared resid	0.001052
Durbin-Watson stat	1.919752		

Equation: KIMBERA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15) *PC4+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 1410

R-squared	0.274220	Mean dependent var	0.000209
Adjusted R-squared	0.269554	S.D. dependent var	0.015126
S.E. of regression	0.012928	Sum squared resid	0.233975
Durbin-Watson stat	1.864498		

Equation: BIMBOA=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)*PC4 +C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 1410

R-squared	0.427527	Mean dependent var	0.000650
Adjusted R-squared	0.423847	S.D. dependent var	0.018661
S.E. of regression	0.014165	Sum squared resid	0.280896
Durbin-Watson stat	1.903879		

Equation: GMODELOC=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35) *PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 1410

R-squared	0.284625	Mean dependent var	0.000384
Adjusted R-squared	0.280026	S.D. dependent var	0.015785
S.E. of regression	0.013394	Sum squared resid	0.251156
Durbin-Watson stat	1.997113		

Equation: FEMSAUBD=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45) *PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 1410

R-squared	0.443803	Mean dependent var	0.000500
Adjusted R-squared	0.440228	S.D. dependent var	0.017475
S.E. of regression	0.013074	Sum squared resid	0.239306
Durbin-Watson stat	1.836734		

Equation: CONTAL_01=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55) *PC4+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 1410

R-squared	0.969128	Mean dependent var	0.000405
Adjusted R-squared	0.968930	S.D. dependent var	0.021111
S.E. of regression	0.003721	Sum squared resid	0.019386
Durbin-Watson stat	1.909330		

Equation: CEMEXCP=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65) *PC4+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 1410

R-squared	0.411717	Mean dependent var	0.000771
Adjusted R-squared	0.407935	S.D. dependent var	0.016155
S.E. of regression	0.012430	Sum squared resid	0.216324
Durbin-Watson stat	1.858554		

Equation: GEOB=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)*PC4 +C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 1410

R-squared	0.976010	Mean dependent var	0.001662
Adjusted R-squared	0.975856	S.D. dependent var	0.024531
S.E. of regression	0.003812	Sum squared resid	0.020341
Durbin-Watson stat	1.968132		

Equation: ARA_01=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)*PC4
+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 1410

R-squared	0.454136	Mean dependent var	0.001007
Adjusted R-squared	0.450627	S.D. dependent var	0.018947
S.E. of regression	0.014044	Sum squared resid	0.276111
Durbin-Watson stat	1.960419		

Equation: WALMEXV=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 1410

R-squared	0.515032	Mean dependent var	0.000655
Adjusted R-squared	0.511914	S.D. dependent var	0.018733
S.E. of regression	0.013088	Sum squared resid	0.239802
Durbin-Watson stat	1.914680		

Equation: SORIANAB=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 1410

R-squared	0.502038	Mean dependent var	0.000171
Adjusted R-squared	0.498837	S.D. dependent var	0.018590
S.E. of regression	0.013160	Sum squared resid	0.242476
Durbin-Watson stat	1.930672		

Equation: COMERUBC=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 1410

R-squared	0.807360	Mean dependent var	0.000498
Adjusted R-squared	0.806122	S.D. dependent var	0.020444
S.E. of regression	0.009002	Sum squared resid	0.113446
Durbin-Watson stat	2.019104		

Equation: ELEKTRA_01=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 1410

R-squared	0.914502	Mean dependent var	0.000526
Adjusted R-squared	0.913952	S.D. dependent var	0.024465
S.E. of regression	0.007176	Sum squared resid	0.072101
Durbin-Watson stat	1.974622		

Equation: TELMEXL=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 1410

R-squared	0.596137	Mean dependent var	0.000215
Adjusted R-squared	0.593541	S.D. dependent var	0.015623
S.E. of regression	0.009960	Sum squared resid	0.138889
Durbin-Watson stat	1.999640		

Equation: TELECOA1=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 1410

R-squared	0.631576	Mean dependent var	0.000252
Adjusted R-squared	0.629208	S.D. dependent var	0.019538
S.E. of regression	0.011897	Sum squared resid	0.198163
Durbin-Watson stat	2.059508		

Equation: TLEVICPO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 1410

R-squared	0.722782	Mean dependent var	0.000171
Adjusted R-squared	0.721000	S.D. dependent var	0.021968
S.E. of regression	0.011603	Sum squared resid	0.188493
Durbin-Watson stat	2.012088		

Equation: TVAZTCPO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 1410

R-squared	0.808455	Mean dependent var	-7.68E-05
Adjusted R-squared	0.807224	S.D. dependent var	0.024418
S.E. of regression	0.010721	Sum squared resid	0.160923
Durbin-Watson stat	1.987663		

Equation: GFNORTEO=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 1410

R-squared	0.653504	Mean dependent var	0.001415
Adjusted R-squared	0.651276	S.D. dependent var	0.020499
S.E. of regression	0.012105	Sum squared resid	0.205159
Durbin-Watson stat	1.918338		

Equation: GFINBURO=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3
+C(185)*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8
+C(190)*PC9
Observations: 1410

R-squared	0.584412	Mean dependent var	0.000502
Adjusted R-squared	0.581741	S.D. dependent var	0.019363
S.E. of regression	0.012523	Sum squared resid	0.219542
Durbin-Watson stat	1.947898		

Equation: GCARSOA1=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3
+C(195)*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8
+C(200)*PC9
Observations: 1410

R-squared	0.484178	Mean dependent var	0.000711
Adjusted R-squared	0.480862	S.D. dependent var	0.019209
S.E. of regression	0.013840	Sum squared resid	0.268171
Durbin-Watson stat	1.909993		

Equation: ALFAA=C(201)+C(202)*PC1+C(203)*PC2+C(204)*PC3+C(205)
*PC4+C(206)*PC5+C(207)*PC6+C(208)*PC7+C(209)*PC8+C(210)
*PC9
Observations: 1410

R-squared	0.978721	Mean dependent var	0.000723
Adjusted R-squared	0.978584	S.D. dependent var	0.024569
S.E. of regression	0.003595	Sum squared resid	0.018098
Durbin-Watson stat	1.839195		

Equation: CIEB=C(211)+C(212)*PC1+C(213)*PC2+C(214)*PC3+C(215)
*PC4+C(216)*PC5+C(217)*PC6+C(218)*PC7+C(219)*PC8+C(220)
*PC9
Observations: 1410

R-squared	0.820211	Mean dependent var	-0.000376
Adjusted R-squared	0.819055	S.D. dependent var	0.021321
S.E. of regression	0.009069	Sum squared resid	0.115152
Durbin-Watson stat	1.915083		

Table 4. *Principal Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of daily excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.15E-05	2.37E-05	-0.483041	0.6291
C(2)	0.118079	0.000424	278.7032	0.0000
C(3)	-0.972958	0.000808	-1204.477	0.0000
C(4)	0.104142	0.001067	97.58214	0.0000
C(5)	-0.098391	0.001126	-87.39225	0.0000
C(6)	0.086144	0.001177	73.19011	0.0000
C(7)	-0.084324	0.001195	-70.57541	0.0000
C(8)	0.005527	0.001253	4.412357	0.0000
C(9)	-0.012651	0.001308	-9.669087	0.0000
C(10)	0.026767	0.001372	19.51193	0.0000
C(11)	-8.46E-06	0.000345	-0.024555	0.9804
C(12)	0.117683	0.006146	19.14706	0.0000
C(13)	-0.004750	0.011719	-0.405342	0.6852
C(14)	0.007423	0.015482	0.479438	0.6316
C(15)	0.181685	0.016333	11.12384	0.0000
C(16)	0.034709	0.017075	2.032771	0.0421
C(17)	-0.043325	0.017333	-2.499501	0.0124
C(18)	0.014334	0.018173	0.788745	0.4303
C(19)	-0.010684	0.018981	-0.562877	0.5735
C(20)	-0.116744	0.019902	-5.866092	0.0000
C(21)	0.000445	0.000378	1.176744	0.2393
C(22)	0.148554	0.006739	22.04282	0.0000
C(23)	-0.034117	0.012849	-2.655165	0.0079
C(24)	-0.014533	0.016976	-0.856097	0.3920
C(25)	0.231737	0.017909	12.93975	0.0000
C(26)	-0.013885	0.018722	-0.741630	0.4583
C(27)	0.154609	0.019006	8.134832	0.0000
C(28)	0.109080	0.019926	5.474109	0.0000
C(29)	-0.335570	0.020812	-16.12353	0.0000
C(30)	-0.133567	0.021822	-6.120823	0.0000
C(31)	4.94E-05	0.000357	0.138189	0.8901
C(32)	0.129964	0.006375	20.38700	0.0000
C(33)	-0.005979	0.012154	-0.491948	0.6228
C(34)	0.093587	0.016058	5.828015	0.0000
C(35)	0.080585	0.016940	4.756996	0.0000
C(36)	0.022776	0.017710	1.286096	0.1984
C(37)	-0.000220	0.017978	-0.012213	0.9903
C(38)	-0.064565	0.018849	-3.425414	0.0006
C(39)	0.170599	0.019687	8.665656	0.0000
C(40)	-0.005777	0.020642	-0.279868	0.7796
C(41)	0.000165	0.000349	0.473800	0.6356
C(42)	0.197273	0.006222	31.70675	0.0000
C(43)	0.049943	0.011863	4.210099	0.0000
C(44)	0.041920	0.015673	2.674723	0.0075
C(45)	0.036959	0.016534	2.235391	0.0254
C(46)	0.020576	0.017284	1.190427	0.2339
C(47)	-0.119149	0.017546	-6.790573	0.0000
C(48)	-0.090113	0.018396	-4.898451	0.0000
C(49)	0.045387	0.019214	2.362157	0.0182
C(50)	-0.069830	0.020146	-3.466192	0.0005
C(51)	-7.92E-05	9.80E-05	-0.807951	0.4191
C(52)	0.132031	0.001748	75.52996	0.0000

C(53)	-0.113837	0.003333	-34.15579	0.0000
C(54)	0.039342	0.004403	8.934584	0.0000
C(55)	0.516046	0.004645	111.0915	0.0000
C(56)	-0.519924	0.004856	-107.0641	0.0000
C(57)	0.517525	0.004930	104.9804	0.0000
C(58)	-0.212240	0.005169	-41.06371	0.0000
C(59)	0.158831	0.005398	29.42213	0.0000
C(60)	0.191227	0.005660	33.78472	0.0000
C(61)	0.000260	0.000331	0.783556	0.4333
C(62)	0.180710	0.005913	30.56267	0.0000
C(63)	0.022115	0.011273	1.961694	0.0498
C(64)	0.014048	0.014894	0.943173	0.3456
C(65)	0.037865	0.015712	2.409883	0.0160
C(66)	-0.005807	0.016426	-0.353538	0.7237
C(67)	-0.029204	0.016675	-1.751393	0.0799
C(68)	-0.040273	0.017483	-2.303591	0.0213
C(69)	0.073900	0.018260	4.047103	0.0001
C(70)	0.078389	0.019145	4.094384	0.0000
C(71)	1.05E-05	0.000102	0.102501	0.9184
C(72)	0.225912	0.001825	123.8159	0.0000
C(73)	-0.066407	0.003479	-19.08899	0.0000
C(74)	-0.888977	0.004596	-193.4211	0.0000
C(75)	-0.175217	0.004849	-36.13772	0.0000
C(76)	-0.117905	0.005069	-23.26107	0.0000
C(77)	0.015256	0.005146	2.964863	0.0030
C(78)	-0.204086	0.005395	-37.82996	0.0000
C(79)	-0.015031	0.005635	-2.667600	0.0076
C(80)	-0.113109	0.005908	-19.14531	0.0000
C(81)	-3.00E-05	0.000373	-0.080411	0.9359
C(82)	0.163461	0.006663	24.53223	0.0000
C(83)	-0.004470	0.012704	-0.351866	0.7249
C(84)	-0.199365	0.016784	-11.87813	0.0000
C(85)	0.074394	0.017706	4.201537	0.0000
C(86)	0.025915	0.018510	1.400008	0.1615
C(87)	-0.059798	0.018791	-3.182323	0.0015
C(88)	0.044059	0.019701	2.236377	0.0253
C(89)	-0.182403	0.020577	-8.864377	0.0000
C(90)	0.393722	0.021575	18.24899	0.0000
C(91)	0.000236	0.000349	0.675594	0.4993
C(92)	0.224583	0.006223	36.09174	0.0000
C(93)	0.025755	0.011864	2.170802	0.0300
C(94)	0.063868	0.015674	4.074668	0.0000
C(95)	0.062880	0.016536	3.802731	0.0001
C(96)	0.068832	0.017287	3.981826	0.0001
C(97)	-0.112600	0.017548	-6.416532	0.0000
C(98)	-0.159478	0.018398	-8.667989	0.0000
C(99)	0.101917	0.019217	5.303609	0.0000
C(100)	0.018598	0.020148	0.923052	0.3560
C(101)	-0.000135	0.000351	-0.385104	0.7002
C(102)	0.218870	0.006267	34.92329	0.0000
C(103)	0.015463	0.011949	1.294067	0.1957
C(104)	0.020838	0.015787	1.319968	0.1869
C(105)	0.085677	0.016654	5.144499	0.0000
C(106)	0.035730	0.017411	2.052191	0.0402
C(107)	-0.111448	0.017674	-6.305672	0.0000
C(108)	-0.021350	0.018530	-1.152165	0.2493
C(109)	0.102211	0.019354	5.281059	0.0000
C(110)	-0.197457	0.020293	-9.730357	0.0000

C(111)	-0.000132	0.000237	-0.556878	0.5776
C(112)	0.194981	0.004220	46.19991	0.0000
C(113)	-0.004605	0.008047	-0.572297	0.5671
C(114)	-0.051674	0.010631	-4.860672	0.0000
C(115)	0.103868	0.011215	9.261437	0.0000
C(116)	0.087896	0.011724	7.496849	0.0000
C(117)	0.095774	0.011902	8.046854	0.0000
C(118)	0.363958	0.012479	29.16662	0.0000
C(119)	0.642165	0.013033	49.27064	0.0000
C(120)	-0.303190	0.013665	-22.18659	0.0000
C(121)	-4.76E-05	0.000192	-0.248054	0.8041
C(122)	0.294716	0.003424	86.07976	0.0000
C(123)	0.034451	0.006528	5.277617	0.0000
C(124)	0.098407	0.008624	11.41034	0.0000
C(125)	-0.417046	0.009098	-45.83850	0.0000
C(126)	-0.414493	0.009511	-43.57875	0.0000
C(127)	0.136446	0.009655	14.13157	0.0000
C(128)	0.549216	0.010123	54.25339	0.0000
C(129)	-0.105643	0.010573	-9.991574	0.0000
C(130)	0.155258	0.011086	14.00484	0.0000
C(131)	-0.000158	0.000266	-0.594370	0.5523
C(132)	0.190680	0.004739	40.23689	0.0000
C(133)	0.039544	0.009035	4.376564	0.0000
C(134)	0.086025	0.011937	7.206409	0.0000
C(135)	0.036033	0.012593	2.861336	0.0042
C(136)	0.079554	0.013165	6.042837	0.0000
C(137)	-0.126301	0.013364	-9.450578	0.0000
C(138)	-0.209399	0.014012	-14.94445	0.0000
C(139)	0.029353	0.014635	2.005689	0.0449
C(140)	0.078784	0.015345	5.134362	0.0000
C(141)	-0.000239	0.000318	-0.752252	0.4519
C(142)	0.251431	0.005667	44.36884	0.0000
C(143)	0.044788	0.010805	4.145253	0.0000
C(144)	0.094781	0.014275	6.639805	0.0000
C(145)	0.077718	0.015059	5.160918	0.0000
C(146)	0.176687	0.015743	11.22334	0.0000
C(147)	-0.135186	0.015981	-8.459087	0.0000
C(148)	-0.188568	0.016755	-11.25417	0.0000
C(149)	-0.006760	0.017500	-0.386272	0.6993
C(150)	0.104312	0.018349	5.684886	0.0000
C(151)	-0.000200	0.000310	-0.646396	0.5180
C(152)	0.297497	0.005523	53.86584	0.0000
C(153)	0.085533	0.010530	8.122736	0.0000
C(154)	0.109895	0.013912	7.899210	0.0000
C(155)	-0.110632	0.014676	-7.538082	0.0000
C(156)	-0.103030	0.015343	-6.715103	0.0000
C(157)	-0.183195	0.015575	-11.76191	0.0000
C(158)	-0.319764	0.016330	-19.58154	0.0000
C(159)	0.021612	0.017056	1.267145	0.2051
C(160)	0.079015	0.017883	4.418439	0.0000
C(161)	8.53E-05	0.000286	0.297770	0.7659
C(162)	0.313559	0.005109	61.37423	0.0000
C(163)	0.083178	0.009741	8.539084	0.0000
C(164)	0.261388	0.012869	20.31089	0.0000
C(165)	-0.359072	0.013576	-26.44821	0.0000
C(166)	-0.347054	0.014193	-24.45248	0.0000
C(167)	-0.091471	0.014408	-6.348678	0.0000
C(168)	-0.204962	0.015106	-13.56835	0.0000

C(169)	-0.053859	0.015778	-3.413627	0.0006
C(170)	-0.204059	0.016543	-12.33528	0.0000
C(171)	0.000184	0.000321	0.574409	0.5657
C(172)	0.213831	0.005719	37.38998	0.0000
C(173)	0.060804	0.010904	5.576323	0.0000
C(174)	-0.127953	0.014406	-8.881953	0.0000
C(175)	0.039005	0.015197	2.566561	0.0103
C(176)	0.150508	0.015888	9.473353	0.0000
C(177)	-0.194530	0.016128	-12.06151	0.0000
C(178)	0.280767	0.016909	16.60411	0.0000
C(179)	0.317314	0.017661	17.96661	0.0000
C(180)	0.356557	0.018518	19.25483	0.0000
C(181)	-0.000251	0.000336	-0.745298	0.4561
C(182)	0.178692	0.006001	29.77830	0.0000
C(183)	0.053612	0.011441	4.685888	0.0000
C(184)	-0.010548	0.015116	-0.697849	0.4853
C(185)	0.211963	0.015946	13.29246	0.0000
C(186)	0.136967	0.016670	8.216219	0.0000
C(187)	-0.063631	0.016923	-3.760062	0.0002
C(188)	0.213966	0.017743	12.05941	0.0000
C(189)	-0.275140	0.018531	-14.84716	0.0000
C(190)	0.387564	0.019430	19.94646	0.0000
C(191)	0.000344	0.000369	0.931663	0.3515
C(192)	0.221816	0.006587	33.67530	0.0000
C(193)	0.038297	0.012559	3.049443	0.0023
C(194)	0.105070	0.016592	6.332478	0.0000
C(195)	0.140427	0.017504	8.022675	0.0000
C(196)	0.137694	0.018299	7.524764	0.0000
C(197)	-0.068860	0.018576	-3.706972	0.0002
C(198)	0.014821	0.019476	0.761019	0.4467
C(199)	-0.052385	0.020342	-2.575260	0.0100
C(200)	0.007832	0.021328	0.367222	0.7135
C(201)	-6.29E-05	9.55E-05	-0.658342	0.5103
C(202)	0.278381	0.001704	163.3238	0.0000
C(203)	0.061437	0.003250	18.90479	0.0000
C(204)	0.060906	0.004294	14.18543	0.0000
C(205)	-0.266147	0.004529	-58.75974	0.0000
C(206)	0.539109	0.004735	113.8533	0.0000
C(207)	0.694619	0.004807	144.5066	0.0000
C(208)	-0.091003	0.005040	-18.05722	0.0000
C(209)	-0.107861	0.005264	-20.49128	0.0000
C(210)	-0.049547	0.005519	-8.977395	0.0000
C(211)	-0.000221	0.000245	-0.902440	0.3668
C(212)	0.229171	0.004367	52.47897	0.0000
C(213)	0.005552	0.008326	0.666877	0.5049
C(214)	-0.041423	0.011000	-3.765663	0.0002
C(215)	0.332039	0.011604	28.61302	0.0000
C(216)	-0.012116	0.012132	-0.998720	0.3179
C(217)	-0.149154	0.012315	-12.11135	0.0000
C(218)	0.261816	0.012912	20.27720	0.0000
C(219)	-0.390327	0.013486	-28.94330	0.0000
C(220)	-0.502186	0.014140	-35.51546	0.0000

Equation: PE_OLES_01=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 1410

R-squared	0.999095	Mean dependent var	0.000805
Adjusted R-squared	0.999089	S.D. dependent var	0.029496
S.E. of regression	0.000890	Sum squared resid	0.001110
Durbin-Watson stat	1.916113		

Equation: KIMBERA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)
*PC4+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 1410

R-squared	0.275613	Mean dependent var	-1.66E-05
Adjusted R-squared	0.270956	S.D. dependent var	0.015126
S.E. of regression	0.012915	Sum squared resid	0.233508
Durbin-Watson stat	1.868259		

Equation: BIMBOA=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)*PC4
+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 1410

R-squared	0.428045	Mean dependent var	0.000397
Adjusted R-squared	0.424368	S.D. dependent var	0.018665
S.E. of regression	0.014161	Sum squared resid	0.280744
Durbin-Watson stat	1.904802		

Equation: GMODELOC=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 1410

R-squared	0.284637	Mean dependent var	0.000143
Adjusted R-squared	0.280038	S.D. dependent var	0.015787
S.E. of regression	0.013395	Sum squared resid	0.251197
Durbin-Watson stat	1.997184		

Equation: FEMSAUBD=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 1410

R-squared	0.443636	Mean dependent var	0.000231
Adjusted R-squared	0.440059	S.D. dependent var	0.017471
S.E. of regression	0.013073	Sum squared resid	0.239280
Durbin-Watson stat	1.841278		

Equation: CONTAL_01=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)
*PC4+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 1410

R-squared	0.969923	Mean dependent var	0.000161
Adjusted R-squared	0.969729	S.D. dependent var	0.021112
S.E. of regression	0.003673	Sum squared resid	0.018888
Durbin-Watson stat	1.911017		

Equation: CEMEXCP=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)
*PC4+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 1410

R-squared	0.411584	Mean dependent var	0.000550
Adjusted R-squared	0.407801	S.D. dependent var	0.016145
S.E. of regression	0.012424	Sum squared resid	0.216102
Durbin-Watson stat	1.862335		

Equation: GEOB=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)*PC4
+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 1410

R-squared	0.975764	Mean dependent var	0.001474
Adjusted R-squared	0.975608	S.D. dependent var	0.024548
S.E. of regression	0.003834	Sum squared resid	0.020578
Durbin-Watson stat	1.969803		

Equation: ARA_01=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)*PC4
+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 1410

R-squared	0.457565	Mean dependent var	0.000797
Adjusted R-squared	0.454078	S.D. dependent var	0.018949
S.E. of regression	0.014001	Sum squared resid	0.274429
Durbin-Watson stat	1.959397		

Equation: WALMEXV=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 1410

R-squared	0.515386	Mean dependent var	0.000450
Adjusted R-squared	0.512270	S.D. dependent var	0.018722
S.E. of regression	0.013075	Sum squared resid	0.239338
Durbin-Watson stat	1.919344		

Equation: SORIANAB=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 1410

R-squared	0.501307	Mean dependent var	-8.42E-05
Adjusted R-squared	0.498101	S.D. dependent var	0.018588
S.E. of regression	0.013169	Sum squared resid	0.242783
Durbin-Watson stat	1.931736		

Equation: COMERUBC=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 1410

R-squared	0.813137	Mean dependent var	0.000260
Adjusted R-squared	0.811936	S.D. dependent var	0.020449
S.E. of regression	0.008868	Sum squared resid	0.110098
Durbin-Watson stat	2.022106		

Equation: ELEKTRA_01=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 1410

R-squared	0.914114	Mean dependent var	0.000287
Adjusted R-squared	0.913562	S.D. dependent var	0.024469
S.E. of regression	0.007194	Sum squared resid	0.072457
Durbin-Watson stat	1.978284		

Equation: TELMEXL=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 1410

R-squared	0.595737	Mean dependent var	-1.50E-07
Adjusted R-squared	0.593139	S.D. dependent var	0.015611
S.E. of regression	0.009958	Sum squared resid	0.138815
Durbin-Watson stat	2.005761		

Equation: TELECOA1=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 1410

R-squared	0.631193	Mean dependent var	2.74E-05
Adjusted R-squared	0.628823	S.D. dependent var	0.019544
S.E. of regression	0.011907	Sum squared resid	0.198499
Durbin-Watson stat	2.061218		

Equation: TLEVICPO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 1410

R-squared	0.722699	Mean dependent var	-5.84E-05
Adjusted R-squared	0.720916	S.D. dependent var	0.021967
S.E. of regression	0.011605	Sum squared resid	0.188544
Durbin-Watson stat	2.014552		

Equation: TVAZTCPO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 1410

R-squared	0.808108	Mean dependent var	-0.000324
Adjusted R-squared	0.806875	S.D. dependent var	0.024428
S.E. of regression	0.010735	Sum squared resid	0.161340
Durbin-Watson stat	1.988435		

Equation: GFNORTEO=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 1410

R-squared	0.658517	Mean dependent var	0.001169
Adjusted R-squared	0.656322	S.D. dependent var	0.020498
S.E. of regression	0.012017	Sum squared resid	0.202166
Durbin-Watson stat	1.923406		

Equation: GFINBURO=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3
+C(185)*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8
+C(190)*PC9
Observations: 1410

R-squared	0.578003	Mean dependent var	0.000276
Adjusted R-squared	0.575290	S.D. dependent var	0.019348
S.E. of regression	0.012609	Sum squared resid	0.222579
Durbin-Watson stat	1.958173		

Equation: GCARSOA1=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3
+C(195)*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8
+C(200)*PC9
Observations: 1410

R-squared	0.484555	Mean dependent var	0.000455
Adjusted R-squared	0.481241	S.D. dependent var	0.019216
S.E. of regression	0.013841	Sum squared resid	0.268186
Durbin-Watson stat	1.910104		

Equation: ALFAA=C(201)+C(202)*PC1+C(203)*PC2+C(204)*PC3+C(205)
*PC4+C(206)*PC5+C(207)*PC6+C(208)*PC7+C(209)*PC8+C(210)
*PC9
Observations: 1410

R-squared	0.978882	Mean dependent var	0.000496
Adjusted R-squared	0.978746	S.D. dependent var	0.024567
S.E. of regression	0.003581	Sum squared resid	0.017958
Durbin-Watson stat	1.837752		

Equation: CIEB=C(211)+C(212)*PC1+C(213)*PC2+C(214)*PC3+C(215)
*PC4+C(216)*PC5+C(217)*PC6+C(218)*PC7+C(219)*PC8+C(220)
*PC9
Observations: 1410

R-squared	0.815813	Mean dependent var	-0.000633
Adjusted R-squared	0.814629	S.D. dependent var	0.021312
S.E. of regression	0.009176	Sum squared resid	0.117876
Durbin-Watson stat	1.915608		

Table 5. *Factor Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of weekly returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.002221	0.003370	0.658880	0.5100
C(2)	0.009629	0.003296	2.921327	0.0035
C(3)	0.004203	0.003165	1.328025	0.1842
C(4)	0.008389	0.002830	2.964347	0.0030
C(5)	0.003289	0.003290	0.999590	0.3176
C(6)	-0.002067	0.003286	-0.629004	0.5294
C(7)	0.015692	0.002544	6.167879	0.0000
C(8)	-0.007586	0.002336	-3.247802	0.0012
C(9)	0.013560	0.002033	6.670244	0.0000
C(10)	-0.006778	0.001923	-3.524531	0.0004
C(11)	0.004100	0.001961	2.091487	0.0365
C(12)	0.009749	0.001917	5.084560	0.0000
C(13)	0.009747	0.001841	5.293852	0.0000
C(14)	0.001816	0.001646	1.103182	0.2700
C(15)	0.007814	0.001914	4.082051	0.0000
C(16)	0.001202	0.001911	0.628652	0.5296
C(17)	-0.004691	0.001480	-3.169851	0.0015
C(18)	-0.002888	0.001359	-2.125499	0.0336
C(19)	0.011802	0.001183	9.980128	0.0000
C(20)	-0.002531	0.001119	-2.262370	0.0237
C(21)	4.67E-06	2.57E-06	1.818372	0.0691
C(22)	0.021039	2.51E-06	8373.642	0.0000
C(23)	-0.000397	2.41E-06	-164.3519	0.0000
C(24)	-1.45E-05	2.16E-06	-6.717644	0.0000
C(25)	-0.023029	2.51E-06	-9180.697	0.0000
C(26)	-0.007402	2.50E-06	-2955.204	0.0000
C(27)	2.84E-05	1.94E-06	14.64745	0.0000
C(28)	-1.69E-05	1.78E-06	-9.519070	0.0000
C(29)	3.15E-06	1.55E-06	2.035356	0.0419
C(30)	-7.83E-06	1.47E-06	-5.340861	0.0000
C(31)	-0.000217	0.001479	-0.146653	0.8834
C(32)	0.019823	0.001447	13.70216	0.0000
C(33)	0.013886	0.001389	9.995613	0.0000
C(34)	0.014335	0.001242	11.53993	0.0000
C(35)	0.000535	0.001444	0.370313	0.7112
C(36)	0.000828	0.001442	0.573856	0.5661
C(37)	-0.006752	0.001117	-6.046145	0.0000
C(38)	0.007700	0.001025	7.510409	0.0000
C(39)	0.006005	0.000892	6.729579	0.0000
C(40)	0.001701	0.000844	2.015154	0.0439
C(41)	0.000660	0.002066	0.319447	0.7494
C(42)	0.012749	0.002020	6.310967	0.0000
C(43)	0.004389	0.001940	2.262388	0.0237
C(44)	0.008250	0.001735	4.756285	0.0000
C(45)	0.003650	0.002017	1.809814	0.0704
C(46)	-0.000274	0.002014	-0.135881	0.8919
C(47)	2.72E-05	0.001559	0.017423	0.9861
C(48)	-0.003368	0.001432	-2.352827	0.0187
C(49)	0.011949	0.001246	9.589986	0.0000
C(50)	0.003770	0.001179	3.198673	0.0014
C(51)	-0.000302	0.000817	-0.369172	0.7120
C(52)	0.023693	0.000799	29.63701	0.0000

C(53)	0.010908	0.000768	14.20968	0.0000
C(54)	0.030054	0.000686	43.78173	0.0000
C(55)	0.007289	0.000798	9.133325	0.0000
C(56)	0.009365	0.000797	11.75030	0.0000
C(57)	0.029412	0.000617	47.66116	0.0000
C(58)	-0.001585	0.000567	-2.797047	0.0052
C(59)	-0.004425	0.000493	-8.973353	0.0000
C(60)	-0.008015	0.000466	-17.18329	0.0000
C(61)	0.001396	0.001908	0.731857	0.4643
C(62)	0.012591	0.001866	6.747648	0.0000
C(63)	0.010341	0.001792	5.771237	0.0000
C(64)	0.009801	0.001602	6.117523	0.0000
C(65)	0.005938	0.001863	3.187864	0.0014
C(66)	-0.001875	0.001860	-1.007819	0.3136
C(67)	0.007792	0.001440	5.409764	0.0000
C(68)	-0.002889	0.001322	-2.184757	0.0289
C(69)	0.003796	0.001151	3.298048	0.0010
C(70)	0.003231	0.001089	2.968300	0.0030
C(71)	0.000873	0.001210	0.721354	0.4707
C(72)	0.019203	0.001183	16.23024	0.0000
C(73)	0.012218	0.001136	10.75413	0.0000
C(74)	0.008153	0.001016	8.025684	0.0000
C(75)	0.002408	0.001181	2.039066	0.0415
C(76)	0.004630	0.001180	3.925315	0.0001
C(77)	-0.005041	0.000913	-5.520199	0.0000
C(78)	0.015460	0.000838	18.43860	0.0000
C(79)	-0.001604	0.000730	-2.197994	0.0280
C(80)	-0.000659	0.000690	-0.954331	0.3400
C(81)	-0.000864	0.001609	-0.536992	0.5913
C(82)	0.025828	0.001574	16.41384	0.0000
C(83)	0.009555	0.001511	6.323722	0.0000
C(84)	0.009876	0.001351	7.309500	0.0000
C(85)	0.003841	0.001571	2.445240	0.0145
C(86)	0.001350	0.001569	0.860402	0.3896
C(87)	-0.006021	0.001215	-4.956970	0.0000
C(88)	0.001045	0.001115	0.937460	0.3486
C(89)	-0.008807	0.000971	-9.074307	0.0000
C(90)	-0.002127	0.000918	-2.316504	0.0206
C(91)	-4.84E-06	4.04E-06	-1.198742	0.2307
C(92)	0.033530	3.95E-06	8483.676	0.0000
C(93)	-0.000911	3.80E-06	-239.9798	0.0000
C(94)	-0.000259	3.39E-06	-76.39801	0.0000
C(95)	0.023501	3.95E-06	5956.176	0.0000
C(96)	-0.019347	3.94E-06	-4910.006	0.0000
C(97)	5.19E-05	3.05E-06	17.02638	0.0000
C(98)	2.67E-05	2.80E-06	9.521014	0.0000
C(99)	-5.71E-06	2.44E-06	-2.343685	0.0191
C(100)	-2.32E-05	2.31E-06	-10.05051	0.0000
C(101)	-0.002216	0.001895	-1.169688	0.2422
C(102)	0.032444	0.001853	17.50861	0.0000
C(103)	0.009432	0.001779	5.300856	0.0000
C(104)	0.008058	0.001591	5.064297	0.0000
C(105)	0.005220	0.001850	2.821536	0.0048
C(106)	0.011134	0.001847	6.026982	0.0000
C(107)	0.009093	0.001430	6.357332	0.0000
C(108)	-0.000512	0.001313	-0.389648	0.6968
C(109)	0.006245	0.001143	5.463822	0.0000
C(110)	0.014227	0.001081	13.15910	0.0000

C(111)	0.000344	0.001019	0.338076	0.7353
C(112)	0.017544	0.000996	17.61132	0.0000
C(113)	0.020703	0.000957	21.64313	0.0000
C(114)	-0.003978	0.000855	-4.650150	0.0000
C(115)	0.000488	0.000994	0.490262	0.6240
C(116)	0.002824	0.000993	2.843508	0.0045
C(117)	-0.000627	0.000769	-0.815807	0.4146
C(118)	0.002124	0.000706	3.008751	0.0026
C(119)	0.000251	0.000614	0.407947	0.6833
C(120)	-0.002132	0.000581	-3.667679	0.0002
C(121)	-0.000237	0.000290	-0.817097	0.4139
C(122)	0.022022	0.000283	77.76472	0.0000
C(123)	0.035284	0.000272	129.7543	0.0000
C(124)	-0.008214	0.000243	-33.77911	0.0000
C(125)	0.000758	0.000283	2.680442	0.0074
C(126)	0.001975	0.000282	6.996105	0.0000
C(127)	0.002018	0.000219	9.230564	0.0000
C(128)	-0.001889	0.000201	-9.412253	0.0000
C(129)	-0.000136	0.000175	-0.780405	0.4352
C(130)	-0.000471	0.000165	-2.853075	0.0043
C(131)	-0.001408	0.001300	-1.082509	0.2791
C(132)	0.028704	0.001272	22.57176	0.0000
C(133)	0.017759	0.001221	14.54305	0.0000
C(134)	0.008797	0.001092	8.056603	0.0000
C(135)	0.002722	0.001270	2.144120	0.0321
C(136)	0.007136	0.001268	5.628798	0.0000
C(137)	-0.003890	0.000982	-3.962752	0.0001
C(138)	0.012450	0.000901	13.81527	0.0000
C(139)	0.004494	0.000784	5.729076	0.0000
C(140)	-0.004526	0.000742	-6.099710	0.0000
C(141)	1.08E-05	9.05E-06	1.190237	0.2340
C(142)	0.043241	8.85E-06	4883.686	0.0000
C(143)	-0.001596	8.50E-06	-187.7504	0.0000
C(144)	-0.000411	7.60E-06	-54.09975	0.0000
C(145)	0.005152	8.84E-06	582.8812	0.0000
C(146)	0.029489	8.83E-06	3340.766	0.0000
C(147)	-1.20E-05	6.83E-06	-1.760493	0.0784
C(148)	-7.87E-05	6.27E-06	-12.53579	0.0000
C(149)	-9.33E-06	5.46E-06	-1.708372	0.0876
C(150)	-3.39E-05	5.17E-06	-6.563199	0.0000
C(151)	0.003265	0.001805	1.809327	0.0705
C(152)	0.020388	0.001765	11.55238	0.0000
C(153)	0.009793	0.001695	5.778867	0.0000
C(154)	0.010042	0.001515	6.626957	0.0000
C(155)	0.004801	0.001762	2.725127	0.0064
C(156)	0.001086	0.001759	0.617076	0.5372
C(157)	0.001053	0.001362	0.772613	0.4398
C(158)	0.002760	0.001251	2.206457	0.0274
C(159)	-0.009402	0.001089	-8.637762	0.0000
C(160)	0.004587	0.001030	4.454424	0.0000
C(161)	0.000571	0.001736	0.329089	0.7421
C(162)	0.014630	0.001698	8.615494	0.0000
C(163)	0.016462	0.001631	10.09538	0.0000
C(164)	0.012985	0.001458	8.905013	0.0000
C(165)	0.006573	0.001695	3.877224	0.0001
C(166)	0.000535	0.001693	0.316043	0.7520
C(167)	-0.003244	0.001311	-2.474635	0.0134
C(168)	-0.006876	0.001203	-5.714186	0.0000

C(169)	-0.005041	0.001047	-4.812971	0.0000
C(170)	0.001921	0.000991	1.938723	0.0526
C(171)	0.001016	0.001425	0.713183	0.4758
C(172)	0.023859	0.001394	17.11768	0.0000
C(173)	0.019062	0.001338	14.24251	0.0000
C(174)	0.004728	0.001197	3.950414	0.0001
C(175)	0.002876	0.001391	2.066731	0.0388
C(176)	0.002349	0.001390	1.690689	0.0910
C(177)	-0.005364	0.001076	-4.985677	0.0000
C(178)	-0.001397	0.000988	-1.414485	0.1573
C(179)	-0.005880	0.000860	-6.839766	0.0000
C(180)	0.009357	0.000813	11.50566	0.0000
C(181)	-0.002110	0.002424	-0.870543	0.3840
C(182)	0.030779	0.002370	12.98487	0.0000
C(183)	0.014388	0.002276	6.321354	0.0000
C(184)	0.013717	0.002035	6.739669	0.0000
C(185)	0.004327	0.002366	1.828715	0.0675
C(186)	0.003554	0.002363	1.503894	0.1327
C(187)	0.004867	0.001830	2.659870	0.0078
C(188)	0.000977	0.001680	0.581438	0.5610
C(189)	0.004957	0.001462	3.390454	0.0007
C(190)	0.014523	0.001383	10.50145	0.0000
C(191)	-0.000940	0.000782	-1.201902	0.2295
C(192)	0.027029	0.000765	35.32056	0.0000
C(193)	0.012200	0.000735	16.60216	0.0000
C(194)	0.019444	0.000657	29.59181	0.0000
C(195)	0.006150	0.000764	8.050093	0.0000
C(196)	0.000869	0.000763	1.139597	0.2545
C(197)	-0.016698	0.000591	-28.26883	0.0000
C(198)	-0.014130	0.000542	-26.05603	0.0000
C(199)	0.001197	0.000472	2.536413	0.0112
C(200)	-0.004561	0.000446	-10.21661	0.0000

Equation: PE_OLES_01=C(1)+C(2)*F1+C(3)*F2+C(4)*F3+C(5)*F4+C(6)*F5 +C(7)*F6+C(8)*F7+C(9)*F8+C(10)*F9

Observations: 291

R-squared	0.302134	Mean dependent var	0.004729
Adjusted R-squared	0.279782	S.D. dependent var	0.067404
S.E. of regression	0.057203	Sum squared resid	0.919475
Durbin-Watson stat	1.944887		

Equation: BIMBOA=C(11)+C(12)*F1+C(13)*F2+C(14)*F3+C(15)*F4+C(16) *F5+C(17)*F6+C(18)*F7+C(19)*F8+C(20)*F9

Observations: 291

R-squared	0.396816	Mean dependent var	0.003161
Adjusted R-squared	0.377497	S.D. dependent var	0.042175
S.E. of regression	0.033276	Sum squared resid	0.311142
Durbin-Watson stat	2.016096		

Equation: GMODELOC=C(21)+C(22)*F1+C(23)*F2+C(24)*F3+C(25)*F4 +C(26)*F5+C(27)*F6+C(28)*F7+C(29)*F8+C(30)*F9

Observations: 291

R-squared	0.999998	Mean dependent var	0.001865
Adjusted R-squared	0.999998	S.D. dependent var	0.032142
S.E. of regression	4.36E-05	Sum squared resid	5.34E-07
Durbin-Watson stat	2.065627		

Equation: FEMSAUBD=C(31)+C(32)*F1+C(33)*F2+C(34)*F3+C(35)*F4
+C(36)*F5+C(37)*F6+C(38)*F7+C(39)*F8+C(40)*F9
Observations: 291

R-squared	0.659493	Mean dependent var	0.002358
Adjusted R-squared	0.648587	S.D. dependent var	0.042355
S.E. of regression	0.025108	Sum squared resid	0.177148
Durbin-Watson stat	2.299263		

Equation: CONTAL_01=C(41)+C(42)*F1+C(43)*F2+C(44)*F3+C(45)*F4
+C(46)*F5+C(47)*F6+C(48)*F7+C(49)*F8+C(50)*F9
Observations: 291

R-squared	0.380321	Mean dependent var	0.002039
Adjusted R-squared	0.360474	S.D. dependent var	0.043841
S.E. of regression	0.035060	Sum squared resid	0.345406
Durbin-Watson stat	2.113680		

Equation: GEOB=C(51)+C(52)*F1+C(53)*F2+C(54)*F3+C(55)*F4+C(56)*F5
+C(57)*F6+C(58)*F7+C(59)*F8+C(60)*F9
Observations: 291

R-squared	0.952796	Mean dependent var	0.008191
Adjusted R-squared	0.951285	S.D. dependent var	0.062862
S.E. of regression	0.013875	Sum squared resid	0.054095
Durbin-Watson stat	2.099735		

Equation: ARA_01=C(61)+C(62)*F1+C(63)*F2+C(64)*F3+C(65)*F4+C(66)
*F5+C(67)*F6+C(68)*F7+C(69)*F8+C(70)*F9
Observations: 291

R-squared	0.383692	Mean dependent var	0.004898
Adjusted R-squared	0.363953	S.D. dependent var	0.040605
S.E. of regression	0.032383	Sum squared resid	0.294679
Durbin-Watson stat	2.136564		

Equation: WALMEXV=C(71)+C(72)*F1+C(73)*F2+C(74)*F3+C(75)*F4
+C(76)*F5+C(77)*F6+C(78)*F7+C(79)*F8+C(80)*F9
Observations: 291

R-squared	0.742534	Mean dependent var	0.003334
Adjusted R-squared	0.734288	S.D. dependent var	0.039835
S.E. of regression	0.020534	Sum squared resid	0.118479
Durbin-Watson stat	2.361338		

Equation: SORIANAB=C(81)+C(82)*F1+C(83)*F2+C(84)*F3+C(85)*F4
+C(86)*F5+C(87)*F6+C(88)*F7+C(89)*F8+C(90)*F9
Observations: 291

R-squared	0.623891	Mean dependent var	0.000746
Adjusted R-squared	0.611845	S.D. dependent var	0.043833
S.E. of regression	0.027309	Sum squared resid	0.209562
Durbin-Watson stat	2.271616		

Equation: COMERUBC=C(91)+C(92)*F1+C(93)*F2+C(94)*F3+C(95)*F4
+C(96)*F5+C(97)*F6+C(98)*F7+C(99)*F8+C(100)*F9
Observations: 291

R-squared	0.999998	Mean dependent var	0.002256
Adjusted R-squared	0.999998	S.D. dependent var	0.045411
S.E. of regression	6.86E-05	Sum squared resid	1.32E-06
Durbin-Watson stat	2.113368		

Equation: ELEKTRA_01=C(101)+C(102)*F1+C(103)*F2+C(104)*F3+C(105)
*F4+C(106)*F5+C(107)*F6+C(108)*F7+C(109)*F8+C(110)*F9
Observations: 291

R-squared	0.690151	Mean dependent var	0.002654
Adjusted R-squared	0.680227	S.D. dependent var	0.056871
S.E. of regression	0.032160	Sum squared resid	0.290628
Durbin-Watson stat	2.145126		

Equation: TELMEXL=C(111)+C(112)*F1+C(113)*F2+C(114)*F3+C(115)*F4 +C(116)*F5+C(117)*F6+C(118)*F7+C(119)*F8+C(120)*F9

Observations: 291

R-squared	0.740843	Mean dependent var	0.001198
Adjusted R-squared	0.732542	S.D. dependent var	0.033430
S.E. of regression	0.017289	Sum squared resid	0.083991
Durbin-Watson stat	2.244640		

Equation: TELECOA1=C(121)+C(122)*F1+C(123)*F2+C(124)*F3+C(125) *F4+C(126)*F5+C(127)*F6+C(128)*F7+C(129)*F8+C(130)*F9

Observations: 291

R-squared	0.988149	Mean dependent var	0.001320
Adjusted R-squared	0.987769	S.D. dependent var	0.044440
S.E. of regression	0.004915	Sum squared resid	0.006787
Durbin-Watson stat	2.308975		

Equation: TLEVICPO=C(131)+C(132)*F1+C(133)*F2+C(134)*F3+C(135) *F4+C(136)*F5+C(137)*F6+C(138)*F7+C(139)*F8+C(140)*F9

Observations: 291

R-squared	0.790613	Mean dependent var	0.000899
Adjusted R-squared	0.783906	S.D. dependent var	0.047478
S.E. of regression	0.022071	Sum squared resid	0.136878
Durbin-Watson stat	2.112495		

Equation: TVAZTCPO=C(141)+C(142)*F1+C(143)*F2+C(144)*F3+C(145) *F4+C(146)*F5+C(147)*F6+C(148)*F7+C(149)*F8+C(150)*F9

Observations: 291

R-squared	0.999992	Mean dependent var	-0.000334
Adjusted R-squared	0.999992	S.D. dependent var	0.052751
S.E. of regression	0.000154	Sum squared resid	6.64E-06
Durbin-Watson stat	2.064724		

Equation: GFNORTEO=C(151)+C(152)*F1+C(153)*F2+C(154)*F3+C(155) *F4+C(156)*F5+C(157)*F6+C(158)*F7+C(159)*F8+C(160)*F9

Observations: 291

R-squared	0.522555	Mean dependent var	0.006851
Adjusted R-squared	0.507263	S.D. dependent var	0.043634
S.E. of regression	0.030629	Sum squared resid	0.263619
Durbin-Watson stat	2.179748		

Equation: GFINBURO=C(161)+C(162)*F1+C(163)*F2+C(164)*F3+C(165) *F4+C(166)*F5+C(167)*F6+C(168)*F7+C(169)*F8+C(170)*F9

Observations: 291

R-squared	0.536088	Mean dependent var	0.002456
Adjusted R-squared	0.521230	S.D. dependent var	0.042593
S.E. of regression	0.029472	Sum squared resid	0.244070
Durbin-Watson stat	2.210548		

Equation: GCARSOA1=C(171)+C(172)*F1+C(173)*F2+C(174)*F3+C(175) *F4+C(176)*F5+C(177)*F6+C(178)*F7+C(179)*F8+C(180)*F9

Observations: 291

R-squared	0.713476	Mean dependent var	0.003413
Adjusted R-squared	0.704299	S.D. dependent var	0.044485
S.E. of regression	0.024190	Sum squared resid	0.164432
Durbin-Watson stat	2.161129		

Equation: ALFAA=C(181)+C(182)*F1+C(183)*F2+C(184)*F3+C(185)*F4 +C(186)*F5+C(187)*F6+C(188)*F7+C(189)*F8+C(190)*F9

Observations: 291

R-squared	0.571923	Mean dependent var	0.003559
Adjusted R-squared	0.558212	S.D. dependent var	0.061893
S.E. of regression	0.041138	Sum squared resid	0.475554
Durbin-Watson stat	2.245936		

Equation: CIEB=C(191)+C(192)*F1+C(193)*F2+C(194)*F3+C(195)*F4
+C(196)*F5+C(197)*F6+C(198)*F7+C(199)*F8+C(200)*F9
Observations: 291

R-squared	0.933024	Mean dependent var	-0.001948
Adjusted R-squared	0.930878	S.D. dependent var	0.050515
S.E. of regression	0.013281	Sum squared resid	0.049563
Durbin-Watson stat	2.062797		

Table 6. *Factor Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of weekly excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.001642	0.003356	0.489405	0.6246
C(2)	0.009858	0.003296	2.990897	0.0028
C(3)	0.004299	0.003163	1.358862	0.1742
C(4)	0.008548	0.002828	3.022641	0.0025
C(5)	0.003281	0.003291	0.997156	0.3187
C(6)	-0.002085	0.003286	-0.634602	0.5257
C(7)	0.015826	0.002541	6.228713	0.0000
C(8)	-0.007313	0.002333	-3.134575	0.0017
C(9)	0.013530	0.002033	6.654278	0.0000
C(10)	-0.006844	0.001922	-3.560022	0.0004
C(11)	0.003321	0.001951	1.701886	0.0888
C(12)	0.009862	0.001916	5.146104	0.0000
C(13)	0.009772	0.001839	5.312826	0.0000
C(14)	0.001756	0.001644	1.067713	0.2857
C(15)	0.007845	0.001913	4.100498	0.0000
C(16)	0.001225	0.001910	0.641174	0.5214
C(17)	-0.004592	0.001477	-3.108293	0.0019
C(18)	-0.002983	0.001356	-2.199186	0.0279
C(19)	0.011817	0.001182	9.996664	0.0000
C(20)	-0.002588	0.001118	-2.315798	0.0206
C(21)	3.65E-06	2.57E-06	1.421095	0.1553
C(22)	0.021115	2.52E-06	8362.753	0.0000
C(23)	-0.000393	2.42E-06	-162.2875	0.0000
C(24)	-1.39E-05	2.17E-06	-6.420674	0.0000
C(25)	-0.022994	2.52E-06	-9122.257	0.0000
C(26)	-0.007401	2.52E-06	-2940.407	0.0000
C(27)	2.82E-05	1.95E-06	14.46996	0.0000
C(28)	-1.64E-05	1.79E-06	-9.198750	0.0000
C(29)	3.13E-06	1.56E-06	2.012007	0.0443
C(30)	-7.89E-06	1.47E-06	-5.359486	0.0000
C(31)	-3.06E-05	0.001474	-0.020727	0.9835
C(32)	0.019924	0.001448	13.76253	0.0000
C(33)	0.013974	0.001389	10.05726	0.0000
C(34)	0.014234	0.001242	11.45917	0.0000
C(35)	0.000564	0.001445	0.389955	0.6966
C(36)	0.000844	0.001443	0.584927	0.5586
C(37)	-0.006993	0.001116	-6.266294	0.0000
C(38)	0.007491	0.001025	7.310823	0.0000
C(39)	0.006016	0.000893	6.736366	0.0000
C(40)	0.001689	0.000844	2.000857	0.0455
C(41)	0.000160	0.002055	0.077683	0.9381
C(42)	0.012794	0.002018	6.338714	0.0000
C(43)	0.004409	0.001937	2.276063	0.0229
C(44)	0.008226	0.001732	4.749781	0.0000
C(45)	0.003703	0.002015	1.837514	0.0662
C(46)	-0.000234	0.002012	-0.116065	0.9076
C(47)	6.12E-05	0.001556	0.039316	0.9686
C(48)	-0.003416	0.001429	-2.391244	0.0168
C(49)	0.011954	0.001245	9.600817	0.0000
C(50)	0.003733	0.001177	3.171342	0.0015
C(51)	-0.000121	0.000817	-0.148575	0.8819

C(52)	0.023950	0.000802	29.85186	0.0000
C(53)	0.011092	0.000770	14.40466	0.0000
C(54)	0.030303	0.000688	44.02075	0.0000
C(55)	0.007260	0.000801	9.063803	0.0000
C(56)	0.009337	0.000800	11.67326	0.0000
C(57)	0.029144	0.000618	47.12186	0.0000
C(58)	-0.001189	0.000568	-2.093182	0.0364
C(59)	-0.004471	0.000495	-9.033512	0.0000
C(60)	-0.007997	0.000468	-17.09014	0.0000
C(61)	0.000872	0.001899	0.458958	0.6463
C(62)	0.012694	0.001865	6.805739	0.0000
C(63)	0.010403	0.001790	5.811481	0.0000
C(64)	0.009826	0.001600	6.140238	0.0000
C(65)	0.005973	0.001862	3.207662	0.0013
C(66)	-0.001852	0.001859	-0.995767	0.3194
C(67)	0.007799	0.001438	5.424460	0.0000
C(68)	-0.002856	0.001320	-2.163507	0.0305
C(69)	0.003767	0.001151	3.274222	0.0011
C(70)	0.003180	0.001088	2.923198	0.0035
C(71)	0.000575	0.001200	0.478684	0.6322
C(72)	0.019255	0.001179	16.33355	0.0000
C(73)	0.012266	0.001131	10.84127	0.0000
C(74)	0.008089	0.001011	7.997144	0.0000
C(75)	0.002453	0.001177	2.083925	0.0372
C(76)	0.004665	0.001175	3.969076	0.0001
C(77)	-0.005336	0.000909	-5.871535	0.0000
C(78)	0.015380	0.000834	18.43390	0.0000
C(79)	-0.001629	0.000727	-2.239428	0.0252
C(80)	-0.000553	0.000688	-0.804857	0.4209
C(81)	-0.001007	0.001604	-0.627639	0.5303
C(82)	0.026002	0.001575	16.50686	0.0000
C(83)	0.009636	0.001512	6.373716	0.0000
C(84)	0.009815	0.001352	7.261978	0.0000
C(85)	0.003841	0.001573	2.442449	0.0146
C(86)	0.001342	0.001570	0.854443	0.3929
C(87)	-0.006150	0.001214	-5.064417	0.0000
C(88)	0.000907	0.001115	0.813978	0.4157
C(89)	-0.008739	0.000972	-8.993453	0.0000
C(90)	-0.002135	0.000919	-2.323400	0.0202
C(91)	-3.20E-06	4.05E-06	-0.791358	0.4288
C(92)	0.033628	3.98E-06	8459.625	0.0000
C(93)	-0.000910	3.82E-06	-238.4476	0.0000
C(94)	-0.000257	3.41E-06	-75.48171	0.0000
C(95)	0.023536	3.97E-06	5930.754	0.0000
C(96)	-0.019321	3.96E-06	-4875.348	0.0000
C(97)	5.24E-05	3.06E-06	17.09381	0.0000
C(98)	2.81E-05	2.81E-06	9.977810	0.0000
C(99)	-5.93E-06	2.45E-06	-2.419119	0.0156
C(100)	-2.29E-05	2.32E-06	-9.890411	0.0000
C(101)	-0.001884	0.001886	-0.998847	0.3179
C(102)	0.032576	0.001852	17.58564	0.0000
C(103)	0.009481	0.001778	5.332637	0.0000
C(104)	0.008108	0.001589	5.101206	0.0000
C(105)	0.005225	0.001849	2.825671	0.0047
C(106)	0.011139	0.001847	6.031969	0.0000
C(107)	0.009015	0.001428	6.313172	0.0000
C(108)	-0.000492	0.001311	-0.375099	0.7076
C(109)	0.006234	0.001143	5.455566	0.0000

C(110)	0.014234	0.001080	13.17458	0.0000
C(111)	-2.33E-05	0.001010	-0.023068	0.9816
C(112)	0.017619	0.000992	17.75728	0.0000
C(113)	0.020705	0.000952	21.74261	0.0000
C(114)	-0.004099	0.000851	-4.815259	0.0000
C(115)	0.000525	0.000991	0.529757	0.5963
C(116)	0.002849	0.000989	2.880139	0.0040
C(117)	-0.000575	0.000765	-0.752139	0.4520
C(118)	0.002104	0.000702	2.995447	0.0028
C(119)	0.000222	0.000612	0.362075	0.7173
C(120)	-0.002143	0.000579	-3.703324	0.0002
C(121)	-0.000112	0.000295	-0.379380	0.7044
C(122)	0.022136	0.000290	76.39500	0.0000
C(123)	0.035217	0.000278	126.6340	0.0000
C(124)	-0.008330	0.000249	-33.50668	0.0000
C(125)	0.000779	0.000289	2.691302	0.0071
C(126)	0.001983	0.000289	6.866146	0.0000
C(127)	0.002120	0.000223	9.489509	0.0000
C(128)	-0.001869	0.000205	-9.111857	0.0000
C(129)	-0.000138	0.000179	-0.770401	0.4411
C(130)	-0.000469	0.000169	-2.774627	0.0055
C(131)	-0.000933	0.001293	-0.721087	0.4709
C(132)	0.028853	0.001270	22.71388	0.0000
C(133)	0.017847	0.001219	14.63914	0.0000
C(134)	0.008718	0.001090	7.998518	0.0000
C(135)	0.002726	0.001268	2.149828	0.0316
C(136)	0.007135	0.001266	5.634621	0.0000
C(137)	-0.004150	0.000979	-4.238559	0.0000
C(138)	0.012364	0.000899	13.75287	0.0000
C(139)	0.004513	0.000784	5.759622	0.0000
C(140)	-0.004486	0.000741	-6.055325	0.0000
C(141)	8.81E-06	9.03E-06	0.976301	0.3290
C(142)	0.043353	8.86E-06	4890.754	0.0000
C(143)	-0.001595	8.51E-06	-187.4300	0.0000
C(144)	-0.000409	7.61E-06	-53.83492	0.0000
C(145)	0.005148	8.85E-06	581.7731	0.0000
C(146)	0.029497	8.84E-06	3337.951	0.0000
C(147)	-8.23E-06	6.83E-06	-1.205086	0.2282
C(148)	-7.81E-05	6.27E-06	-12.44955	0.0000
C(149)	-9.63E-06	5.47E-06	-1.760634	0.0784
C(150)	-3.44E-05	5.17E-06	-6.644969	0.0000
C(151)	0.002806	0.001793	1.565248	0.1176
C(152)	0.020451	0.001761	11.61445	0.0000
C(153)	0.009838	0.001690	5.821357	0.0000
C(154)	0.010007	0.001511	6.623673	0.0000
C(155)	0.004843	0.001758	2.755329	0.0059
C(156)	0.001118	0.001755	0.636705	0.5243
C(157)	0.000920	0.001357	0.678075	0.4978
C(158)	0.002700	0.001246	2.166455	0.0303
C(159)	-0.009464	0.001086	-8.713762	0.0000
C(160)	0.004620	0.001027	4.499190	0.0000
C(161)	9.69E-05	0.001725	0.056177	0.9552
C(162)	0.014730	0.001694	8.696068	0.0000
C(163)	0.016527	0.001626	10.16662	0.0000
C(164)	0.012888	0.001453	8.867861	0.0000
C(165)	0.006607	0.001691	3.907025	0.0001
C(166)	0.000559	0.001689	0.331184	0.7405
C(167)	-0.003271	0.001306	-2.504919	0.0123

C(168)	-0.007070	0.001199	-5.897348	0.0000
C(169)	-0.005040	0.001045	-4.823379	0.0000
C(170)	0.001812	0.000988	1.833779	0.0667
C(171)	0.000940	0.001422	0.660849	0.5087
C(172)	0.024000	0.001397	17.18537	0.0000
C(173)	0.019116	0.001340	14.26263	0.0000
C(174)	0.004610	0.001198	3.847362	0.0001
C(175)	0.002888	0.001394	2.071263	0.0384
C(176)	0.002352	0.001392	1.689508	0.0912
C(177)	-0.005413	0.001077	-5.028493	0.0000
C(178)	-0.001621	0.000988	-1.640493	0.1010
C(179)	-0.005834	0.000861	-6.772742	0.0000
C(180)	0.009290	0.000814	11.40579	0.0000
C(181)	-0.001511	0.002408	-0.627442	0.5304
C(182)	0.030977	0.002365	13.10042	0.0000
C(183)	0.014497	0.002269	6.388271	0.0000
C(184)	0.013746	0.002029	6.775671	0.0000
C(185)	0.004316	0.002361	1.828238	0.0676
C(186)	0.003537	0.002357	1.500417	0.1336
C(187)	0.004701	0.001823	2.579248	0.0099
C(188)	0.000910	0.001674	0.543498	0.5868
C(189)	0.005004	0.001459	3.430739	0.0006
C(190)	0.014577	0.001379	10.56991	0.0000
C(191)	-0.000615	0.000796	-0.772626	0.4398
C(192)	0.027105	0.000781	34.68451	0.0000
C(193)	0.012251	0.000750	16.33491	0.0000
C(194)	0.019107	0.000670	28.49708	0.0000
C(195)	0.006183	0.000780	7.924919	0.0000
C(196)	0.000894	0.000779	1.147683	0.2511
C(197)	-0.016564	0.000602	-27.49685	0.0000
C(198)	-0.014311	0.000553	-25.87447	0.0000
C(199)	0.001225	0.000482	2.541653	0.0111
C(200)	-0.004656	0.000456	-10.21598	0.0000

Equation: PE_OLES_01=C(1)+C(2)*F1+C(3)*F2+C(4)*F3+C(5)*F4+C(6)*F5
+C(7)*F6+C(8)*F7+C(9)*F8+C(10)*F9
Observations: 291

R-squared	0.303663	Mean dependent var	0.003041
Adjusted R-squared	0.281360	S.D. dependent var	0.067481
S.E. of regression	0.057205	Sum squared resid	0.919555
Durbin-Watson stat	1.944252		

Equation: BIMBOA=C(11)+C(12)*F1+C(13)*F2+C(14)*F3+C(15)*F4+C(16)
*F5+C(17)*F6+C(18)*F7+C(19)*F8+C(20)*F9
Observations: 291

R-squared	0.398596	Mean dependent var	0.001472
Adjusted R-squared	0.379334	S.D. dependent var	0.042216
S.E. of regression	0.033259	Sum squared resid	0.310827
Durbin-Watson stat	2.014698		

Equation: GMODELOC=C(21)+C(22)*F1+C(23)*F2+C(24)*F3+C(25)*F4
+C(26)*F5+C(27)*F6+C(28)*F7+C(29)*F8+C(30)*F9
Observations: 291

R-squared	0.999998	Mean dependent var	0.000176
Adjusted R-squared	0.999998	S.D. dependent var	0.032167
S.E. of regression	4.38E-05	Sum squared resid	5.40E-07
Durbin-Watson stat	2.069948		

Equation: FEMSAUBD=C(31)+C(32)*F1+C(33)*F2+C(34)*F3+C(35)*F4
+C(36)*F5+C(37)*F6+C(38)*F7+C(39)*F8+C(40)*F9
Observations: 291

R-squared	0.659832	Mean dependent var	0.000669
Adjusted R-squared	0.648937	S.D. dependent var	0.042404
S.E. of regression	0.025125	Sum squared resid	0.177383
Durbin-Watson stat	2.299181		

Equation: CONTAL_01=C(41)+C(42)*F1+C(43)*F2+C(44)*F3+C(45)*F4
+C(46)*F5+C(47)*F6+C(48)*F7+C(49)*F8+C(50)*F9
Observations: 291

R-squared	0.381197	Mean dependent var	0.000350
Adjusted R-squared	0.361378	S.D. dependent var	0.043836
S.E. of regression	0.035031	Sum squared resid	0.344828
Durbin-Watson stat	2.115737		

Equation: GEOB=C(51)+C(52)*F1+C(53)*F2+C(54)*F3+C(55)*F4+C(56)*F5
+C(57)*F6+C(58)*F7+C(59)*F8+C(60)*F9
Observations: 291

R-squared	0.952640	Mean dependent var	0.006502
Adjusted R-squared	0.951123	S.D. dependent var	0.062982
S.E. of regression	0.013924	Sum squared resid	0.054481
Durbin-Watson stat	2.100483		

Equation: ARA_01=C(61)+C(62)*F1+C(63)*F2+C(64)*F3+C(65)*F4+C(66)
*F5+C(67)*F6+C(68)*F7+C(69)*F8+C(70)*F9
Observations: 291

R-squared	0.385357	Mean dependent var	0.003209
Adjusted R-squared	0.365671	S.D. dependent var	0.040644
S.E. of regression	0.032371	Sum squared resid	0.294449
Durbin-Watson stat	2.138521		

Equation: WALMEXV=C(71)+C(72)*F1+C(73)*F2+C(74)*F3+C(75)*F4
+C(76)*F5+C(77)*F6+C(78)*F7+C(79)*F8+C(80)*F9
Observations: 291

R-squared	0.744583	Mean dependent var	0.001645
Adjusted R-squared	0.736403	S.D. dependent var	0.039850
S.E. of regression	0.020460	Sum squared resid	0.117627
Durbin-Watson stat	2.363038		

Equation: SORIANAB=C(81)+C(82)*F1+C(83)*F2+C(84)*F3+C(85)*F4
+C(86)*F5+C(87)*F6+C(88)*F7+C(89)*F8+C(90)*F9
Observations: 291

R-squared	0.625060	Mean dependent var	-0.000943
Adjusted R-squared	0.613051	S.D. dependent var	0.043948
S.E. of regression	0.027338	Sum squared resid	0.210007
Durbin-Watson stat	2.271911		

Equation: COMERUBC=C(91)+C(92)*F1+C(93)*F2+C(94)*F3+C(95)*F4
+C(96)*F5+C(97)*F6+C(98)*F7+C(99)*F8+C(100)*F9
Observations: 291

R-squared	0.999998	Mean dependent var	0.000568
Adjusted R-squared	0.999998	S.D. dependent var	0.045490
S.E. of regression	6.90E-05	Sum squared resid	1.34E-06
Durbin-Watson stat	2.111820		

Equation: ELEKTRA_01=C(101)+C(102)*F1+C(103)*F2+C(104)*F3+C(105)
*F4+C(106)*F5+C(107)*F6+C(108)*F7+C(109)*F8+C(110)*F9
Observations: 291

R-squared	0.691218	Mean dependent var	0.000965
Adjusted R-squared	0.681328	S.D. dependent var	0.056950
S.E. of regression	0.032149	Sum squared resid	0.290427
Durbin-Watson stat	2.145642		

Equation: TELMEXL=C(111)+C(112)*F1+C(113)*F2+C(114)*F3+C(115)*F4 +C(116)*F5+C(117)*F6+C(118)*F7+C(119)*F8+C(120)*F9
Observations: 291

R-squared	0.743433	Mean dependent var	-0.000491
Adjusted R-squared	0.735216	S.D. dependent var	0.033465
S.E. of regression	0.017220	Sum squared resid	0.083325
Durbin-Watson stat	2.247655		

Equation: TELECOA1=C(121)+C(122)*F1+C(123)*F2+C(124)*F3+C(125) *F4+C(126)*F5+C(127)*F6+C(128)*F7+C(129)*F8+C(130)*F9
Observations: 291

R-squared	0.987629	Mean dependent var	-0.000369
Adjusted R-squared	0.987232	S.D. dependent var	0.044505
S.E. of regression	0.005029	Sum squared resid	0.007106
Durbin-Watson stat	2.311543		

Equation: TLEVICPO=C(131)+C(132)*F1+C(133)*F2+C(134)*F3+C(135) *F4+C(136)*F5+C(137)*F6+C(138)*F7+C(139)*F8+C(140)*F9
Observations: 291

R-squared	0.791923	Mean dependent var	-0.000790
Adjusted R-squared	0.785258	S.D. dependent var	0.047574
S.E. of regression	0.022046	Sum squared resid	0.136572
Durbin-Watson stat	2.116130		

Equation: TVAZTCPO=C(141)+C(142)*F1+C(143)*F2+C(144)*F3+C(145) *F4+C(146)*F5+C(147)*F6+C(148)*F7+C(149)*F8+C(150)*F9
Observations: 291

R-squared	0.999992	Mean dependent var	-0.002023
Adjusted R-squared	0.999992	S.D. dependent var	0.052847
S.E. of regression	0.000154	Sum squared resid	6.65E-06
Durbin-Watson stat	2.066727		

Equation: GFNORTEO=C(151)+C(152)*F1+C(153)*F2+C(154)*F3+C(155) *F4+C(156)*F5+C(157)*F6+C(158)*F7+C(159)*F8+C(160)*F9
Observations: 291

R-squared	0.525270	Mean dependent var	0.005163
Adjusted R-squared	0.510065	S.D. dependent var	0.043658
S.E. of regression	0.030559	Sum squared resid	0.262409
Durbin-Watson stat	2.183523		

Equation: GFINBURO=C(161)+C(162)*F1+C(163)*F2+C(164)*F3+C(165) *F4+C(166)*F5+C(167)*F6+C(168)*F7+C(169)*F8+C(170)*F9
Observations: 291

R-squared	0.539321	Mean dependent var	0.000767
Adjusted R-squared	0.524566	S.D. dependent var	0.042633
S.E. of regression	0.029397	Sum squared resid	0.242828
Durbin-Watson stat	2.212381		

Equation: GCARSOA1=C(171)+C(172)*F1+C(173)*F2+C(174)*F3+C(175) *F4+C(176)*F5+C(177)*F6+C(178)*F7+C(179)*F8+C(180)*F9
Observations: 291

R-squared	0.713483	Mean dependent var	0.001724
Adjusted R-squared	0.704306	S.D. dependent var	0.044571
S.E. of regression	0.024237	Sum squared resid	0.165065
Durbin-Watson stat	2.161704		

Equation: ALFAA=C(181)+C(182)*F1+C(183)*F2+C(184)*F3+C(185)*F4 +C(186)*F5+C(187)*F6+C(188)*F7+C(189)*F8+C(190)*F9
Observations: 291

R-squared	0.575415	Mean dependent var	0.001871
Adjusted R-squared	0.561816	S.D. dependent var	0.061994
S.E. of regression	0.041037	Sum squared resid	0.473218
Durbin-Watson stat	2.248414		

Equation: CIEB=C(191)+C(192)*F1+C(193)*F2+C(194)*F3+C(195)*F4
+C(196)*F5+C(197)*F6+C(198)*F7+C(199)*F8+C(200)*F9
Observations: 291

R-squared	0.930273	Mean dependent var	-0.003637
Adjusted R-squared	0.928040	S.D. dependent var	0.050558
S.E. of regression	0.013562	Sum squared resid	0.051686
Durbin-Watson stat	2.060123		

Table 7. *Factor Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of daily returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000304	0.000657	0.462068	0.6440
C(2)	0.004406	0.000637	6.921585	0.0000
C(3)	0.001995	0.000558	3.573825	0.0004
C(4)	0.002206	0.000498	4.428499	0.0000
C(5)	0.002532	0.000400	6.325931	0.0000
C(6)	0.003044	0.000379	8.025707	0.0000
C(7)	0.001843	0.000384	4.796170	0.0000
C(8)	0.005437	0.000334	16.29213	0.0000
C(9)	0.003992	0.000330	12.09747	0.0000
C(10)	0.000570	0.000295	1.930953	0.0535
C(11)	8.85E-05	0.000279	0.316741	0.7514
C(12)	0.006252	0.000271	23.10988	0.0000
C(13)	0.001452	0.000237	6.118659	0.0000
C(14)	0.003115	0.000212	14.71596	0.0000
C(15)	0.001575	0.000170	9.260985	0.0000
C(16)	0.000684	0.000161	4.244365	0.0000
C(17)	0.001334	0.000163	8.167413	0.0000
C(18)	0.001781	0.000142	12.55835	0.0000
C(19)	-0.002668	0.000140	-19.02270	0.0000
C(20)	0.001112	0.000125	8.859308	0.0000
C(21)	0.000244	0.000390	0.625610	0.5316
C(22)	0.007350	0.000378	19.45786	0.0000
C(23)	0.002033	0.000331	6.134419	0.0000
C(24)	0.002759	0.000296	9.334950	0.0000
C(25)	0.001877	0.000237	7.904984	0.0000
C(26)	0.003416	0.000225	15.17701	0.0000
C(27)	0.000856	0.000228	3.752425	0.0002
C(28)	0.000491	0.000198	2.477468	0.0132
C(29)	0.001596	0.000196	8.151831	0.0000
C(30)	-0.000844	0.000175	-4.819616	0.0000
C(31)	-5.08E-06	0.000278	-0.018274	0.9854
C(32)	0.006974	0.000269	25.90609	0.0000
C(33)	0.001412	0.000236	5.977878	0.0000
C(34)	0.001527	0.000211	7.248653	0.0000
C(35)	0.001408	0.000169	8.320076	0.0000
C(36)	-0.003040	0.000160	-18.95626	0.0000
C(37)	0.001587	0.000162	9.769232	0.0000
C(38)	0.003316	0.000141	23.49482	0.0000
C(39)	-0.000530	0.000140	-3.796197	0.0001
C(40)	0.000227	0.000125	1.818854	0.0689
C(41)	0.000177	0.000220	0.803274	0.4218
C(42)	0.010816	0.000214	50.65574	0.0000
C(43)	0.001894	0.000187	10.11055	0.0000
C(44)	0.001182	0.000167	7.073457	0.0000
C(45)	-0.001317	0.000134	-9.808437	0.0000
C(46)	-0.001098	0.000127	-8.632433	0.0000
C(47)	0.004127	0.000129	32.01711	0.0000
C(48)	-0.002428	0.000112	-21.68434	0.0000
C(49)	-0.001104	0.000111	-9.972256	0.0000
C(50)	-0.002131	9.90E-05	-21.51204	0.0000
C(51)	-8.98E-05	0.000410	-0.218975	0.8267

C(52)	0.006177	0.000397	15.54954	0.0000
C(53)	0.002546	0.000348	7.305803	0.0000
C(54)	0.001894	0.000311	6.092142	0.0000
C(55)	0.002714	0.000250	10.86680	0.0000
C(56)	0.002886	0.000237	12.19344	0.0000
C(57)	0.003102	0.000240	12.93663	0.0000
C(58)	0.004032	0.000208	19.36101	0.0000
C(59)	0.002289	0.000206	11.11594	0.0000
C(60)	0.000442	0.000184	2.397502	0.0165
C(61)	4.94E-05	0.000244	0.202630	0.8394
C(62)	0.009883	0.000236	41.83075	0.0000
C(63)	0.001615	0.000207	7.790973	0.0000
C(64)	0.001175	0.000185	6.355506	0.0000
C(65)	-0.003057	0.000149	-20.57778	0.0000
C(66)	0.000586	0.000141	4.164358	0.0000
C(67)	0.003264	0.000143	22.88664	0.0000
C(68)	-0.000190	0.000124	-1.536756	0.1244
C(69)	0.000397	0.000122	3.237993	0.0012
C(70)	-0.001545	0.000110	-14.09498	0.0000
C(71)	0.000364	0.000490	0.741947	0.4581
C(72)	0.010238	0.000475	21.57030	0.0000
C(73)	0.004078	0.000416	9.794634	0.0000
C(74)	0.002680	0.000371	7.215685	0.0000
C(75)	-0.003554	0.000298	-11.90919	0.0000
C(76)	0.002849	0.000283	10.07467	0.0000
C(77)	-0.000616	0.000286	-2.150847	0.0315
C(78)	0.000357	0.000249	1.435413	0.1512
C(79)	0.003062	0.000246	12.44368	0.0000
C(80)	0.002278	0.000220	10.34666	0.0000
C(81)	0.000112	0.000319	0.349854	0.7265
C(82)	0.008084	0.000309	26.16741	0.0000
C(83)	0.002684	0.000271	9.902838	0.0000
C(84)	0.002378	0.000242	9.836081	0.0000
C(85)	-0.002897	0.000194	-14.91563	0.0000
C(86)	0.003426	0.000184	18.61197	0.0000
C(87)	-0.000448	0.000186	-2.403215	0.0163
C(88)	-0.001327	0.000162	-8.191035	0.0000
C(89)	0.001889	0.000160	11.79593	0.0000
C(90)	0.003203	0.000143	22.35138	0.0000
C(91)	3.97E-06	0.000243	0.016353	0.9870
C(92)	0.012047	0.000235	51.22923	0.0000
C(93)	0.002804	0.000206	13.59242	0.0000
C(94)	0.001747	0.000184	9.495408	0.0000
C(95)	0.001271	0.000148	8.600296	0.0000
C(96)	-0.004371	0.000140	-31.19640	0.0000
C(97)	0.001190	0.000142	8.386559	0.0000
C(98)	0.000206	0.000123	1.671840	0.0946
C(99)	0.000992	0.000122	8.135169	0.0000
C(100)	0.002504	0.000109	22.95941	0.0000
C(101)	-0.000219	0.000346	-0.632236	0.5272
C(102)	0.011291	0.000335	33.72168	0.0000
C(103)	0.003894	0.000294	13.25693	0.0000
C(104)	0.001791	0.000262	6.835626	0.0000
C(105)	0.001600	0.000211	7.601124	0.0000
C(106)	-0.001580	0.000199	-7.921035	0.0000
C(107)	0.000239	0.000202	1.180214	0.2379
C(108)	-0.000366	0.000176	-2.084639	0.0371
C(109)	-0.000317	0.000174	-1.828139	0.0675

C(110)	-0.000795	0.000155	-5.116680	0.0000
C(111)	-0.000366	0.000409	-0.893259	0.3717
C(112)	0.009443	0.000397	23.81062	0.0000
C(113)	0.003613	0.000348	10.38688	0.0000
C(114)	0.002724	0.000310	8.778925	0.0000
C(115)	-0.001013	0.000249	-4.062053	0.0000
C(116)	0.000223	0.000236	0.944888	0.3447
C(117)	-0.000641	0.000239	-2.677616	0.0074
C(118)	0.001908	0.000208	9.174650	0.0000
C(119)	0.000928	0.000206	4.514295	0.0000
C(120)	-0.002796	0.000184	-15.19975	0.0000
C(121)	-0.000289	0.000431	-0.670366	0.5026
C(122)	0.014104	0.000417	33.78378	0.0000
C(123)	0.006692	0.000366	18.27309	0.0000
C(124)	-0.002196	0.000327	-6.724125	0.0000
C(125)	-0.001233	0.000262	-4.698752	0.0000
C(126)	0.001050	0.000249	4.223126	0.0000
C(127)	-0.001434	0.000252	-5.690083	0.0000
C(128)	0.000919	0.000219	4.199820	0.0000
C(129)	0.002105	0.000216	9.728309	0.0000
C(130)	-0.002324	0.000194	-12.00298	0.0000
C(131)	2.07E-05	4.70E-05	0.439074	0.6606
C(132)	0.012857	4.56E-05	282.0912	0.0000
C(133)	-0.006884	4.00E-05	-172.1931	0.0000
C(134)	-0.000509	3.57E-05	-14.27734	0.0000
C(135)	-0.000201	2.87E-05	-6.998671	0.0000
C(136)	0.000469	2.72E-05	17.26299	0.0000
C(137)	0.000112	2.75E-05	4.084583	0.0000
C(138)	0.000343	2.39E-05	14.34705	0.0000
C(139)	-0.000223	2.36E-05	-9.425262	0.0000
C(140)	-8.63E-05	2.11E-05	-4.082026	0.0000
C(141)	-0.000150	0.000245	-0.614046	0.5392
C(142)	0.015022	0.000237	63.30797	0.0000
C(143)	-0.003426	0.000208	-16.45803	0.0000
C(144)	0.001394	0.000186	7.506121	0.0000
C(145)	0.001868	0.000149	12.52254	0.0000
C(146)	-0.000755	0.000141	-5.341698	0.0000
C(147)	-0.002844	0.000143	-19.85494	0.0000
C(148)	-0.000728	0.000124	-5.849773	0.0000
C(149)	0.001070	0.000123	8.695586	0.0000
C(150)	-7.70E-05	0.000110	-0.699904	0.4840
C(151)	-0.000314	0.000256	-1.229869	0.2188
C(152)	0.016463	0.000248	66.50769	0.0000
C(153)	0.002259	0.000217	10.40563	0.0000
C(154)	-0.003104	0.000194	-16.02421	0.0000
C(155)	-0.001938	0.000156	-12.45122	0.0000
C(156)	-0.000845	0.000147	-5.728911	0.0000
C(157)	0.002342	0.000149	15.67498	0.0000
C(158)	-0.001872	0.000130	-14.42067	0.0000
C(159)	0.000164	0.000128	1.280457	0.2004
C(160)	0.002888	0.000115	25.15660	0.0000
C(161)	0.000192	0.000112	1.710507	0.0872
C(162)	0.016902	0.000109	155.6906	0.0000
C(163)	0.006641	9.52E-05	69.73786	0.0000
C(164)	-0.010784	8.49E-05	-126.9540	0.0000
C(165)	0.001135	6.83E-05	16.63129	0.0000
C(166)	0.000812	6.47E-05	12.54856	0.0000
C(167)	-0.001268	6.55E-05	-19.35277	0.0000

C(168)	0.000815	5.69E-05	14.31378	0.0000
C(169)	-0.001061	5.63E-05	-18.84919	0.0000
C(170)	-0.000210	5.04E-05	-4.173790	0.0000
C(171)	0.000137	0.000154	0.888745	0.3741
C(172)	0.010954	0.000149	73.37237	0.0000
C(173)	0.003613	0.000131	27.58789	0.0000
C(174)	0.004103	0.000117	35.12867	0.0000
C(175)	-0.005958	9.39E-05	-63.47633	0.0000
C(176)	-0.001681	8.89E-05	-18.90001	0.0000
C(177)	-0.004571	9.01E-05	-50.72312	0.0000
C(178)	0.002340	7.83E-05	29.90024	0.0000
C(179)	-0.002739	7.74E-05	-35.39010	0.0000
C(180)	-1.64E-05	6.92E-05	-0.236137	0.8133
C(181)	1.28E-05	0.000384	0.033437	0.9733
C(182)	0.009040	0.000372	24.32717	0.0000
C(183)	0.002436	0.000326	7.474442	0.0000
C(184)	0.003206	0.000291	11.02744	0.0000
C(185)	0.000578	0.000234	2.474285	0.0134
C(186)	0.001108	0.000221	5.002805	0.0000
C(187)	-0.002706	0.000224	-12.06569	0.0000
C(188)	-0.002680	0.000195	-13.75613	0.0000
C(189)	0.001036	0.000193	5.377366	0.0000
C(190)	-0.000281	0.000172	-1.631075	0.1029
C(191)	0.000447	0.000295	1.515642	0.1296
C(192)	0.011721	0.000285	41.05635	0.0000
C(193)	0.002417	0.000250	9.652877	0.0000
C(194)	0.002930	0.000223	13.11810	0.0000
C(195)	0.003680	0.000179	20.50622	0.0000
C(196)	-0.002162	0.000170	-12.71157	0.0000
C(197)	-0.001671	0.000172	-9.698611	0.0000
C(198)	-0.002181	0.000150	-14.57290	0.0000
C(199)	0.000656	0.000148	4.434727	0.0000
C(200)	-0.000699	0.000132	-5.279834	0.0000
C(201)	-0.000243	0.000475	-0.510300	0.6098
C(202)	0.013488	0.000460	29.29537	0.0000
C(203)	0.003696	0.000404	9.151360	0.0000
C(204)	0.000707	0.000360	1.962857	0.0497
C(205)	-0.000110	0.000289	-0.380547	0.7035
C(206)	-0.000648	0.000274	-2.363097	0.0181
C(207)	-0.001457	0.000278	-5.240793	0.0000
C(208)	-4.57E-05	0.000241	-0.189465	0.8497
C(209)	0.003773	0.000239	15.80928	0.0000
C(210)	-0.001701	0.000214	-7.966192	0.0000
C(211)	-0.000264	0.000231	-1.141193	0.2538
C(212)	0.011381	0.000224	50.75608	0.0000
C(213)	0.004892	0.000197	24.87338	0.0000
C(214)	0.004317	0.000175	24.60910	0.0000
C(215)	0.003249	0.000141	23.04575	0.0000
C(216)	0.004715	0.000134	35.29873	0.0000
C(217)	-0.000265	0.000135	-1.959728	0.0500
C(218)	-0.001385	0.000118	-11.77704	0.0000
C(219)	-0.004385	0.000116	-37.72457	0.0000
C(220)	0.000550	0.000104	5.284240	0.0000

Equation: PE_OLES_01=C(1)+C(2)*F1+C(3)*F2+C(4)*F3+C(5)*F4+C(6)*F5
+C(7)*F6+C(8)*F7+C(9)*F8+C(10)*F9
Observations: 1410

R-squared	0.306524	Mean dependent var	0.001028
Adjusted R-squared	0.302066	S.D. dependent var	0.029462
S.E. of regression	0.024613	Sum squared resid	0.848137
Durbin-Watson stat	1.925699		

Equation: KIMBERA=C(11)+C(12)*F1+C(13)*F2+C(14)*F3+C(15)*F4+C(16)
*F5+C(17)*F6+C(18)*F7+C(19)*F8+C(20)*F9
Observations: 1410

R-squared	0.524711	Mean dependent var	0.000209
Adjusted R-squared	0.521655	S.D. dependent var	0.015126
S.E. of regression	0.010462	Sum squared resid	0.153222
Durbin-Watson stat	1.935444		

Equation: BIMBOA=C(21)+C(22)*F1+C(23)*F2+C(24)*F3+C(25)*F4+C(26)
*F5+C(27)*F6+C(28)*F7+C(29)*F8+C(30)*F9
Observations: 1410

R-squared	0.391221	Mean dependent var	0.000650
Adjusted R-squared	0.387307	S.D. dependent var	0.018661
S.E. of regression	0.014607	Sum squared resid	0.298710
Durbin-Watson stat	1.881518		

Equation: GMODELOC=C(31)+C(32)*F1+C(33)*F2+C(34)*F3+C(35)*F4
+C(36)*F5+C(37)*F6+C(38)*F7+C(39)*F8+C(40)*F9
Observations: 1410

R-squared	0.567900	Mean dependent var	0.000384
Adjusted R-squared	0.565122	S.D. dependent var	0.015785
S.E. of regression	0.010410	Sum squared resid	0.151703
Durbin-Watson stat	1.917907		

Equation: FEMSAUBD=C(41)+C(42)*F1+C(43)*F2+C(44)*F3+C(45)*F4
+C(46)*F5+C(47)*F6+C(48)*F7+C(49)*F8+C(50)*F9
Observations: 1410

R-squared	0.778180	Mean dependent var	0.000500
Adjusted R-squared	0.776754	S.D. dependent var	0.017475
S.E. of regression	0.008257	Sum squared resid	0.095439
Durbin-Watson stat	1.995952		

Equation: CONTAL_01=C(51)+C(52)*F1+C(53)*F2+C(54)*F3+C(55)*F4
+C(56)*F5+C(57)*F6+C(58)*F7+C(59)*F8+C(60)*F9
Observations: 1410

R-squared	0.473991	Mean dependent var	0.000405
Adjusted R-squared	0.470609	S.D. dependent var	0.021111
S.E. of regression	0.015360	Sum squared resid	0.330307
Durbin-Watson stat	1.989090		

Equation: CEMEXCP=C(61)+C(62)*F1+C(63)*F2+C(64)*F3+C(65)*F4
+C(66)*F5+C(67)*F6+C(68)*F7+C(69)*F8+C(70)*F9
Observations: 1410

R-squared	0.682218	Mean dependent var	0.000771
Adjusted R-squared	0.680175	S.D. dependent var	0.016155
S.E. of regression	0.009136	Sum squared resid	0.116855
Durbin-Watson stat	1.949455		

Equation: GEOB=C(71)+C(72)*F1+C(73)*F2+C(74)*F3+C(75)*F4+C(76)*F5
+C(77)*F6+C(78)*F7+C(79)*F8+C(80)*F9
Observations: 1410

R-squared	0.443829	Mean dependent var	0.001662
Adjusted R-squared	0.440254	S.D. dependent var	0.024531
S.E. of regression	0.018353	Sum squared resid	0.471566
Durbin-Watson stat	1.720838		

Equation: ARA_01=C(81)+C(82)*F1+C(83)*F2+C(84)*F3+C(85)*F4+C(86)*F5+C(87)*F6+C(88)*F7+C(89)*F8+C(90)*F9
Observations: 1410

R-squared	0.605045	Mean dependent var	0.001007
Adjusted R-squared	0.602506	S.D. dependent var	0.018947
S.E. of regression	0.011946	Sum squared resid	0.199778
Durbin-Watson stat	1.874364		

Equation: WALMEXV=C(91)+C(92)*F1+C(93)*F2+C(94)*F3+C(95)*F4+C(96)*F5+C(97)*F6+C(98)*F7+C(99)*F8+C(100)*F9
Observations: 1410

R-squared	0.765896	Mean dependent var	0.000655
Adjusted R-squared	0.764392	S.D. dependent var	0.018733
S.E. of regression	0.009093	Sum squared resid	0.115757
Durbin-Watson stat	1.908075		

Equation: SORIANAB=C(101)+C(102)*F1+C(103)*F2+C(104)*F3+C(105)*F4+C(106)*F5+C(107)*F6+C(108)*F7+C(109)*F8+C(110)*F9
Observations: 1410

R-squared	0.518015	Mean dependent var	0.000171
Adjusted R-squared	0.514917	S.D. dependent var	0.018590
S.E. of regression	0.012948	Sum squared resid	0.234695
Durbin-Watson stat	1.863937		

Equation: COMERUBC=C(111)+C(112)*F1+C(113)*F2+C(114)*F3+C(115)*F4+C(116)*F5+C(117)*F6+C(118)*F7+C(119)*F8+C(120)*F9
Observations: 1410

R-squared	0.440931	Mean dependent var	0.000498
Adjusted R-squared	0.437337	S.D. dependent var	0.020444
S.E. of regression	0.015335	Sum squared resid	0.329236
Durbin-Watson stat	2.087763		

Equation: ELEKTRA_01=C(121)+C(122)*F1+C(123)*F2+C(124)*F3+C(125)*F4+C(126)*F5+C(127)*F6+C(128)*F7+C(129)*F8+C(130)*F9
Observations: 1410

R-squared	0.567366	Mean dependent var	0.000526
Adjusted R-squared	0.564584	S.D. dependent var	0.024465
S.E. of regression	0.016143	Sum squared resid	0.364844
Durbin-Watson stat	1.942258		

Equation: TELMEXL=C(131)+C(132)*F1+C(133)*F2+C(134)*F3+C(135)*F4+C(136)*F5+C(137)*F6+C(138)*F7+C(139)*F8+C(140)*F9
Observations: 1410

R-squared	0.987356	Mean dependent var	0.000215
Adjusted R-squared	0.987275	S.D. dependent var	0.015623
S.E. of regression	0.001762	Sum squared resid	0.004348
Durbin-Watson stat	2.136919		

Equation: TELECOA1=C(141)+C(142)*F1+C(143)*F2+C(144)*F3+C(145)*F4+C(146)*F5+C(147)*F6+C(148)*F7+C(149)*F8+C(150)*F9
Observations: 1410

R-squared	0.780886	Mean dependent var	0.000252
Adjusted R-squared	0.779477	S.D. dependent var	0.019538
S.E. of regression	0.009175	Sum squared resid	0.117854
Durbin-Watson stat	2.185444		

Equation: TLEVICPO=C(151)+C(152)*F1+C(153)*F2+C(154)*F3+C(155)*F4+C(156)*F5+C(157)*F6+C(158)*F7+C(159)*F8+C(160)*F9
Observations: 1410

R-squared	0.811354	Mean dependent var	0.000171
Adjusted R-squared	0.810142	S.D. dependent var	0.021968
S.E. of regression	0.009572	Sum squared resid	0.128268
Durbin-Watson stat	1.948855		

Equation: TVAZTCPO=C(161)+C(162)*F1+C(163)*F2+C(164)*F3+C(165)*F4+C(166)*F5+C(167)*F6+C(168)*F7+C(169)*F8+C(170)*F9
Observations: 1410

R-squared	0.970635	Mean dependent var	-7.68E-05
Adjusted R-squared	0.970446	S.D. dependent var	0.024418
S.E. of regression	0.004198	Sum squared resid	0.024670
Durbin-Watson stat	1.986941		

Equation: GFNORTEO=C(171)+C(172)*F1+C(173)*F2+C(174)*F3+C(175)*F4+C(176)*F5+C(177)*F6+C(178)*F7+C(179)*F8+C(180)*F9
Observations: 1410

R-squared	0.921205	Mean dependent var	0.001415
Adjusted R-squared	0.920698	S.D. dependent var	0.020499
S.E. of regression	0.005773	Sum squared resid	0.046654
Durbin-Watson stat	1.939089		

Equation: GFINBURO=C(181)+C(182)*F1+C(183)*F2+C(184)*F3+C(185)*F4+C(186)*F5+C(187)*F6+C(188)*F7+C(189)*F8+C(190)*F9
Observations: 1410

R-squared	0.452814	Mean dependent var	0.000502
Adjusted R-squared	0.449297	S.D. dependent var	0.019363
S.E. of regression	0.014369	Sum squared resid	0.289062
Durbin-Watson stat	2.034833		

Equation: GCARSOA1=C(191)+C(192)*F1+C(193)*F2+C(194)*F3+C(195)*F4+C(196)*F5+C(197)*F6+C(198)*F7+C(199)*F8+C(200)*F9
Observations: 1410

R-squared	0.671860	Mean dependent var	0.000711
Adjusted R-squared	0.669751	S.D. dependent var	0.019209
S.E. of regression	0.011039	Sum squared resid	0.170596
Durbin-Watson stat	1.931628		

Equation: ALFAA=C(201)+C(202)*F1+C(203)*F2+C(204)*F3+C(205)*F4+C(206)*F5+C(207)*F6+C(208)*F7+C(209)*F8+C(210)*F9
Observations: 1410

R-squared	0.478250	Mean dependent var	0.000723
Adjusted R-squared	0.474896	S.D. dependent var	0.024569
S.E. of regression	0.017804	Sum squared resid	0.443752
Durbin-Watson stat	1.759372		

Equation: CIEB=C(211)+C(212)*F1+C(213)*F2+C(214)*F3+C(215)*F4+C(216)*F5+C(217)*F6+C(218)*F7+C(219)*F8+C(220)*F9
Observations: 1410

R-squared	0.835687	Mean dependent var	-0.000376
Adjusted R-squared	0.834631	S.D. dependent var	0.021321
S.E. of regression	0.008670	Sum squared resid	0.105240
Durbin-Watson stat	1.957247		

Table 8. *Factor Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of daily excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000178	0.000625	0.285003	0.7756
C(2)	0.004509	0.000605	7.453823	0.0000
C(3)	0.001781	0.000524	3.401647	0.0007
C(4)	0.002272	0.000474	4.790457	0.0000
C(5)	0.002361	0.000387	6.101814	0.0000
C(6)	0.002484	0.000358	6.935238	0.0000
C(7)	0.003027	0.000370	8.177315	0.0000
C(8)	0.007124	0.000313	22.77484	0.0000
C(9)	0.002491	0.000317	7.846910	0.0000
C(10)	-0.001249	0.000283	-4.416970	0.0000
C(11)	0.000108	0.000276	0.389812	0.6967
C(12)	0.006293	0.000268	23.51839	0.0000
C(13)	0.001244	0.000232	5.372352	0.0000
C(14)	0.003108	0.000210	14.81785	0.0000
C(15)	0.001556	0.000171	9.092524	0.0000
C(16)	5.20E-05	0.000158	0.328527	0.7425
C(17)	0.001429	0.000164	8.725383	0.0000
C(18)	-0.001345	0.000138	-9.719257	0.0000
C(19)	0.003250	0.000140	23.14927	0.0000
C(20)	-0.000639	0.000125	-5.110651	0.0000
C(21)	0.000232	0.000390	0.593671	0.5527
C(22)	0.007417	0.000378	19.61946	0.0000
C(23)	0.001782	0.000327	5.445676	0.0000
C(24)	0.002702	0.000296	9.117486	0.0000
C(25)	0.001889	0.000242	7.809907	0.0000
C(26)	0.003077	0.000224	13.74975	0.0000
C(27)	0.001926	0.000231	8.327056	0.0000
C(28)	0.001242	0.000195	6.352221	0.0000
C(29)	-0.000221	0.000198	-1.115541	0.2646
C(30)	0.001125	0.000177	6.370489	0.0000
C(31)	-2.84E-05	0.000277	-0.102718	0.9182
C(32)	0.007019	0.000268	26.20013	0.0000
C(33)	0.001161	0.000232	5.006351	0.0000
C(34)	0.001488	0.000210	7.083680	0.0000
C(35)	0.001424	0.000171	8.307204	0.0000
C(36)	-0.003584	0.000159	-22.60141	0.0000
C(37)	0.000699	0.000164	4.264990	0.0000
C(38)	0.001481	0.000139	10.69294	0.0000
C(39)	0.002828	0.000141	20.11836	0.0000
C(40)	0.000128	0.000125	1.022609	0.3065
C(41)	9.58E-05	0.000279	0.343529	0.7312
C(42)	0.010844	0.000270	40.13923	0.0000
C(43)	0.001479	0.000234	6.326887	0.0000
C(44)	0.001054	0.000212	4.975457	0.0000
C(45)	-0.001073	0.000173	-6.209317	0.0000
C(46)	-0.001880	0.000160	-11.75423	0.0000
C(47)	0.003126	0.000165	18.90748	0.0000
C(48)	-0.002038	0.000140	-14.58929	0.0000
C(49)	-0.001319	0.000142	-9.305574	0.0000
C(50)	0.000825	0.000126	6.532205	0.0000
C(51)	-3.08E-05	0.000429	-0.071808	0.9428
C(52)	0.006236	0.000416	15.00535	0.0000

C(53)	0.002372	0.000360	6.593432	0.0000
C(54)	0.001846	0.000326	5.666339	0.0000
C(55)	0.002503	0.000266	9.414447	0.0000
C(56)	0.001658	0.000246	6.738001	0.0000
C(57)	0.003953	0.000254	15.54533	0.0000
C(58)	0.003432	0.000215	15.97157	0.0000
C(59)	0.002108	0.000218	9.668130	0.0000
C(60)	0.000602	0.000194	3.099141	0.0019
C(61)	8.18E-05	0.000193	0.423439	0.6720
C(62)	0.009964	0.000187	53.22816	0.0000
C(63)	0.001421	0.000162	8.771689	0.0000
C(64)	0.001285	0.000147	8.759896	0.0000
C(65)	-0.003376	0.000120	-28.19121	0.0000
C(66)	-0.000498	0.000111	-4.491772	0.0000
C(67)	0.003859	0.000115	33.68750	0.0000
C(68)	-0.000399	9.68E-05	-4.123068	0.0000
C(69)	-0.000721	9.82E-05	-7.340845	0.0000
C(70)	0.002194	8.75E-05	25.07573	0.0000
C(71)	0.000250	0.000422	0.592925	0.5532
C(72)	0.010376	0.000409	25.38492	0.0000
C(73)	0.003901	0.000354	11.02743	0.0000
C(74)	0.002967	0.000320	9.259665	0.0000
C(75)	-0.003435	0.000261	-13.13771	0.0000
C(76)	0.003323	0.000242	13.73483	0.0000
C(77)	0.000238	0.000250	0.950981	0.3416
C(78)	0.003506	0.000211	16.59064	0.0000
C(79)	-0.001502	0.000214	-7.005140	0.0000
C(80)	-0.004135	0.000191	-21.64793	0.0000
C(81)	9.64E-05	0.000339	0.283903	0.7765
C(82)	0.008145	0.000329	24.77147	0.0000
C(83)	0.002448	0.000285	8.603374	0.0000
C(84)	0.002454	0.000258	9.519216	0.0000
C(85)	-0.002498	0.000210	-11.87663	0.0000
C(86)	0.003363	0.000195	17.27876	0.0000
C(87)	0.000505	0.000201	2.509094	0.0121
C(88)	0.000599	0.000170	3.526185	0.0004
C(89)	-0.001791	0.000173	-10.38332	0.0000
C(90)	-0.003042	0.000154	-19.79391	0.0000
C(91)	4.93E-05	0.000250	0.197141	0.8437
C(92)	0.012111	0.000242	50.03209	0.0000
C(93)	0.002382	0.000210	11.37053	0.0000
C(94)	0.001750	0.000190	9.220987	0.0000
C(95)	0.001500	0.000155	9.687793	0.0000
C(96)	-0.004465	0.000143	-31.16391	0.0000
C(97)	6.25E-05	0.000148	0.422129	0.6729
C(98)	0.000872	0.000125	6.968210	0.0000
C(99)	-0.000556	0.000127	-4.378664	0.0000
C(100)	-0.002282	0.000113	-20.17366	0.0000
C(101)	-0.000278	0.000350	-0.794156	0.4271
C(102)	0.011419	0.000339	33.71654	0.0000
C(103)	0.003480	0.000293	11.87311	0.0000
C(104)	0.001766	0.000265	6.651318	0.0000
C(105)	0.001702	0.000217	7.854567	0.0000
C(106)	-0.001497	0.000200	-7.467384	0.0000
C(107)	-0.000191	0.000207	-0.922508	0.3563
C(108)	-0.000162	0.000175	-0.923200	0.3559
C(109)	-0.000264	0.000178	-1.484169	0.1378
C(110)	-8.92E-05	0.000158	-0.563341	0.5732

C(111)	-0.000365	0.000424	-0.861970	0.3887
C(112)	0.009554	0.000411	23.26564	0.0000
C(113)	0.003301	0.000355	9.287602	0.0000
C(114)	0.002768	0.000322	8.597583	0.0000
C(115)	-0.000925	0.000263	-3.519800	0.0004
C(116)	0.000286	0.000243	1.176717	0.2393
C(117)	-0.000371	0.000251	-1.475793	0.1400
C(118)	0.001919	0.000212	9.036942	0.0000
C(119)	0.000659	0.000215	3.057186	0.0022
C(120)	0.002195	0.000192	11.43650	0.0000
C(121)	-0.000242	0.000431	-0.560620	0.5751
C(122)	0.014264	0.000417	34.16716	0.0000
C(123)	0.006459	0.000361	17.87471	0.0000
C(124)	-0.002070	0.000327	-6.326198	0.0000
C(125)	-0.001111	0.000267	-4.160948	0.0000
C(126)	0.001346	0.000247	5.446542	0.0000
C(127)	-0.000928	0.000255	-3.631433	0.0003
C(128)	0.002140	0.000216	9.913723	0.0000
C(129)	-0.000696	0.000219	-3.176008	0.0015
C(130)	0.002382	0.000195	12.21143	0.0000
C(131)	2.05E-05	5.62E-05	0.363817	0.7160
C(132)	0.012604	5.45E-05	231.3854	0.0000
C(133)	-0.006993	4.71E-05	-148.3335	0.0000
C(134)	-0.000670	4.27E-05	-15.67987	0.0000
C(135)	-0.000321	3.48E-05	-9.212426	0.0000
C(136)	0.000434	3.22E-05	13.47003	0.0000
C(137)	0.000262	3.33E-05	7.855490	0.0000
C(138)	9.77E-06	2.82E-05	0.347032	0.7286
C(139)	0.000483	2.86E-05	16.90657	0.0000
C(140)	5.83E-05	2.55E-05	2.291028	0.0220
C(141)	-0.000140	0.000240	-0.582109	0.5605
C(142)	0.014978	0.000233	64.41102	0.0000
C(143)	-0.004053	0.000201	-20.13547	0.0000
C(144)	0.001229	0.000182	6.741125	0.0000
C(145)	0.001935	0.000149	13.00657	0.0000
C(146)	0.000303	0.000138	2.201886	0.0277
C(147)	-0.002807	0.000142	-19.72834	0.0000
C(148)	0.000728	0.000120	6.054257	0.0000
C(149)	-0.001107	0.000122	-9.071535	0.0000
C(150)	8.97E-05	0.000109	0.825099	0.4093
C(151)	-0.000255	0.000268	-0.953071	0.3406
C(152)	0.016500	0.000260	63.54947	0.0000
C(153)	0.001843	0.000225	8.199208	0.0000
C(154)	-0.003072	0.000204	-15.09184	0.0000
C(155)	-0.001738	0.000166	-10.46244	0.0000
C(156)	-0.001395	0.000154	-9.076510	0.0000
C(157)	0.001865	0.000159	11.73669	0.0000
C(158)	-0.001217	0.000134	-9.061851	0.0000
C(159)	-0.001517	0.000136	-11.13163	0.0000
C(160)	-0.002720	0.000121	-22.41559	0.0000
C(161)	0.000165	0.000112	1.463789	0.1433
C(162)	0.017049	0.000109	156.5213	0.0000
C(163)	0.006434	9.43E-05	68.24593	0.0000
C(164)	-0.010730	8.54E-05	-125.6662	0.0000
C(165)	0.000871	6.97E-05	12.49959	0.0000
C(166)	0.001013	6.45E-05	15.71515	0.0000
C(167)	-0.001082	6.67E-05	-16.22603	0.0000
C(168)	-0.000274	5.63E-05	-4.859291	0.0000

C(169)	0.001362	5.72E-05	23.82575	0.0000
C(170)	0.000286	5.09E-05	5.623610	0.0000
C(171)	0.000117	0.000139	0.844255	0.3985
C(172)	0.011103	0.000134	82.55485	0.0000
C(173)	0.003340	0.000116	28.69542	0.0000
C(174)	0.004402	0.000105	41.75127	0.0000
C(175)	-0.006111	8.60E-05	-71.03101	0.0000
C(176)	-0.000750	7.96E-05	-9.414943	0.0000
C(177)	-0.005231	8.23E-05	-63.55247	0.0000
C(178)	-0.000627	6.95E-05	-9.019689	0.0000
C(179)	0.003106	7.06E-05	44.01316	0.0000
C(180)	0.000292	6.29E-05	4.650718	0.0000
C(181)	2.29E-05	0.000370	0.061844	0.9507
C(182)	0.009111	0.000359	25.39537	0.0000
C(183)	0.002167	0.000311	6.978891	0.0000
C(184)	0.003245	0.000281	11.53626	0.0000
C(185)	0.000850	0.000229	3.702603	0.0002
C(186)	0.001925	0.000212	9.063073	0.0000
C(187)	-0.002113	0.000220	-9.624450	0.0000
C(188)	-0.001223	0.000186	-6.590655	0.0000
C(189)	-0.002835	0.000188	-15.05776	0.0000
C(190)	0.001295	0.000168	7.721300	0.0000
C(191)	0.000433	0.000291	1.487226	0.1370
C(192)	0.011811	0.000282	41.89144	0.0000
C(193)	0.001948	0.000244	7.981998	0.0000
C(194)	0.002834	0.000221	12.82187	0.0000
C(195)	0.003967	0.000180	21.99474	0.0000
C(196)	-0.001470	0.000167	-8.805855	0.0000
C(197)	-0.002066	0.000173	-11.97262	0.0000
C(198)	-0.000809	0.000146	-5.550956	0.0000
C(199)	-0.002211	0.000148	-14.94618	0.0000
C(200)	0.000920	0.000132	6.980211	0.0000
C(201)	-0.000192	0.000476	-0.404099	0.6861
C(202)	0.013595	0.000461	29.51856	0.0000
C(203)	0.003317	0.000399	8.321845	0.0000
C(204)	0.000744	0.000361	2.061597	0.0393
C(205)	0.000140	0.000295	0.475995	0.6341
C(206)	-0.000110	0.000273	-0.405275	0.6853
C(207)	-0.001185	0.000282	-4.203327	0.0000
C(208)	0.002895	0.000238	12.15501	0.0000
C(209)	-0.002432	0.000242	-10.06285	0.0000
C(210)	0.001845	0.000215	8.571586	0.0000
C(211)	-0.000241	0.000241	-1.000070	0.3173
C(212)	0.011516	0.000234	49.24378	0.0000
C(213)	0.004459	0.000202	22.03065	0.0000
C(214)	0.004229	0.000183	23.06793	0.0000
C(215)	0.003238	0.000150	21.64740	0.0000
C(216)	0.004426	0.000138	31.97243	0.0000
C(217)	0.000783	0.000143	5.472587	0.0000
C(218)	-0.004171	0.000121	-34.49413	0.0000
C(219)	0.001939	0.000123	15.79816	0.0000
C(220)	-0.000817	0.000109	-7.471566	0.0000

Equation: PE_OLES_01=C(1)+C(2)*F1+C(3)*F2+C(4)*F3+C(5)*F4+C(6)*F5
+C(7)*F6+C(8)*F7+C(9)*F8+C(10)*F9
Observations: 1410

R-squared	0.373905	Mean dependent var	0.000805
Adjusted R-squared	0.369880	S.D. dependent var	0.029496
S.E. of regression	0.023414	Sum squared resid	0.767504
Durbin-Watson stat	1.917975		

Equation: KIMBERA=C(11)+C(12)*F1+C(13)*F2+C(14)*F3+C(15)*F4+C(16)
*F5+C(17)*F6+C(18)*F7+C(19)*F8+C(20)*F9
Observations: 1410

R-squared	0.534182	Mean dependent var	-1.66E-05
Adjusted R-squared	0.531187	S.D. dependent var	0.015126
S.E. of regression	0.010356	Sum squared resid	0.150158
Durbin-Watson stat	1.947969		

Equation: BIMBOA=C(21)+C(22)*F1+C(23)*F2+C(24)*F3+C(25)*F4+C(26)
*F5+C(27)*F6+C(28)*F7+C(29)*F8+C(30)*F9
Observations: 1410

R-squared	0.389419	Mean dependent var	0.000397
Adjusted R-squared	0.385494	S.D. dependent var	0.018665
S.E. of regression	0.014631	Sum squared resid	0.299703
Durbin-Watson stat	1.881179		

Equation: GMODELOC=C(31)+C(32)*F1+C(33)*F2+C(34)*F3+C(35)*F4
+C(36)*F5+C(37)*F6+C(38)*F7+C(39)*F8+C(40)*F9
Observations: 1410

R-squared	0.571408	Mean dependent var	0.000143
Adjusted R-squared	0.568653	S.D. dependent var	0.015787
S.E. of regression	0.010368	Sum squared resid	0.150498
Durbin-Watson stat	1.924389		

Equation: FEMSAUBD=C(41)+C(42)*F1+C(43)*F2+C(44)*F3+C(45)*F4
+C(46)*F5+C(47)*F6+C(48)*F7+C(49)*F8+C(50)*F9
Observations: 1410

R-squared	0.644143	Mean dependent var	0.000231
Adjusted R-squared	0.641855	S.D. dependent var	0.017471
S.E. of regression	0.010456	Sum squared resid	0.153046
Durbin-Watson stat	1.986808		

Equation: CONTAL_01=C(51)+C(52)*F1+C(53)*F2+C(54)*F3+C(55)*F4
+C(56)*F5+C(57)*F6+C(58)*F7+C(59)*F8+C(60)*F9
Observations: 1410

R-squared	0.423218	Mean dependent var	0.000161
Adjusted R-squared	0.419511	S.D. dependent var	0.021112
S.E. of regression	0.016085	Sum squared resid	0.362211
Durbin-Watson stat	1.983031		

Equation: CEMEXCP=C(61)+C(62)*F1+C(63)*F2+C(64)*F3+C(65)*F4
+C(66)*F5+C(67)*F6+C(68)*F7+C(69)*F8+C(70)*F9
Observations: 1410

R-squared	0.799897	Mean dependent var	0.000550
Adjusted R-squared	0.798610	S.D. dependent var	0.016145
S.E. of regression	0.007245	Sum squared resid	0.073490
Durbin-Watson stat	1.945266		

Equation: GEOB=C(71)+C(72)*F1+C(73)*F2+C(74)*F3+C(75)*F4+C(76)*F5
+C(77)*F6+C(78)*F7+C(79)*F8+C(80)*F9
Observations: 1410

R-squared	0.587338	Mean dependent var	0.001474
Adjusted R-squared	0.584686	S.D. dependent var	0.024548
S.E. of regression	0.015820	Sum squared resid	0.350370
Durbin-Watson stat	1.798144		

Equation: ARA_01=C(81)+C(82)*F1+C(83)*F2+C(84)*F3+C(85)*F4+C(86)
*F5+C(87)*F6+C(88)*F7+C(89)*F8+C(90)*F9
Observations: 1410

R-squared	0.551842	Mean dependent var	0.000797
Adjusted R-squared	0.548961	S.D. dependent var	0.018949
S.E. of regression	0.012726	Sum squared resid	0.226733
Durbin-Watson stat	1.856775		

Equation: WALMEXV=C(91)+C(92)*F1+C(93)*F2+C(94)*F3+C(95)*F4
+C(96)*F5+C(97)*F6+C(98)*F7+C(99)*F8+C(100)*F9
Observations: 1410

R-squared	0.751211	Mean dependent var	0.000450
Adjusted R-squared	0.749612	S.D. dependent var	0.018722
S.E. of regression	0.009368	Sum squared resid	0.122870
Durbin-Watson stat	1.893770		

Equation: SORIANAB=C(101)+C(102)*F1+C(103)*F2+C(104)*F3+C(105)
*F4+C(106)*F5+C(107)*F6+C(108)*F7+C(109)*F8+C(110)*F9
Observations: 1410

R-squared	0.505904	Mean dependent var	-8.42E-05
Adjusted R-squared	0.502727	S.D. dependent var	0.018588
S.E. of regression	0.013108	Sum squared resid	0.240545
Durbin-Watson stat	1.845889		

Equation: COMERUBC=C(111)+C(112)*F1+C(113)*F2+C(114)*F3+C(115)
*F4+C(116)*F5+C(117)*F6+C(118)*F7+C(119)*F8+C(120)*F9
Observations: 1410

R-squared	0.399802	Mean dependent var	0.000260
Adjusted R-squared	0.395944	S.D. dependent var	0.020449
S.E. of regression	0.015893	Sum squared resid	0.353632
Durbin-Watson stat	2.073514		

Equation: ELEKTRA_01=C(121)+C(122)*F1+C(123)*F2+C(124)*F3+C(125)
*F4+C(126)*F5+C(127)*F6+C(128)*F7+C(129)*F8+C(130)*F9
Observations: 1410

R-squared	0.566764	Mean dependent var	0.000287
Adjusted R-squared	0.563979	S.D. dependent var	0.024469
S.E. of regression	0.016158	Sum squared resid	0.365497
Durbin-Watson stat	1.941677		

Equation: TELMEXL=C(131)+C(132)*F1+C(133)*F2+C(134)*F3+C(135)*F4
+C(136)*F5+C(137)*F6+C(138)*F7+C(139)*F8+C(140)*F9
Observations: 1410

R-squared	0.981881	Mean dependent var	-1.50E-07
Adjusted R-squared	0.981764	S.D. dependent var	0.015611
S.E. of regression	0.002108	Sum squared resid	0.006222
Durbin-Watson stat	2.139029		

Equation: TELECOA1=C(141)+C(142)*F1+C(143)*F2+C(144)*F3+C(145)
*F4+C(146)*F5+C(147)*F6+C(148)*F7+C(149)*F8+C(150)*F9
Observations: 1410

R-squared	0.789317	Mean dependent var	2.74E-05
Adjusted R-squared	0.787962	S.D. dependent var	0.019544
S.E. of regression	0.009000	Sum squared resid	0.113394
Durbin-Watson stat	2.188685		

Equation: TLEVICPO=C(151)+C(152)*F1+C(153)*F2+C(154)*F3+C(155)
*F4+C(156)*F5+C(157)*F6+C(158)*F7+C(159)*F8+C(160)*F9
Observations: 1410

R-squared	0.792085	Mean dependent var	-5.84E-05
Adjusted R-squared	0.790748	S.D. dependent var	0.021967
S.E. of regression	0.010049	Sum squared resid	0.141367
Durbin-Watson stat	1.943614		

Equation: TVAZTCPO=C(161)+C(162)*F1+C(163)*F2+C(164)*F3+C(165)
*F4+C(166)*F5+C(167)*F6+C(168)*F7+C(169)*F8+C(170)*F9
Observations: 1410

R-squared	0.970408	Mean dependent var	-0.000324
Adjusted R-squared	0.970218	S.D. dependent var	0.024428
S.E. of regression	0.004216	Sum squared resid	0.024881
Durbin-Watson stat	1.980370		

Equation: GFNORTEO=C(171)+C(172)*F1+C(173)*F2+C(174)*F3+C(175)
*F4+C(176)*F5+C(177)*F6+C(178)*F7+C(179)*F8+C(180)*F9
Observations: 1410

R-squared	0.935924	Mean dependent var	0.001169
Adjusted R-squared	0.935512	S.D. dependent var	0.020498
S.E. of regression	0.005205	Sum squared resid	0.037935
Durbin-Watson stat	1.946273		

Equation: GFINBURO=C(181)+C(182)*F1+C(183)*F2+C(184)*F3+C(185)
*F4+C(186)*F5+C(187)*F6+C(188)*F7+C(189)*F8+C(190)*F9
Observations: 1410

R-squared	0.488200	Mean dependent var	0.000276
Adjusted R-squared	0.484910	S.D. dependent var	0.019348
S.E. of regression	0.013886	Sum squared resid	0.269944
Durbin-Watson stat	2.039507		

Equation: GCARSOA1=C(191)+C(192)*F1+C(193)*F2+C(194)*F3+C(195)
*F4+C(196)*F5+C(197)*F6+C(198)*F7+C(199)*F8+C(200)*F9
Observations: 1410

R-squared	0.679588	Mean dependent var	0.000455
Adjusted R-squared	0.677528	S.D. dependent var	0.019216
S.E. of regression	0.010912	Sum squared resid	0.166710
Durbin-Watson stat	1.926562		

Equation: ALFAA=C(201)+C(202)*F1+C(203)*F2+C(204)*F3+C(205)*F4
+C(206)*F5+C(207)*F6+C(208)*F7+C(209)*F8+C(210)*F9
Observations: 1410

R-squared	0.476884	Mean dependent var	0.000496
Adjusted R-squared	0.473521	S.D. dependent var	0.024567
S.E. of regression	0.017825	Sum squared resid	0.444836
Durbin-Watson stat	1.761414		

Equation: CIEB=C(211)+C(212)*F1+C(213)*F2+C(214)*F3+C(215)*F4
+C(216)*F5+C(217)*F6+C(218)*F7+C(219)*F8+C(220)*F9
Observations: 1410

R-squared	0.820804	Mean dependent var	-0.000633
Adjusted R-squared	0.819652	S.D. dependent var	0.021312
S.E. of regression	0.009051	Sum squared resid	0.114682
Durbin-Watson stat	1.963791		

Appendix_1 (Chapter 5)

Table 9. *Independent Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of weekly returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.001368	0.000601	-2.274993	0.0229
C(2)	-0.012767	0.005087	-2.509499	0.0121
C(3)	-0.012336	0.005062	-2.437212	0.0148
C(4)	-0.034002	0.005062	-6.717751	0.0000
C(5)	-0.036268	0.005063	-7.163728	0.0000
C(6)	-0.035363	0.005073	-6.971341	0.0000
C(7)	-0.174141	0.005062	-34.40050	0.0000
C(8)	-0.154268	0.005066	-30.45451	0.0000
C(9)	0.011862	0.005070	2.339569	0.0193
C(10)	0.516080	0.005073	101.7228	0.0000
C(11)	0.002929	0.001472	1.989907	0.0466
C(12)	0.012329	0.012453	0.990074	0.3222
C(13)	-0.134081	0.012389	-10.82227	0.0000
C(14)	-0.189827	0.012389	-15.32184	0.0000
C(15)	0.006463	0.012392	0.521531	0.6020
C(16)	0.013762	0.012417	1.108319	0.2678
C(17)	-0.167391	0.012391	-13.50922	0.0000
C(18)	0.025539	0.012399	2.059730	0.0395
C(19)	-0.026878	0.012411	-2.165703	0.0304
C(20)	-0.022708	0.012418	-1.828547	0.0675
C(21)	0.001725	0.001582	1.090541	0.2755
C(22)	-0.028982	0.013379	-2.166137	0.0303
C(23)	-0.025701	0.013311	-1.930775	0.0536
C(24)	0.131136	0.013311	9.851573	0.0000
C(25)	0.001212	0.013314	0.091019	0.9275
C(26)	0.042247	0.013340	3.166865	0.0015
C(27)	-0.044834	0.013313	-3.367732	0.0008
C(28)	-0.018247	0.013322	-1.369739	0.1708
C(29)	0.022388	0.013334	1.679030	0.0932
C(30)	-0.004930	0.013342	-0.369467	0.7118
C(31)	-8.17E-05	0.001562	-0.052322	0.9583
C(32)	-0.157323	0.013217	-11.90296	0.0000
C(33)	-0.127534	0.013150	-9.698533	0.0000
C(34)	0.110203	0.013150	8.380592	0.0000
C(35)	-0.105255	0.013153	-8.002510	0.0000
C(36)	-0.020903	0.013179	-1.586137	0.1128
C(37)	-0.093536	0.013151	-7.112247	0.0000
C(38)	0.079821	0.013160	6.065397	0.0000
C(39)	0.015738	0.013172	1.194769	0.2322
C(40)	0.012016	0.013181	0.911654	0.3620
C(41)	0.000963	0.001111	0.866680	0.3862
C(42)	0.031415	0.009400	3.341958	0.0008
C(43)	-0.075419	0.009352	-8.064331	0.0000
C(44)	0.059418	0.009352	6.353439	0.0000
C(45)	-0.172986	0.009354	-18.49270	0.0000
C(46)	0.017206	0.009373	1.835777	0.0664
C(47)	-0.260805	0.009353	-27.88393	0.0000
C(48)	-0.010615	0.009359	-1.134118	0.2568
C(49)	0.070259	0.009368	7.499740	0.0000

C(50)	-0.022223	0.009374	-2.370654	0.0178
C(51)	0.001697	0.001503	1.129105	0.2589
C(52)	-0.212195	0.012711	-16.69367	0.0000
C(53)	-0.260124	0.012646	-20.56909	0.0000
C(54)	0.035362	0.012646	2.796199	0.0052
C(55)	0.018874	0.012649	1.492104	0.1357
C(56)	-0.319361	0.012674	-25.19782	0.0000
C(57)	-0.102635	0.012648	-8.114822	0.0000
C(58)	-0.117817	0.012656	-9.309032	0.0000
C(59)	-0.014985	0.012668	-1.182863	0.2369
C(60)	0.045918	0.012676	3.622448	0.0003
C(61)	0.002131	0.001893	1.125661	0.2604
C(62)	-0.151417	0.016017	-9.453710	0.0000
C(63)	-0.061775	0.015935	-3.876646	0.0001
C(64)	-0.033847	0.015935	-2.124047	0.0337
C(65)	-0.049611	0.015939	-3.112645	0.0019
C(66)	0.027727	0.015970	1.736176	0.0826
C(67)	-0.095705	0.015937	-6.005209	0.0000
C(68)	0.026926	0.015948	1.688402	0.0914
C(69)	0.058273	0.015962	3.650662	0.0003
C(70)	0.042625	0.015972	2.668675	0.0076
C(71)	0.001042	0.001686	0.617882	0.5367
C(72)	-0.136857	0.014263	-9.595163	0.0000
C(73)	-0.073254	0.014190	-5.162188	0.0000
C(74)	0.119958	0.014190	8.453484	0.0000
C(75)	-0.004769	0.014194	-0.336022	0.7369
C(76)	-0.007609	0.014222	-0.535029	0.5927
C(77)	-0.105899	0.014192	-7.461800	0.0000
C(78)	-0.064269	0.014202	-4.525503	0.0000
C(79)	0.045970	0.014215	3.233951	0.0012
C(80)	-0.028585	0.014224	-2.009718	0.0445
C(81)	-8.17E-05	0.001647	-0.049612	0.9604
C(82)	-0.041651	0.013929	-2.990128	0.0028
C(83)	-0.174562	0.013858	-12.59610	0.0000
C(84)	0.144037	0.013858	10.39352	0.0000
C(85)	0.118244	0.013862	8.530392	0.0000
C(86)	0.012086	0.013889	0.870226	0.3842
C(87)	-0.103805	0.013860	-7.489512	0.0000
C(88)	0.001242	0.013869	0.089551	0.9286
C(89)	0.074667	0.013882	5.378624	0.0000
C(90)	-0.006245	0.013891	-0.449587	0.6530
C(91)	0.001720	0.001878	0.915915	0.3598
C(92)	-0.030499	0.015885	-1.919976	0.0549
C(93)	-0.144437	0.015804	-9.139275	0.0000
C(94)	0.101540	0.015804	6.425011	0.0000
C(95)	0.098050	0.015808	6.202718	0.0000
C(96)	0.080191	0.015839	5.062972	0.0000
C(97)	-0.145403	0.015806	-9.199313	0.0000
C(98)	0.037597	0.015816	2.377085	0.0175
C(99)	0.051612	0.015831	3.260176	0.0011
C(100)	0.059106	0.015841	3.731235	0.0002
C(101)	0.001912	0.001116	1.713276	0.0867
C(102)	-0.194373	0.009442	-20.58572	0.0000
C(103)	-0.230002	0.009394	-24.48384	0.0000
C(104)	0.109354	0.009394	11.64087	0.0000
C(105)	-0.088996	0.009396	-9.471514	0.0000
C(106)	0.136142	0.009415	14.46068	0.0000
C(107)	-0.085833	0.009395	-9.135869	0.0000

C(108)	-0.036559	0.009401	-3.888746	0.0001
C(109)	-0.260815	0.009410	-27.71650	0.0000
C(110)	0.055082	0.009416	5.849847	0.0000
C(111)	-0.000693	0.001072	-0.646509	0.5180
C(112)	-0.176716	0.009071	-19.48052	0.0000
C(113)	-0.055716	0.009025	-6.173443	0.0000
C(114)	0.011342	0.009025	1.256672	0.2089
C(115)	0.055673	0.009027	6.167283	0.0000
C(116)	0.083757	0.009045	9.259982	0.0000
C(117)	-0.106982	0.009026	-11.85239	0.0000
C(118)	-0.013046	0.009032	-1.444421	0.1487
C(119)	0.036848	0.009041	4.075867	0.0000
C(120)	-0.006061	0.009046	-0.670014	0.5029
C(121)	-0.001366	0.001214	-1.125247	0.2605
C(122)	-0.243882	0.010272	-23.74355	0.0000
C(123)	-0.095438	0.010219	-9.339132	0.0000
C(124)	-0.027511	0.010219	-2.692109	0.0071
C(125)	0.070791	0.010221	6.925699	0.0000
C(126)	0.127036	0.010242	12.40390	0.0000
C(127)	-0.136893	0.010220	-13.39410	0.0000
C(128)	-0.010093	0.010227	-0.986905	0.3237
C(129)	0.062864	0.010237	6.141087	0.0000
C(130)	-0.005955	0.010243	-0.581405	0.5610
C(131)	-0.002517	0.001548	-1.625578	0.1041
C(132)	-0.225997	0.013100	-17.25195	0.0000
C(133)	-0.114721	0.013033	-8.802320	0.0000
C(134)	0.106550	0.013033	8.175391	0.0000
C(135)	0.012223	0.013036	0.937646	0.3485
C(136)	-0.010611	0.013062	-0.812408	0.4166
C(137)	-0.181876	0.013035	-13.95338	0.0000
C(138)	-0.067351	0.013043	-5.163702	0.0000
C(139)	0.019521	0.013055	1.495280	0.1349
C(140)	-0.031829	0.013063	-2.436454	0.0149
C(141)	-0.000335	0.000905	-0.370830	0.7108
C(142)	-0.082808	0.007653	-10.82068	0.0000
C(143)	-0.220040	0.007614	-28.90040	0.0000
C(144)	0.153903	0.007614	20.21389	0.0000
C(145)	0.124484	0.007615	16.34626	0.0000
C(146)	0.064322	0.007630	8.429556	0.0000
C(147)	-0.208528	0.007615	-27.38516	0.0000
C(148)	-0.137382	0.007620	-18.02984	0.0000
C(149)	-0.146965	0.007627	-19.26960	0.0000
C(150)	-0.048224	0.007632	-6.318979	0.0000
C(151)	0.004630	0.001780	2.601503	0.0093
C(152)	-0.144652	0.015057	-9.607236	0.0000
C(153)	-0.140925	0.014980	-9.407643	0.0000
C(154)	0.145457	0.014980	9.710201	0.0000
C(155)	0.078824	0.014983	5.260817	0.0000
C(156)	0.005845	0.015013	0.389348	0.6970
C(157)	-0.013145	0.014982	-0.877395	0.3803
C(158)	-0.007644	0.014992	-0.509887	0.6102
C(159)	0.035280	0.015006	2.351133	0.0188
C(160)	0.058716	0.015015	3.910506	0.0001
C(161)	1.80E-05	0.001362	0.013234	0.9894
C(162)	-0.152498	0.011526	-13.23083	0.0000
C(163)	-0.220113	0.011467	-19.19497	0.0000
C(164)	-0.023794	0.011467	-2.074937	0.0380
C(165)	0.059975	0.011470	5.228928	0.0000

C(166)	-0.007954	0.011492	-0.692092	0.4889
C(167)	-0.037361	0.011469	-3.257667	0.0011
C(168)	0.106724	0.011476	9.299637	0.0000
C(169)	0.057026	0.011487	4.964461	0.0000
C(170)	0.041651	0.011494	3.623703	0.0003
C(171)	0.001691	0.001559	1.084833	0.2780
C(172)	-0.179941	0.013187	-13.64538	0.0000
C(173)	-0.121136	0.013120	-9.233060	0.0000
C(174)	0.086386	0.013120	6.584433	0.0000
C(175)	0.064333	0.013123	4.902414	0.0000
C(176)	0.111298	0.013149	8.464621	0.0000
C(177)	-0.120093	0.013121	-9.152540	0.0000
C(178)	0.045973	0.013130	3.501334	0.0005
C(179)	0.077598	0.013142	5.904426	0.0000
C(180)	-0.003311	0.013150	-0.251799	0.8012
C(181)	0.000517	0.000622	0.830427	0.4063
C(182)	-0.105565	0.005264	-20.05523	0.0000
C(183)	-0.379684	0.005237	-72.50189	0.0000
C(184)	0.047561	0.005237	9.082016	0.0000
C(185)	-0.128422	0.005238	-24.51707	0.0000
C(186)	0.157987	0.005248	30.10204	0.0000
C(187)	0.008243	0.005237	1.573764	0.1156
C(188)	-0.219870	0.005241	-41.95219	0.0000
C(189)	0.151297	0.005246	28.84123	0.0000
C(190)	-0.010118	0.005249	-1.927577	0.0540
C(191)	-0.002647	0.001328	-1.994118	0.0462
C(192)	-0.026916	0.011231	-2.396635	0.0166
C(193)	-0.280997	0.011173	-25.14870	0.0000
C(194)	0.112047	0.011173	10.02803	0.0000
C(195)	0.020773	0.011176	1.858753	0.0631
C(196)	0.015963	0.011198	1.425543	0.1541
C(197)	-0.146787	0.011175	-13.13562	0.0000
C(198)	0.171918	0.011182	15.37439	0.0000
C(199)	0.041013	0.011193	3.664298	0.0003
C(200)	0.054851	0.011200	4.897610	0.0000

Equation: PE_OLES_01=C(1)+C(2)*IC1+C(3)*IC2+C(4)*IC3+C(5)*IC4
+C(6)*IC5+C(7)*IC6+C(8)*IC7+C(9)*IC8+C(10)*IC9
Observations: 291

R-squared	0.977372	Mean dependent var	0.004729
Adjusted R-squared	0.976647	S.D. dependent var	0.067404
S.E. of regression	0.010300	Sum squared resid	0.029814
Durbin-Watson stat	2.258163		

Equation: BIMBOA=C(11)+C(12)*IC1+C(13)*IC2+C(14)*IC3+C(15)*IC4
+C(16)*IC5+C(17)*IC6+C(18)*IC7+C(19)*IC8+C(20)*IC9
Observations: 291

R-squared	0.653712	Mean dependent var	0.003161
Adjusted R-squared	0.642621	S.D. dependent var	0.042175
S.E. of regression	0.025213	Sum squared resid	0.178627
Durbin-Watson stat	1.998779		

Equation: GMODELOC=C(21)+C(22)*IC1+C(23)*IC2+C(24)*IC3+C(25)
*IC4+C(26)*IC5+C(27)*IC6+C(28)*IC7+C(29)*IC8+C(30)*IC9
Observations: 291

R-squared	0.311757	Mean dependent var	0.001865
Adjusted R-squared	0.289714	S.D. dependent var	0.032142
S.E. of regression	0.027089	Sum squared resid	0.206196
Durbin-Watson stat	2.280189		

Equation: FEMSAUBD=C(31)+C(32)*IC1+C(33)*IC2+C(34)*IC3+C(35)*IC4+C(36)*IC5+C(37)*IC6+C(38)*IC7+C(39)*IC8+C(40)*IC9
Observations: 291

R-squared	0.613209	Mean dependent var	0.002358
Adjusted R-squared	0.600821	S.D. dependent var	0.042355
S.E. of regression	0.026760	Sum squared resid	0.201227
Durbin-Watson stat	2.160279		

Equation: CONTAL_01=C(41)+C(42)*IC1+C(43)*IC2+C(44)*IC3+C(45)*IC4+C(46)*IC5+C(47)*IC6+C(48)*IC7+C(49)*IC8+C(50)*IC9
Observations: 291

R-squared	0.817398	Mean dependent var	0.002039
Adjusted R-squared	0.811549	S.D. dependent var	0.043841
S.E. of regression	0.019032	Sum squared resid	0.101782
Durbin-Watson stat	2.238104		

Equation: GEOB=C(51)+C(52)*IC1+C(53)*IC2+C(54)*IC3+C(55)*IC4+C(56)*IC5+C(57)*IC6+C(58)*IC7+C(59)*IC8+C(60)*IC9
Observations: 291

R-squared	0.837596	Mean dependent var	0.008191
Adjusted R-squared	0.832394	S.D. dependent var	0.062862
S.E. of regression	0.025736	Sum squared resid	0.186113
Durbin-Watson stat	2.334525		

Equation: ARA_01=C(61)+C(62)*IC1+C(63)*IC2+C(64)*IC3+C(65)*IC4+C(66)*IC5+C(67)*IC6+C(68)*IC7+C(69)*IC8+C(70)*IC9
Observations: 291

R-squared	0.381978	Mean dependent var	0.004898
Adjusted R-squared	0.362184	S.D. dependent var	0.040605
S.E. of regression	0.032428	Sum squared resid	0.295499
Durbin-Watson stat	2.125986		

Equation: WALMEXV=C(71)+C(72)*IC1+C(73)*IC2+C(74)*IC3+C(75)*IC4+C(76)*IC5+C(77)*IC6+C(78)*IC7+C(79)*IC8+C(80)*IC9
Observations: 291

R-squared	0.490768	Mean dependent var	0.003334
Adjusted R-squared	0.474458	S.D. dependent var	0.039835
S.E. of regression	0.028878	Sum squared resid	0.234335
Durbin-Watson stat	2.538214		

Equation: SORIANAB=C(81)+C(82)*IC1+C(83)*IC2+C(84)*IC3+C(85)*IC4+C(86)*IC5+C(87)*IC6+C(88)*IC7+C(89)*IC8+C(90)*IC9
Observations: 291

R-squared	0.598882	Mean dependent var	0.000746
Adjusted R-squared	0.586035	S.D. dependent var	0.043833
S.E. of regression	0.028202	Sum squared resid	0.223497
Durbin-Watson stat	2.258559		

Equation: COMERUBC=C(91)+C(92)*IC1+C(93)*IC2+C(94)*IC3+C(95)*IC4+C(96)*IC5+C(97)*IC6+C(98)*IC7+C(99)*IC8+C(100)*IC9
Observations: 291

R-squared	0.513962	Mean dependent var	0.002256
Adjusted R-squared	0.498395	S.D. dependent var	0.045411
S.E. of regression	0.032162	Sum squared resid	0.290657
Durbin-Watson stat	2.161451		

Equation: ELEKTRA_01=C(101)+C(102)*IC1+C(103)*IC2+C(104)*IC3
+C(105)*IC4+C(106)*IC5+C(107)*IC6+C(108)*IC7+C(109)*IC8
+C(110)*IC9
Observations: 291

R-squared	0.890513	Mean dependent var	0.002654
Adjusted R-squared	0.887006	S.D. dependent var	0.056871
S.E. of regression	0.019117	Sum squared resid	0.102695
Durbin-Watson stat	2.168836		

Equation: TELMEXL=C(111)+C(112)*IC1+C(113)*IC2+C(114)*IC3
+C(115)*IC4+C(116)*IC5+C(117)*IC6+C(118)*IC7+C(119)*IC8
+C(120)*IC9
Observations: 291

R-squared	0.707525	Mean dependent var	0.001198
Adjusted R-squared	0.698157	S.D. dependent var	0.033430
S.E. of regression	0.018366	Sum squared resid	0.094789
Durbin-Watson stat	2.101021		

Equation: TELECOA1=C(121)+C(122)*IC1+C(123)*IC2+C(124)*IC3
+C(125)*IC4+C(126)*IC5+C(127)*IC6+C(128)*IC7+C(129)*IC8
+C(130)*IC9
Observations: 291

R-squared	0.787804	Mean dependent var	0.001320
Adjusted R-squared	0.781008	S.D. dependent var	0.044440
S.E. of regression	0.020796	Sum squared resid	0.121528
Durbin-Watson stat	2.242494		

Equation: TLEVICPO=C(131)+C(132)*IC1+C(133)*IC2+C(134)*IC3
+C(135)*IC4+C(136)*IC5+C(137)*IC6+C(138)*IC7+C(139)*IC8
+C(140)*IC9
Observations: 291

R-squared	0.697621	Mean dependent var	0.000899
Adjusted R-squared	0.687936	S.D. dependent var	0.047478
S.E. of regression	0.026523	Sum squared resid	0.197668
Durbin-Watson stat	2.115810		

Equation: TVAZTCPO=C(141)+C(142)*IC1+C(143)*IC2+C(144)*IC3
+C(145)*IC4+C(146)*IC5+C(147)*IC6+C(148)*IC7+C(149)*IC8
+C(150)*IC9
Observations: 291

R-squared	0.916404	Mean dependent var	-0.000334
Adjusted R-squared	0.913726	S.D. dependent var	0.052751
S.E. of regression	0.015494	Sum squared resid	0.067459
Durbin-Watson stat	2.197551		

Equation: GFNORTEO=C(151)+C(152)*IC1+C(153)*IC2+C(154)*IC3
+C(155)*IC4+C(156)*IC5+C(157)*IC6+C(158)*IC7+C(159)*IC8
+C(160)*IC9
Observations: 291

R-squared	0.527060	Mean dependent var	0.006851
Adjusted R-squared	0.511912	S.D. dependent var	0.043634
S.E. of regression	0.030484	Sum squared resid	0.261132
Durbin-Watson stat	2.177658		

Equation: GFINBURO=C(161)+C(162)*IC1+C(163)*IC2+C(164)*IC3
+C(165)*IC4+C(166)*IC5+C(167)*IC6+C(168)*IC7+C(169)*IC8
+C(170)*IC9
Observations: 291

R-squared	0.709140	Mean dependent var	0.002456
Adjusted R-squared	0.699824	S.D. dependent var	0.042593
S.E. of regression	0.023336	Sum squared resid	0.153025
Durbin-Watson stat	2.116904		

Equation: GCARSOA1=C(171)+C(172)*IC1+C(173)*IC2+C(174)*IC3
+C(175)*IC4+C(176)*IC5+C(177)*IC6+C(178)*IC7+C(179)*IC8
+C(180)*IC9
Observations: 291

R-squared	0.650960	Mean dependent var	0.003413
Adjusted R-squared	0.639780	S.D. dependent var	0.044485
S.E. of regression	0.026699	Sum squared resid	0.200308
Durbin-Watson stat	2.200741		

Equation: ALFAA=C(181)+C(182)*IC1+C(183)*IC2+C(184)*IC3+C(185)
*IC4+C(186)*IC5+C(187)*IC6+C(188)*IC7+C(189)*IC8+C(190)*IC9
Observations: 291

R-squared	0.971271	Mean dependent var	0.003559
Adjusted R-squared	0.970351	S.D. dependent var	0.061893
S.E. of regression	0.010657	Sum squared resid	0.031915
Durbin-Watson stat	1.939524		

Equation: CIEB=C(191)+C(192)*IC1+C(193)*IC2+C(194)*IC3+C(195)
*IC4+C(196)*IC5+C(197)*IC6+C(198)*IC7+C(199)*IC8+C(200)*IC9
Observations: 291

R-squared	0.803673	Mean dependent var	-0.001948
Adjusted R-squared	0.797385	S.D. dependent var	0.050515
S.E. of regression	0.022738	Sum squared resid	0.145284
Durbin-Watson stat	2.148308		

Table 10. *Independent Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of weekly excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.001423	0.000797	1.785959	0.0742
C(2)	-0.227177	0.006724	-33.78679	0.0000
C(3)	-0.027222	0.006712	-4.055800	0.0001
C(4)	0.018121	0.006705	2.702371	0.0069
C(5)	-0.064798	0.006707	-9.661126	0.0000
C(6)	0.307902	0.006717	45.84223	0.0000
C(7)	-0.077076	0.006721	-11.46777	0.0000
C(8)	-0.130278	0.006712	-19.40839	0.0000
C(9)	0.367506	0.006721	54.67944	0.0000
C(10)	0.087132	0.006718	12.97012	0.0000
C(11)	0.003270	0.001890	1.729978	0.0837
C(12)	-0.014020	0.015955	-0.878737	0.3796
C(13)	0.071543	0.015926	4.492088	0.0000
C(14)	-0.102355	0.015911	-6.432846	0.0000
C(15)	0.133377	0.015915	8.380467	0.0000
C(16)	-0.002661	0.015938	-0.166946	0.8674
C(17)	0.016414	0.015948	1.029186	0.3034
C(18)	-0.106938	0.015928	-6.713805	0.0000
C(19)	0.072439	0.015948	4.542063	0.0000
C(20)	-0.072367	0.015941	-4.539711	0.0000
C(21)	0.000365	0.001428	0.255845	0.7981
C(22)	-0.085915	0.012048	-7.130836	0.0000
C(23)	0.107972	0.012027	8.977617	0.0000
C(24)	0.007851	0.012015	0.653436	0.5135
C(25)	-0.063290	0.012018	-5.266108	0.0000
C(26)	-0.075505	0.012035	-6.273560	0.0000
C(27)	-0.042784	0.012043	-3.552496	0.0004
C(28)	-0.020888	0.012028	-1.736597	0.0825
C(29)	0.023930	0.012044	1.986962	0.0470
C(30)	0.036910	0.012038	3.066206	0.0022
C(31)	0.000711	0.001689	0.421341	0.6735
C(32)	-0.129522	0.014251	-9.088786	0.0000
C(33)	0.096841	0.014225	6.807696	0.0000
C(34)	-0.138931	0.014212	-9.775828	0.0000
C(35)	0.042600	0.014215	2.996814	0.0027
C(36)	-0.095134	0.014235	-6.682985	0.0000
C(37)	-0.094311	0.014245	-6.620662	0.0000
C(38)	-0.072260	0.014227	-5.079187	0.0000
C(39)	0.024495	0.014245	1.719530	0.0856
C(40)	-0.023607	0.014238	-1.658007	0.0974
C(41)	0.001508	0.001231	1.224935	0.2207
C(42)	0.001794	0.010387	0.172720	0.8629
C(43)	-0.003170	0.010368	-0.305756	0.7598
C(44)	-0.094837	0.010358	-9.155505	0.0000
C(45)	-0.065913	0.010361	-6.361640	0.0000
C(46)	-0.069693	0.010376	-6.716927	0.0000
C(47)	-0.081078	0.010383	-7.808937	0.0000
C(48)	-0.284430	0.010369	-27.42974	0.0000
C(49)	-0.018169	0.010383	-1.749953	0.0802
C(50)	0.046644	0.010378	4.494636	0.0000
C(51)	0.000544	0.001146	0.475174	0.6347
C(52)	-0.373971	0.009668	-38.68086	0.0000
C(53)	-0.120249	0.009651	-12.45997	0.0000

C(54)	-0.226831	0.009642	-23.52620	0.0000
C(55)	-0.084080	0.009644	-8.718307	0.0000
C(56)	0.038431	0.009658	3.979376	0.0001
C(57)	-0.023132	0.009664	-2.393618	0.0167
C(58)	-0.021412	0.009652	-2.218498	0.0266
C(59)	-0.114226	0.009664	-11.81950	0.0000
C(60)	0.186462	0.009660	19.30343	0.0000
C(61)	0.001220	0.001446	0.843799	0.3988
C(62)	-0.125621	0.012204	-10.29310	0.0000
C(63)	0.078867	0.012182	6.473788	0.0000
C(64)	-0.122443	0.012171	-10.06032	0.0000
C(65)	-0.046634	0.012174	-3.830598	0.0001
C(66)	0.102040	0.012191	8.370001	0.0000
C(67)	-0.095682	0.012199	-7.843200	0.0000
C(68)	-0.074784	0.012184	-6.138013	0.0000
C(69)	-0.103418	0.012199	-8.477329	0.0000
C(70)	-0.043887	0.012194	-3.599243	0.0003
C(71)	0.001441	0.001518	0.949474	0.3424
C(72)	-0.108247	0.012811	-8.449253	0.0000
C(73)	0.065488	0.012788	5.120903	0.0000
C(74)	-0.110329	0.012776	-8.635429	0.0000
C(75)	0.073741	0.012780	5.770252	0.0000
C(76)	-0.152221	0.012798	-11.89455	0.0000
C(77)	-0.066954	0.012806	-5.228253	0.0000
C(78)	-0.003986	0.012790	-0.311627	0.7553
C(79)	0.051321	0.012806	4.007541	0.0001
C(80)	0.060970	0.012800	4.763235	0.0000
C(81)	-0.000255	0.001583	-0.161024	0.8721
C(82)	-0.169153	0.013364	-12.65723	0.0000
C(83)	0.106242	0.013340	7.964074	0.0000
C(84)	-0.106058	0.013328	-7.957833	0.0000
C(85)	-0.084742	0.013331	-6.356837	0.0000
C(86)	-0.149305	0.013350	-11.18420	0.0000
C(87)	-0.042908	0.013359	-3.212042	0.0013
C(88)	0.026472	0.013342	1.984217	0.0473
C(89)	0.065133	0.013359	4.875703	0.0000
C(90)	-0.031173	0.013352	-2.334658	0.0196
C(91)	0.001227	0.001714	0.715900	0.4741
C(92)	-0.142283	0.014466	-9.835703	0.0000
C(93)	0.150823	0.014440	10.44477	0.0000
C(94)	0.008284	0.014426	0.574205	0.5659
C(95)	-0.137738	0.014430	-9.545283	0.0000
C(96)	-0.070358	0.014450	-4.868933	0.0000
C(97)	-0.104248	0.014460	-7.209386	0.0000
C(98)	-0.062056	0.014442	-4.297066	0.0000
C(99)	0.018430	0.014460	1.274511	0.2025
C(100)	-0.086369	0.014453	-5.975775	0.0000
C(101)	0.001089	0.001304	0.835370	0.4035
C(102)	-0.114833	0.011003	-10.43631	0.0000
C(103)	0.329107	0.010983	29.96387	0.0000
C(104)	-0.222339	0.010973	-20.26232	0.0000
C(105)	-0.075643	0.010976	-6.891793	0.0000
C(106)	0.074187	0.010991	6.749613	0.0000
C(107)	0.058892	0.010999	5.354457	0.0000
C(108)	-0.017533	0.010985	-1.596127	0.1105
C(109)	-0.031562	0.010999	-2.869606	0.0041
C(110)	0.114778	0.010993	10.44065	0.0000
C(111)	-0.001223	0.001125	-1.087602	0.2768

C(112)	-0.144206	0.009493	-15.19053	0.0000
C(113)	0.124157	0.009476	13.10201	0.0000
C(114)	-0.045100	0.009467	-4.763843	0.0000
C(115)	0.096259	0.009470	10.16513	0.0000
C(116)	-0.050609	0.009483	-5.336921	0.0000
C(117)	-0.062521	0.009489	-6.588553	0.0000
C(118)	-0.032137	0.009477	-3.391011	0.0007
C(119)	0.011638	0.009489	1.226418	0.2201
C(120)	0.001767	0.009485	0.186292	0.8522
C(121)	-0.001788	0.001279	-1.397665	0.1623
C(122)	-0.200016	0.010798	-18.52353	0.0000
C(123)	0.178365	0.010779	16.54806	0.0000
C(124)	-0.055179	0.010768	-5.124200	0.0000
C(125)	0.144794	0.010771	13.44292	0.0000
C(126)	-0.039581	0.010786	-3.669588	0.0002
C(127)	-0.103512	0.010793	-9.590223	0.0000
C(128)	-0.041436	0.010780	-3.843927	0.0001
C(129)	-0.002702	0.010794	-0.250320	0.8023
C(130)	-0.013111	0.010788	-1.215312	0.2243
C(131)	-0.000930	0.001502	-0.619271	0.5358
C(132)	-0.179406	0.012680	-14.14821	0.0000
C(133)	0.126012	0.012658	9.955277	0.0000
C(134)	-0.171772	0.012646	-13.58338	0.0000
C(135)	0.101795	0.012649	8.047730	0.0000
C(136)	-0.118754	0.012667	-9.375239	0.0000
C(137)	-0.069637	0.012675	-5.493909	0.0000
C(138)	-0.078233	0.012659	-6.180000	0.0000
C(139)	0.057368	0.012675	4.526002	0.0000
C(140)	0.035504	0.012669	2.802386	0.0051
C(141)	-0.000407	0.001366	-0.297850	0.7658
C(142)	-0.137930	0.011525	-11.96757	0.0000
C(143)	0.201054	0.011505	17.47592	0.0000
C(144)	-0.206934	0.011494	-18.00409	0.0000
C(145)	-0.062244	0.011497	-5.414095	0.0000
C(146)	-0.140475	0.011513	-12.20166	0.0000
C(147)	0.080046	0.011521	6.948090	0.0000
C(148)	-0.036327	0.011506	-3.157267	0.0016
C(149)	0.087234	0.011521	7.572028	0.0000
C(150)	0.151703	0.011515	13.17427	0.0000
C(151)	0.003600	0.001791	2.009727	0.0445
C(152)	-0.154974	0.015118	-10.25095	0.0000
C(153)	0.058549	0.015091	3.879716	0.0001
C(154)	-0.096937	0.015077	-6.429652	0.0000
C(155)	-0.023351	0.015080	-1.548403	0.1216
C(156)	-0.106642	0.015102	-7.061608	0.0000
C(157)	-0.083053	0.015112	-5.495904	0.0000
C(158)	0.126262	0.015092	8.365892	0.0000
C(159)	0.011981	0.015112	0.792805	0.4279
C(160)	0.021966	0.015105	1.454245	0.1459
C(161)	-4.05E-05	0.001401	-0.028909	0.9769
C(162)	-0.113793	0.011823	-9.624961	0.0000
C(163)	0.023648	0.011802	2.003815	0.0451
C(164)	-0.218011	0.011790	-18.49064	0.0000
C(165)	0.033178	0.011793	2.813281	0.0049
C(166)	0.022046	0.011810	1.866718	0.0620
C(167)	-0.078951	0.011818	-6.680626	0.0000
C(168)	0.043449	0.011803	3.681251	0.0002
C(169)	-0.009902	0.011818	-0.837902	0.4021

C(170)	-0.143292	0.011812	-12.13084	0.0000
C(171)	0.000932	0.001607	0.580026	0.5619
C(172)	-0.173625	0.013561	-12.80361	0.0000
C(173)	0.176054	0.013536	13.00607	0.0000
C(174)	-0.098264	0.013523	-7.266173	0.0000
C(175)	0.026367	0.013527	1.949253	0.0513
C(176)	-0.088692	0.013546	-6.547536	0.0000
C(177)	-0.099184	0.013555	-7.317170	0.0000
C(178)	-0.005512	0.013538	-0.407151	0.6839
C(179)	-0.030770	0.013555	-2.269991	0.0232
C(180)	-0.026170	0.013549	-1.931577	0.0535
C(181)	-0.000507	0.001015	-0.499433	0.6175
C(182)	-0.003896	0.008565	-0.454834	0.6492
C(183)	0.170098	0.008549	19.89572	0.0000
C(184)	-0.262781	0.008541	-30.76565	0.0000
C(185)	-0.073040	0.008544	-8.549181	0.0000
C(186)	-0.021180	0.008556	-2.475563	0.0133
C(187)	-0.354144	0.008561	-41.36557	0.0000
C(188)	0.024540	0.008550	2.870070	0.0041
C(189)	0.036932	0.008561	4.313822	0.0000
C(190)	0.163243	0.008557	19.07662	0.0000
C(191)	-0.000991	0.001053	-0.940672	0.3469
C(192)	-0.148147	0.008889	-16.66544	0.0000
C(193)	0.065302	0.008874	7.359168	0.0000
C(194)	-0.245903	0.008865	-27.73827	0.0000
C(195)	-0.118529	0.008867	-13.36693	0.0000
C(196)	-0.124645	0.008880	-14.03693	0.0000
C(197)	-0.034527	0.008886	-3.885685	0.0001
C(198)	-0.058188	0.008874	-6.556784	0.0000
C(199)	0.118727	0.008886	13.36140	0.0000
C(200)	-0.167391	0.008882	-18.84706	0.0000

Equation: PE_OLES_01=C(1)+C(2)*IC1+C(3)*IC2+C(4)*IC3+C(5)*IC4
+C(6)*IC5+C(7)*IC6+C(8)*IC7+C(9)*IC8+C(10)*IC9
Observations: 291

R-squared	0.960371	Mean dependent var	0.003041
Adjusted R-squared	0.959101	S.D. dependent var	0.067481
S.E. of regression	0.013647	Sum squared resid	0.052333
Durbin-Watson stat	2.138073		

Equation: BIMBOA=C(11)+C(12)*IC1+C(13)*IC2+C(14)*IC3+C(15)*IC4
+C(16)*IC5+C(17)*IC6+C(18)*IC7+C(19)*IC8+C(20)*IC9
Observations: 291

R-squared	0.429863	Mean dependent var	0.001472
Adjusted R-squared	0.411603	S.D. dependent var	0.042216
S.E. of regression	0.032383	Sum squared resid	0.294667
Durbin-Watson stat	2.060684		

Equation: GMODELOC=C(21)+C(22)*IC1+C(23)*IC2+C(24)*IC3+C(25)
*IC4+C(26)*IC5+C(27)*IC6+C(28)*IC7+C(29)*IC8+C(30)*IC9
Observations: 291

R-squared	0.440001	Mean dependent var	0.000176
Adjusted R-squared	0.422065	S.D. dependent var	0.032167
S.E. of regression	0.024454	Sum squared resid	0.168035
Durbin-Watson stat	2.120731		

Equation: FEMSAUBD=C(31)+C(32)*IC1+C(33)*IC2+C(34)*IC3+C(35)
*IC4+C(36)*IC5+C(37)*IC6+C(38)*IC7+C(39)*IC8+C(40)*IC9
Observations: 291

R-squared	0.549188	Mean dependent var	0.000669
Adjusted R-squared	0.534749	S.D. dependent var	0.042404
S.E. of regression	0.028924	Sum squared resid	0.235079
Durbin-Watson stat	2.328372		

Equation: CONTAL_01=C(41)+C(42)*IC1+C(43)*IC2+C(44)*IC3+C(45)
*IC4+C(46)*IC5+C(47)*IC6+C(48)*IC7+C(49)*IC8+C(50)*IC9
Observations: 291

R-squared	0.775889	Mean dependent var	0.000350
Adjusted R-squared	0.768711	S.D. dependent var	0.043836
S.E. of regression	0.021082	Sum squared resid	0.124886
Durbin-Watson stat	2.035919		

Equation: GEOB=C(51)+C(52)*IC1+C(53)*IC2+C(54)*IC3+C(55)*IC4
+C(56)*IC5+C(57)*IC6+C(58)*IC7+C(59)*IC8+C(60)*IC9
Observations: 291

R-squared	0.905943	Mean dependent var	0.006502
Adjusted R-squared	0.902931	S.D. dependent var	0.062982
S.E. of regression	0.019623	Sum squared resid	0.108199
Durbin-Watson stat	2.328541		

Equation: ARA_01=C(61)+C(62)*IC1+C(63)*IC2+C(64)*IC3+C(65)*IC4
+C(66)*IC5+C(67)*IC6+C(68)*IC7+C(69)*IC8+C(70)*IC9
Observations: 291

R-squared	0.640100	Mean dependent var	0.003209
Adjusted R-squared	0.628573	S.D. dependent var	0.040644
S.E. of regression	0.024770	Sum squared resid	0.172412
Durbin-Watson stat	2.192797		

Equation: WALMEXV=C(71)+C(72)*IC1+C(73)*IC2+C(74)*IC3+C(75)
*IC4+C(76)*IC5+C(77)*IC6+C(78)*IC7+C(79)*IC8+C(80)*IC9
Observations: 291

R-squared	0.587450	Mean dependent var	0.001645
Adjusted R-squared	0.574237	S.D. dependent var	0.039850
S.E. of regression	0.026002	Sum squared resid	0.189991
Durbin-Watson stat	2.380656		

Equation: SORIANAB=C(81)+C(82)*IC1+C(83)*IC2+C(84)*IC3+C(85)
*IC4+C(86)*IC5+C(87)*IC6+C(88)*IC7+C(89)*IC8+C(90)*IC9
Observations: 291

R-squared	0.630898	Mean dependent var	-0.000943
Adjusted R-squared	0.619077	S.D. dependent var	0.043948
S.E. of regression	0.027124	Sum squared resid	0.206737
Durbin-Watson stat	2.199651		

Equation: COMERUBC=C(91)+C(92)*IC1+C(93)*IC2+C(94)*IC3+C(95)
*IC4+C(96)*IC5+C(97)*IC6+C(98)*IC7+C(99)*IC8+C(100)*IC9
Observations: 291

R-squared	0.596350	Mean dependent var	0.000568
Adjusted R-squared	0.583422	S.D. dependent var	0.045490
S.E. of regression	0.029361	Sum squared resid	0.242234
Durbin-Watson stat	2.373684		

Equation: ELEKTRA_01=C(101)+C(102)*IC1+C(103)*IC2+C(104)*IC3
+C(105)*IC4+C(106)*IC5+C(107)*IC6+C(108)*IC7+C(109)*IC8
+C(110)*IC9
Observations: 291

R-squared	0.850999	Mean dependent var	0.000965
Adjusted R-squared	0.846226	S.D. dependent var	0.056950
S.E. of regression	0.022332	Sum squared resid	0.140144
Durbin-Watson stat	2.209381		

Equation: TELMEXL=C(111)+C(112)*IC1+C(113)*IC2+C(114)*IC3
+C(115)*IC4+C(116)*IC5+C(117)*IC6+C(118)*IC7+C(119)*IC8
+C(120)*IC9
Observations: 291

R-squared	0.678792	Mean dependent var	-0.000491
Adjusted R-squared	0.668504	S.D. dependent var	0.033465
S.E. of regression	0.019268	Sum squared resid	0.104318
Durbin-Watson stat	2.196527		

Equation: TELECOA1=C(121)+C(122)*IC1+C(123)*IC2+C(124)*IC3
+C(125)*IC4+C(126)*IC5+C(127)*IC6+C(128)*IC7+C(129)*IC8
+C(130)*IC9
Observations: 291

R-squared	0.765038	Mean dependent var	-0.000369
Adjusted R-squared	0.757512	S.D. dependent var	0.044505
S.E. of regression	0.021916	Sum squared resid	0.134965
Durbin-Watson stat	2.143143		

Equation: TLEVICPO=C(131)+C(132)*IC1+C(133)*IC2+C(134)*IC3
+C(135)*IC4+C(136)*IC5+C(137)*IC6+C(138)*IC7+C(139)*IC8
+C(140)*IC9
Observations: 291

R-squared	0.716421	Mean dependent var	-0.000790
Adjusted R-squared	0.707338	S.D. dependent var	0.047574
S.E. of regression	0.025737	Sum squared resid	0.186128
Durbin-Watson stat	2.090370		

Equation: TVAZTCPO=C(141)+C(142)*IC1+C(143)*IC2+C(144)*IC3
+C(145)*IC4+C(146)*IC5+C(147)*IC6+C(148)*IC7+C(149)*IC8
+C(150)*IC9
Observations: 291

R-squared	0.810152	Mean dependent var	-0.002023
Adjusted R-squared	0.804071	S.D. dependent var	0.052847
S.E. of regression	0.023392	Sum squared resid	0.153760
Durbin-Watson stat	2.051300		

Equation: GFNORTEO=C(151)+C(152)*IC1+C(153)*IC2+C(154)*IC3
+C(155)*IC4+C(156)*IC5+C(157)*IC6+C(158)*IC7+C(159)*IC8
+C(160)*IC9
Observations: 291

R-squared	0.521373	Mean dependent var	0.005163
Adjusted R-squared	0.506044	S.D. dependent var	0.043658
S.E. of regression	0.030684	Sum squared resid	0.264563
Durbin-Watson stat	2.188241		

Equation: GFINBURO=C(161)+C(162)*IC1+C(163)*IC2+C(164)*IC3
+C(165)*IC4+C(166)*IC5+C(167)*IC6+C(168)*IC7+C(169)*IC8
+C(170)*IC9
Observations: 291

R-squared	0.693047	Mean dependent var	0.000767
Adjusted R-squared	0.683215	S.D. dependent var	0.042633
S.E. of regression	0.023996	Sum squared resid	0.161798
Durbin-Watson stat	2.141113		

Equation: GCARSOA1=C(171)+C(172)*IC1+C(173)*IC2+C(174)*IC3
+C(175)*IC4+C(176)*IC5+C(177)*IC6+C(178)*IC7+C(179)*IC8
+C(180)*IC9
Observations: 291

R-squared	0.630519	Mean dependent var	0.001724
Adjusted R-squared	0.618685	S.D. dependent var	0.044571
S.E. of regression	0.027523	Sum squared resid	0.212861
Durbin-Watson stat	2.235721		

Equation: ALFAA=C(181)+C(182)*IC1+C(183)*IC2+C(184)*IC3+C(185)
*IC4+C(186)*IC5+C(187)*IC6+C(188)*IC7+C(189)*IC8+C(190)*IC9
Observations: 291

R-squared	0.923813	Mean dependent var	0.001871
Adjusted R-squared	0.921373	S.D. dependent var	0.061994
S.E. of regression	0.017383	Sum squared resid	0.084914
Durbin-Watson stat	2.286933		

Equation: CIEB=C(191)+C(192)*IC1+C(193)*IC2+C(194)*IC3+C(195)
*IC4+C(196)*IC5+C(197)*IC6+C(198)*IC7+C(199)*IC8+C(200)*IC9
Observations: 291

R-squared	0.876601	Mean dependent var	-0.003637
Adjusted R-squared	0.872649	S.D. dependent var	0.050558
S.E. of regression	0.018042	Sum squared resid	0.091472
Durbin-Watson stat	2.046890		

Table 11. *Independent Component Analysis. Betas estimation for all the equation system via Weighted Least Squares. Database of daily returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-2.01E-05	4.26E-05	-0.471163	0.6375
C(2)	0.017825	0.000795	22.41580	0.0000
C(3)	-0.071532	0.000798	-89.62016	0.0000
C(4)	0.017066	0.000795	21.46093	0.0000
C(5)	-0.037295	0.000795	-46.90062	0.0000
C(6)	0.002327	0.000797	2.921783	0.0035
C(7)	0.002373	0.000795	2.983619	0.0029
C(8)	0.013725	0.000795	17.25851	0.0000
C(9)	0.027212	0.000795	34.22184	0.0000
C(10)	0.545156	0.000795	685.3918	0.0000
C(11)	-8.87E-05	0.000357	-0.248001	0.8041
C(12)	0.069789	0.006670	10.46335	0.0000
C(13)	-0.080806	0.006695	-12.07019	0.0000
C(14)	0.072118	0.006670	10.81249	0.0000
C(15)	0.006285	0.006670	0.942378	0.3460
C(16)	-0.002726	0.006681	-0.408023	0.6833
C(17)	-0.010078	0.006670	-1.510948	0.1308
C(18)	0.009473	0.006670	1.420198	0.1556
C(19)	0.031072	0.006670	4.658865	0.0000
C(20)	0.010246	0.006671	1.535763	0.1246
C(21)	0.000293	0.000318	0.920827	0.3571
C(22)	0.050116	0.005932	8.447715	0.0000
C(23)	-0.093951	0.005955	-15.77813	0.0000
C(24)	0.221996	0.005932	37.42036	0.0000
C(25)	-0.022390	0.005932	-3.774341	0.0002
C(26)	0.015475	0.005942	2.604325	0.0092
C(27)	-0.051052	0.005932	-8.605678	0.0000
C(28)	0.061919	0.005933	10.43680	0.0000
C(29)	0.069755	0.005932	11.75874	0.0000
C(30)	0.020740	0.005934	3.495167	0.0005
C(31)	3.14E-05	0.000370	0.084935	0.9323
C(32)	0.089915	0.006903	13.02588	0.0000
C(33)	-0.088661	0.006928	-12.79660	0.0000
C(34)	-0.000148	0.006903	-0.021487	0.9829
C(35)	0.000593	0.006903	0.085912	0.9315
C(36)	-0.019655	0.006914	-2.842776	0.0045
C(37)	-0.016529	0.006903	-2.394563	0.0166
C(38)	0.038902	0.006903	5.635508	0.0000
C(39)	0.047364	0.006902	6.861898	0.0000
C(40)	0.016753	0.006904	2.426474	0.0153
C(41)	0.000238	0.000355	0.670111	0.5028
C(42)	0.175436	0.006624	26.48656	0.0000
C(43)	-0.073934	0.006648	-11.12083	0.0000
C(44)	0.074180	0.006624	11.19942	0.0000
C(45)	-0.017229	0.006623	-2.601327	0.0093
C(46)	0.016530	0.006634	2.491516	0.0127
C(47)	-0.000973	0.006623	-0.146905	0.8832
C(48)	0.046254	0.006624	6.982896	0.0000
C(49)	0.035813	0.006623	5.407170	0.0000
C(50)	0.000440	0.006625	0.066448	0.9470
C(51)	-0.000132	0.000135	-0.974697	0.3297
C(52)	-0.002412	0.002525	-0.955110	0.3395
C(53)	-0.057722	0.002534	-22.77489	0.0000

C(54)	0.020766	0.002525	8.224079	0.0000
C(55)	-0.015527	0.002525	-6.149481	0.0000
C(56)	0.018122	0.002529	7.165065	0.0000
C(57)	-0.005381	0.002525	-2.130944	0.0331
C(58)	0.029989	0.002525	11.87602	0.0000
C(59)	0.376939	0.002525	149.2855	0.0000
C(60)	0.027399	0.002526	10.84829	0.0000
C(61)	0.000311	0.000343	0.906557	0.3646
C(62)	0.121940	0.006403	19.04291	0.0000
C(63)	-0.096468	0.006427	-15.00923	0.0000
C(64)	0.044026	0.006403	6.875332	0.0000
C(65)	-0.037388	0.006403	-5.838937	0.0000
C(66)	0.023611	0.006414	3.681262	0.0002
C(67)	0.010092	0.006403	1.576108	0.1150
C(68)	0.053221	0.006404	8.310944	0.0000
C(69)	0.056535	0.006403	8.829336	0.0000
C(70)	0.000707	0.006405	0.110437	0.9121
C(71)	-0.000104	0.000137	-0.755167	0.4502
C(72)	0.095509	0.002558	37.34090	0.0000
C(73)	-0.097057	0.002567	-37.80536	0.0000
C(74)	0.038098	0.002558	14.89503	0.0000
C(75)	-0.024573	0.002558	-9.607745	0.0000
C(76)	0.419657	0.002562	163.8063	0.0000
C(77)	0.005868	0.002558	2.294401	0.0218
C(78)	0.073757	0.002558	28.83527	0.0000
C(79)	0.020463	0.002558	8.000879	0.0000
C(80)	0.035254	0.002558	13.77989	0.0000
C(81)	0.000116	0.000376	0.307389	0.7585
C(82)	0.078563	0.007016	11.19767	0.0000
C(83)	-0.140830	0.007042	-19.99844	0.0000
C(84)	0.108783	0.007016	15.50510	0.0000
C(85)	-0.027705	0.007016	-3.948921	0.0001
C(86)	0.084755	0.007027	12.06063	0.0000
C(87)	0.087875	0.007016	12.52512	0.0000
C(88)	0.044563	0.007016	6.351315	0.0000
C(89)	0.042263	0.007016	6.024115	0.0000
C(90)	0.007662	0.007018	1.091761	0.2749
C(91)	1.50E-05	0.000327	0.045748	0.9635
C(92)	0.207020	0.006100	33.94015	0.0000
C(93)	-0.148236	0.006122	-24.21276	0.0000
C(94)	0.028380	0.006100	4.652783	0.0000
C(95)	0.000561	0.006099	0.091905	0.9268
C(96)	0.013932	0.006109	2.280418	0.0226
C(97)	-0.004070	0.006099	-0.667229	0.5046
C(98)	0.047324	0.006100	7.758302	0.0000
C(99)	0.055759	0.006099	9.141937	0.0000
C(100)	0.010772	0.006101	1.765631	0.0775
C(101)	-0.000386	0.000374	-1.032695	0.3018
C(102)	0.158036	0.006977	22.65182	0.0000
C(103)	-0.132436	0.007003	-18.91221	0.0000
C(104)	0.059244	0.006977	8.491598	0.0000
C(105)	-0.027228	0.006977	-3.902853	0.0001
C(106)	0.019469	0.006988	2.786072	0.0053
C(107)	-0.040607	0.006977	-5.820375	0.0000
C(108)	0.053305	0.006977	7.640034	0.0000
C(109)	0.037768	0.006976	5.413753	0.0000
C(110)	0.012722	0.006978	1.823094	0.0683
C(111)	-0.000110	0.000227	-0.482885	0.6292

C(112)	0.093508	0.004236	22.07472	0.0000
C(113)	-0.160848	0.004252	-37.83142	0.0000
C(114)	0.027296	0.004236	6.443934	0.0000
C(115)	-0.060858	0.004236	-14.36752	0.0000
C(116)	0.026010	0.004243	6.130413	0.0000
C(117)	-0.276207	0.004236	-65.20648	0.0000
C(118)	0.067940	0.004236	16.03814	0.0000
C(119)	0.037190	0.004236	8.779959	0.0000
C(120)	0.005429	0.004237	1.281442	0.2000
C(121)	-0.000156	0.000256	-0.609660	0.5421
C(122)	0.079657	0.004778	16.67302	0.0000
C(123)	-0.176873	0.004795	-36.88434	0.0000
C(124)	0.075991	0.004778	15.90575	0.0000
C(125)	-0.358739	0.004777	-75.09087	0.0000
C(126)	0.028552	0.004785	5.966623	0.0000
C(127)	0.040691	0.004778	8.517134	0.0000
C(128)	0.048156	0.004778	10.07908	0.0000
C(129)	0.043862	0.004777	9.181311	0.0000
C(130)	-0.001408	0.004779	-0.294570	0.7683
C(131)	-0.000138	0.000273	-0.505491	0.6132
C(132)	0.189652	0.005099	37.19746	0.0000
C(133)	-0.092553	0.005117	-18.08577	0.0000
C(134)	0.021104	0.005099	4.139155	0.0000
C(135)	0.000287	0.005098	0.056272	0.9551
C(136)	-0.002779	0.005107	-0.544180	0.5863
C(137)	0.023777	0.005098	4.663539	0.0000
C(138)	0.049808	0.005099	9.768579	0.0000
C(139)	0.036087	0.005098	7.078393	0.0000
C(140)	0.006140	0.005100	1.203961	0.2286
C(141)	-0.000346	0.000327	-1.059014	0.2896
C(142)	0.224481	0.006099	36.80386	0.0000
C(143)	-0.150297	0.006122	-24.55007	0.0000
C(144)	0.039664	0.006099	6.502954	0.0000
C(145)	0.014193	0.006099	2.327115	0.0200
C(146)	-0.008461	0.006109	-1.384981	0.1661
C(147)	0.027326	0.006099	4.480195	0.0000
C(148)	0.075133	0.006100	12.31758	0.0000
C(149)	0.028608	0.006099	4.690581	0.0000
C(150)	0.010470	0.006101	1.716251	0.0861
C(151)	-0.000192	0.000312	-0.614444	0.5389
C(152)	0.300127	0.005820	51.56400	0.0000
C(153)	-0.083979	0.005842	-14.37483	0.0000
C(154)	0.036918	0.005820	6.342840	0.0000
C(155)	-0.087187	0.005820	-14.97981	0.0000
C(156)	0.040676	0.005830	6.977096	0.0000
C(157)	0.065726	0.005820	11.29234	0.0000
C(158)	0.073374	0.005821	12.60561	0.0000
C(159)	0.069426	0.005820	11.92853	0.0000
C(160)	-0.001319	0.005822	-0.226558	0.8208
C(161)	7.10E-05	0.000258	0.275212	0.7832
C(162)	0.315097	0.004817	65.41577	0.0000
C(163)	-0.012856	0.004835	-2.659007	0.0078
C(164)	0.041183	0.004817	8.549742	0.0000
C(165)	-0.245562	0.004817	-50.98172	0.0000
C(166)	0.015918	0.004825	3.299275	0.0010
C(167)	0.008446	0.004817	1.753439	0.0795
C(168)	0.109951	0.004817	22.82532	0.0000
C(169)	0.058721	0.004817	12.19152	0.0000

C(170)	0.004780	0.004818	0.992129	0.3211
C(171)	2.06E-05	0.000303	0.067900	0.9459
C(172)	0.082357	0.005662	14.54486	0.0000
C(173)	-0.296812	0.005683	-52.22538	0.0000
C(174)	-0.008843	0.005662	-1.561694	0.1184
C(175)	-0.061881	0.005662	-10.92906	0.0000
C(176)	0.042631	0.005671	7.516841	0.0000
C(177)	0.001896	0.005662	0.334936	0.7377
C(178)	0.029457	0.005662	5.202153	0.0000
C(179)	-0.038448	0.005662	-6.790648	0.0000
C(180)	-0.023610	0.005664	-4.168831	0.0000
C(181)	-0.000223	0.000375	-0.593626	0.5528
C(182)	0.056680	0.006997	8.100740	0.0000
C(183)	-0.176917	0.007023	-25.19144	0.0000
C(184)	0.124597	0.006997	17.80754	0.0000
C(185)	-0.003960	0.006997	-0.565985	0.5714
C(186)	-0.006157	0.007008	-0.878594	0.3796
C(187)	0.107907	0.006997	15.42232	0.0000
C(188)	0.002572	0.006997	0.367543	0.7132
C(189)	0.031246	0.006997	4.465922	0.0000
C(190)	-0.022789	0.006998	-3.256319	0.0011
C(191)	0.000145	0.000388	0.375003	0.7077
C(192)	0.152550	0.007230	21.09833	0.0000
C(193)	-0.153670	0.007257	-21.17445	0.0000
C(194)	0.076998	0.007230	10.64919	0.0000
C(195)	0.008727	0.007230	1.207002	0.2274
C(196)	-0.019060	0.007242	-2.631802	0.0085
C(197)	0.026010	0.007230	3.597353	0.0003
C(198)	0.036341	0.007231	5.025890	0.0000
C(199)	0.032981	0.007230	4.561621	0.0000
C(200)	0.006784	0.007232	0.938109	0.3482
C(201)	-0.000117	0.000129	-0.911274	0.3622
C(202)	0.074296	0.002405	30.89762	0.0000
C(203)	-0.122521	0.002414	-50.76442	0.0000
C(204)	0.059019	0.002405	24.54452	0.0000
C(205)	-0.048551	0.002404	-20.19170	0.0000
C(206)	-0.001870	0.002408	-0.776234	0.4376
C(207)	0.039419	0.002405	16.39336	0.0000
C(208)	0.420289	0.002405	174.7787	0.0000
C(209)	0.011918	0.002404	4.956758	0.0000
C(210)	0.003390	0.002405	1.409431	0.1587
C(211)	-0.000385	0.000334	-1.155136	0.2480
C(212)	0.122768	0.006225	19.72054	0.0000
C(213)	-0.045258	0.006249	-7.243008	0.0000
C(214)	0.290655	0.006225	46.68878	0.0000
C(215)	-0.034213	0.006225	-5.495880	0.0000
C(216)	0.029070	0.006235	4.662116	0.0000
C(217)	-0.032606	0.006225	-5.237708	0.0000
C(218)	0.020799	0.006226	3.340884	0.0008
C(219)	0.010831	0.006225	1.739889	0.0819
C(220)	0.016056	0.006227	2.578590	0.0099

Equation: PE_OLES_01=C(1)+C(2)*IC1+C(3)*IC2+C(4)*IC3+C(5)*IC4
+C(6)*IC5+C(7)*IC6+C(8)*IC7+C(9)*IC8+C(10)*IC9
Observations: 1410

R-squared	0.997084	Mean dependent var	0.001028
Adjusted R-squared	0.997066	S.D. dependent var	0.029462
S.E. of regression	0.001596	Sum squared resid	0.003566
Durbin-Watson stat	1.843278		

Equation:
KIMBERA=C(11)+C(12)*IC1+C(13)*IC2+C(14)*IC3+C(15)*IC4
+C(16)*IC5+C(17)*IC6+C(18)*IC7+C(19)*IC8+C(20)*IC9
Observations: 1410

R-squared	0.221835	Mean dependent var	0.000209
Adjusted R-squared	0.216833	S.D. dependent var	0.015126
S.E. of regression	0.013386	Sum squared resid	0.250863
Durbin-Watson stat	1.831335		

Equation: BIMBOA=C(21)+C(22)*IC1+C(23)*IC2+C(24)*IC3+C(25)*IC4
+C(26)*IC5+C(27)*IC6+C(28)*IC7+C(29)*IC8+C(30)*IC9
Observations: 1410

R-squared	0.595532	Mean dependent var	0.000650
Adjusted R-squared	0.592932	S.D. dependent var	0.018661
S.E. of regression	0.011906	Sum squared resid	0.198460
Durbin-Watson stat	1.880038		

Equation: GMODELOC=C(31)+C(32)*IC1+C(33)*IC2+C(34)*IC3+C(35)
*IC4+C(36)*IC5+C(37)*IC6+C(38)*IC7+C(39)*IC8+C(40)*IC9
Observations: 1410

R-squared	0.234688	Mean dependent var	0.000384
Adjusted R-squared	0.229768	S.D. dependent var	0.015785
S.E. of regression	0.013854	Sum squared resid	0.268688
Durbin-Watson stat	2.007036		

Equation: FEMSAUBD=C(41)+C(42)*IC1+C(43)*IC2+C(44)*IC3+C(45)
*IC4+C(46)*IC5+C(47)*IC6+C(48)*IC7+C(49)*IC8+C(50)*IC9
Observations: 1410

R-squared	0.425010	Mean dependent var	0.000500
Adjusted R-squared	0.421314	S.D. dependent var	0.017475
S.E. of regression	0.013293	Sum squared resid	0.247392
Durbin-Watson stat	1.842175		

Equation: CONTAL_01=C(51)+C(52)*IC1+C(53)*IC2+C(54)*IC3+C(55)
*IC4+C(56)*IC5+C(57)*IC6+C(58)*IC7+C(59)*IC8+C(60)*IC9
Observations: 1410

R-squared	0.942743	Mean dependent var	0.000405
Adjusted R-squared	0.942375	S.D. dependent var	0.021111
S.E. of regression	0.005068	Sum squared resid	0.035954
Durbin-Watson stat	1.881456		

Equation: CEMEXCP=C(61)+C(62)*IC1+C(63)*IC2+C(64)*IC3+C(65)
*IC4+C(66)*IC5+C(67)*IC6+C(68)*IC7+C(69)*IC8+C(70)*IC9
Observations: 1410

R-squared	0.371209	Mean dependent var	0.000771
Adjusted R-squared	0.367167	S.D. dependent var	0.016155
S.E. of regression	0.012851	Sum squared resid	0.231220
Durbin-Watson stat	1.877554		

Equation: GEOB=C(71)+C(72)*IC1+C(73)*IC2+C(74)*IC3+C(75)*IC4
+C(76)*IC5+C(77)*IC6+C(78)*IC7+C(79)*IC8+C(80)*IC9
Observations: 1410

R-squared	0.956490	Mean dependent var	0.001662
Adjusted R-squared	0.956211	S.D. dependent var	0.024531
S.E. of regression	0.005133	Sum squared resid	0.036891
Durbin-Watson stat	1.907998		

Equation: ARA_01=C(81)+C(82)*IC1+C(83)*IC2+C(84)*IC3+C(85)*IC4
+C(86)*IC5+C(87)*IC6+C(88)*IC7+C(89)*IC8+C(90)*IC9
Observations: 1410

R-squared	0.451246	Mean dependent var	0.001007
Adjusted R-squared	0.447718	S.D. dependent var	0.018947
S.E. of regression	0.014081	Sum squared resid	0.277573
Durbin-Watson stat	1.924340		

Equation: WALMEXV=C(91)+C(92)*IC1+C(93)*IC2+C(94)*IC3+C(95)
*IC4+C(96)*IC5+C(97)*IC6+C(98)*IC7+C(99)*IC8+C(100)*IC9
Observations: 1410

R-squared	0.575714	Mean dependent var	0.000655
Adjusted R-squared	0.572987	S.D. dependent var	0.018733
S.E. of regression	0.012242	Sum squared resid	0.209796
Durbin-Watson stat	1.937401		

Equation: SORIANAB=C(101)+C(102)*IC1+C(103)*IC2+C(104)*IC3
+C(105)*IC4+C(106)*IC5+C(107)*IC6+C(108)*IC7+C(109)*IC8
+C(110)*IC9
Observations: 1410

R-squared	0.436316	Mean dependent var	0.000171
Adjusted R-squared	0.432692	S.D. dependent var	0.018590
S.E. of regression	0.014002	Sum squared resid	0.274478
Durbin-Watson stat	1.844564		

Equation: COMERUBC=C(111)+C(112)*IC1+C(113)*IC2+C(114)*IC3
+C(115)*IC4+C(116)*IC5+C(117)*IC6+C(118)*IC7+C(119)*IC8
+C(120)*IC9
Observations: 1410

R-squared	0.828185	Mean dependent var	0.000498
Adjusted R-squared	0.827081	S.D. dependent var	0.020444
S.E. of regression	0.008501	Sum squared resid	0.101182
Durbin-Watson stat	2.009160		

Equation: ELEKTRA_01=C(121)+C(122)*IC1+C(123)*IC2+C(124)*IC3
+C(125)*IC4+C(126)*IC5+C(127)*IC6+C(128)*IC7+C(129)*IC8
+C(130)*IC9
Observations: 1410

R-squared	0.847374	Mean dependent var	0.000526
Adjusted R-squared	0.846393	S.D. dependent var	0.024465
S.E. of regression	0.009588	Sum squared resid	0.128711
Durbin-Watson stat	1.954464		

Equation: TELMEXL=C(131)+C(132)*IC1+C(133)*IC2+C(134)*IC3
+C(135)*IC4+C(136)*IC5+C(137)*IC6+C(138)*IC7+C(139)*IC8
+C(140)*IC9
Observations: 1410

R-squared	0.573761	Mean dependent var	0.000215
Adjusted R-squared	0.571021	S.D. dependent var	0.015623
S.E. of regression	0.010232	Sum squared resid	0.146585
Durbin-Watson stat	2.002171		

Equation: TELECOA1=C(141)+C(142)*IC1+C(143)*IC2+C(144)*IC3
+C(145)*IC4+C(146)*IC5+C(147)*IC6+C(148)*IC7+C(149)*IC8
+C(150)*IC9
Observations: 1410

R-squared	0.609970	Mean dependent var	0.000252
Adjusted R-squared	0.607463	S.D. dependent var	0.019538
S.E. of regression	0.012241	Sum squared resid	0.209784
Durbin-Watson stat	2.050123		

Equation: TLEVICPO=C(151)+C(152)*IC1+C(153)*IC2+C(154)*IC3
+C(155)*IC4+C(156)*IC5+C(157)*IC6+C(158)*IC7+C(159)*IC8
+C(160)*IC9
Observations: 1410

R-squared	0.719041	Mean dependent var	0.000171
Adjusted R-squared	0.717234	S.D. dependent var	0.021968
S.E. of regression	0.011681	Sum squared resid	0.191037
Durbin-Watson stat	2.022355		

Equation: TVAZTCPO=C(161)+C(162)*IC1+C(163)*IC2+C(164)*IC3
+C(165)*IC4+C(166)*IC5+C(167)*IC6+C(168)*IC7+C(169)*IC8
+C(170)*IC9
Observations: 1410

R-squared	0.844269	Mean dependent var	-7.68E-05
Adjusted R-squared	0.843268	S.D. dependent var	0.024418
S.E. of regression	0.009667	Sum squared resid	0.130835
Durbin-Watson stat	1.965004		

Equation: GFNORTEO=C(171)+C(172)*IC1+C(173)*IC2+C(174)*IC3
+C(175)*IC4+C(176)*IC5+C(177)*IC6+C(178)*IC7+C(179)*IC8
+C(180)*IC9
Observations: 1410

R-squared	0.694659	Mean dependent var	0.001415
Adjusted R-squared	0.692696	S.D. dependent var	0.020499
S.E. of regression	0.011364	Sum squared resid	0.180791
Durbin-Watson stat	1.903539		

Equation: GFINBURO=C(181)+C(182)*IC1+C(183)*IC2+C(184)*IC3
+C(185)*IC4+C(186)*IC5+C(187)*IC6+C(188)*IC7+C(189)*IC8
+C(190)*IC9
Observations: 1410

R-squared	0.477418	Mean dependent var	0.000502
Adjusted R-squared	0.474059	S.D. dependent var	0.019363
S.E. of regression	0.014042	Sum squared resid	0.276064
Durbin-Watson stat	1.936692		

Equation: GCARSOA1=C(191)+C(192)*IC1+C(193)*IC2+C(194)*IC3
+C(195)*IC4+C(196)*IC5+C(197)*IC6+C(198)*IC7+C(199)*IC8
+C(200)*IC9
Observations: 1410

R-squared	0.432955	Mean dependent var	0.000711
Adjusted R-squared	0.429310	S.D. dependent var	0.019209
S.E. of regression	0.014511	Sum squared resid	0.294801
Durbin-Watson stat	1.917399		

Equation: ALFAA=C(201)+C(202)*IC1+C(203)*IC2+C(204)*IC3+C(205)
*IC4+C(206)*IC5+C(207)*IC6+C(208)*IC7+C(209)*IC8+C(210)*IC9
Observations: 1410

R-squared	0.961665	Mean dependent var	0.000723
Adjusted R-squared	0.961418	S.D. dependent var	0.024569
S.E. of regression	0.004826	Sum squared resid	0.032605
Durbin-Watson stat	1.949986		

Equation: CIEB=C(211)+C(212)*IC1+C(213)*IC2+C(214)*IC3+C(215)
*IC4+C(216)*IC5+C(217)*IC6+C(218)*IC7+C(219)*IC8+C(220)*IC9
Observations: 1410

R-squared	0.658791	Mean dependent var	-0.000376
Adjusted R-squared	0.656598	S.D. dependent var	0.021321
S.E. of regression	0.012494	Sum squared resid	0.218540
Durbin-Watson stat	1.892553		

Table 12. *Independent Component Analysis. Betas estimation for all the equation s system via Weighted Least Squares. Database of daily excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.30E-05	4.98E-05	-0.261975	0.7933
C(2)	0.031453	0.000932	33.74189	0.0000
C(3)	0.016678	0.000930	17.92975	0.0000
C(4)	-0.031318	0.000931	-33.65319	0.0000
C(5)	0.003498	0.000930	3.761020	0.0002
C(6)	-0.027512	0.000930	-29.58504	0.0000
C(7)	0.018685	0.000930	20.09506	0.0000
C(8)	-0.016649	0.000930	-17.90589	0.0000
C(9)	0.013230	0.000931	14.20986	0.0000
C(10)	0.549238	0.000930	590.4980	0.0000
C(11)	-7.81E-05	0.000346	-0.225811	0.8214
C(12)	0.091731	0.006473	14.17234	0.0000
C(13)	0.069932	0.006459	10.82746	0.0000
C(14)	-0.082432	0.006462	-12.75694	0.0000
C(15)	-0.009987	0.006457	-1.546579	0.1220
C(16)	-0.003873	0.006457	-0.599781	0.5487
C(17)	0.024067	0.006456	3.727683	0.0002
C(18)	-0.030901	0.006456	-4.786182	0.0000
C(19)	-0.003132	0.006465	-0.484508	0.6280
C(20)	0.007666	0.006458	1.186979	0.2352
C(21)	0.000215	0.000419	0.513426	0.6077
C(22)	0.111691	0.007833	14.25866	0.0000
C(23)	0.021636	0.007817	2.768009	0.0056
C(24)	-0.136428	0.007820	-17.44565	0.0000
C(25)	0.003590	0.007815	0.459340	0.6460
C(26)	-0.025652	0.007814	-3.282723	0.0010
C(27)	-0.016057	0.007814	-2.055061	0.0399
C(28)	-0.054930	0.007814	-7.030074	0.0000
C(29)	0.016413	0.007824	2.097830	0.0359
C(30)	0.029529	0.007816	3.778026	0.0002
C(31)	-5.02E-05	0.000353	-0.142256	0.8869
C(32)	0.110765	0.006610	16.75811	0.0000
C(33)	0.093189	0.006596	14.12901	0.0000
C(34)	-0.008954	0.006599	-1.357021	0.1748
C(35)	0.011703	0.006594	1.774830	0.0759
C(36)	-0.029344	0.006594	-4.450288	0.0000
C(37)	0.024199	0.006593	3.670369	0.0002
C(38)	-0.048168	0.006593	-7.305906	0.0000
C(39)	-0.032939	0.006602	-4.989377	0.0000
C(40)	0.022111	0.006595	3.352680	0.0008
C(41)	0.000179	0.000352	0.508486	0.6111
C(42)	0.122709	0.006581	18.64691	0.0000
C(43)	0.156476	0.006567	23.82886	0.0000
C(44)	-0.066371	0.006570	-10.10254	0.0000
C(45)	0.040762	0.006565	6.208787	0.0000
C(46)	-0.013752	0.006565	-2.094779	0.0362
C(47)	0.016254	0.006564	2.476131	0.0133
C(48)	-0.026408	0.006564	-4.023035	0.0001
C(49)	0.002579	0.006573	0.392388	0.6948
C(50)	0.001525	0.006566	0.232239	0.8164
C(51)	-5.33E-05	6.94E-05	-0.766844	0.4432
C(52)	0.070160	0.001300	53.97994	0.0000
C(53)	0.003313	0.001297	2.554041	0.0107

C(54)	-0.029169	0.001298	-22.47960	0.0000
C(55)	0.010938	0.001297	8.435366	0.0000
C(56)	0.012761	0.001297	9.841563	0.0000
C(57)	0.011555	0.001296	8.912664	0.0000
C(58)	-0.382361	0.001296	-294.9259	0.0000
C(59)	0.028242	0.001298	21.75516	0.0000
C(60)	0.038013	0.001297	29.31144	0.0000
C(61)	0.000257	0.000337	0.762351	0.4459
C(62)	0.137193	0.006310	21.74058	0.0000
C(63)	0.107194	0.006297	17.02284	0.0000
C(64)	-0.036761	0.006300	-5.835143	0.0000
C(65)	0.039116	0.006296	6.213191	0.0000
C(66)	-0.017672	0.006295	-2.807212	0.0050
C(67)	0.015190	0.006295	2.413118	0.0158
C(68)	-0.043614	0.006295	-6.928787	0.0000
C(69)	0.014817	0.006303	2.350760	0.0187
C(70)	0.011012	0.006297	1.748867	0.0803
C(71)	-2.42E-05	0.000103	-0.235921	0.8135
C(72)	0.149779	0.001920	77.99778	0.0000
C(73)	0.071752	0.001916	37.44455	0.0000
C(74)	-0.064429	0.001917	-33.60776	0.0000
C(75)	0.030337	0.001916	15.83523	0.0000
C(76)	-0.071647	0.001916	-37.40065	0.0000
C(77)	0.030360	0.001915	15.85014	0.0000
C(78)	-0.002757	0.001915	-1.439531	0.1500
C(79)	0.410121	0.001918	213.8276	0.0000
C(80)	0.031078	0.001916	16.21967	0.0000
C(81)	0.000224	0.000388	0.578724	0.5628
C(82)	0.185545	0.007254	25.57906	0.0000
C(83)	0.063583	0.007238	8.784119	0.0000
C(84)	-0.090778	0.007242	-12.53542	0.0000
C(85)	0.001844	0.007237	0.254880	0.7988
C(86)	0.026530	0.007236	3.666177	0.0002
C(87)	-0.023175	0.007236	-3.202911	0.0014
C(88)	-0.029305	0.007236	-4.050129	0.0001
C(89)	0.056304	0.007245	7.771362	0.0000
C(90)	0.028216	0.007238	3.898351	0.0001
C(91)	0.000101	0.000351	0.287476	0.7737
C(92)	0.170171	0.006575	25.88305	0.0000
C(93)	0.169453	0.006561	25.82883	0.0000
C(94)	-0.030913	0.006564	-4.709684	0.0000
C(95)	0.029287	0.006559	4.465139	0.0000
C(96)	-0.039374	0.006559	-6.003334	0.0000
C(97)	-0.008241	0.006558	-1.256625	0.2089
C(98)	-0.037084	0.006558	-5.654754	0.0000
C(99)	0.002315	0.006567	0.352538	0.7244
C(100)	0.019656	0.006560	2.996232	0.0027
C(101)	-0.000234	0.000381	-0.614176	0.5391
C(102)	0.139901	0.007133	19.61298	0.0000
C(103)	0.139454	0.007118	19.59199	0.0000
C(104)	-0.084166	0.007121	-11.81916	0.0000
C(105)	0.028212	0.007116	3.964363	0.0001
C(106)	-0.009853	0.007116	-1.384685	0.1662
C(107)	0.047273	0.007115	6.643977	0.0000
C(108)	-0.026130	0.007115	-3.672491	0.0002
C(109)	0.011296	0.007125	1.585454	0.1129
C(110)	0.017195	0.007117	2.415893	0.0157
C(111)	-4.43E-05	0.000163	-0.271281	0.7862

C(112)	0.153648	0.003053	50.31900	0.0000
C(113)	0.082099	0.003047	26.94408	0.0000
C(114)	-0.035738	0.003048	-11.72353	0.0000
C(115)	0.036753	0.003046	12.06496	0.0000
C(116)	-0.042645	0.003046	-13.99975	0.0000
C(117)	0.313429	0.003046	102.9049	0.0000
C(118)	-0.031005	0.003046	-10.17968	0.0000
C(119)	-0.002892	0.003050	-0.948099	0.3431
C(120)	0.015754	0.003047	5.170824	0.0000
C(121)	-0.000117	0.000181	-0.644674	0.5191
C(122)	0.218433	0.003395	64.33042	0.0000
C(123)	0.007050	0.003388	2.080615	0.0375
C(124)	-0.068974	0.003390	-20.34737	0.0000
C(125)	0.371244	0.003387	109.5927	0.0000
C(126)	-0.042131	0.003387	-12.43793	0.0000
C(127)	0.016995	0.003387	5.017773	0.0000
C(128)	-0.034265	0.003387	-10.11672	0.0000
C(129)	0.015514	0.003391	4.574548	0.0000
C(130)	0.031197	0.003388	9.208021	0.0000
C(131)	-0.000205	0.000268	-0.766281	0.4435
C(132)	0.133835	0.005013	26.69739	0.0000
C(133)	0.171736	0.005002	34.33076	0.0000
C(134)	-0.026638	0.005005	-5.322716	0.0000
C(135)	0.015651	0.005001	3.129357	0.0018
C(136)	-0.025153	0.005001	-5.029654	0.0000
C(137)	-0.026782	0.005000	-5.355988	0.0000
C(138)	-0.025522	0.005000	-5.103956	0.0000
C(139)	-0.003482	0.005007	-0.695445	0.4868
C(140)	0.015218	0.005002	3.042300	0.0023
C(141)	-0.000343	0.000336	-1.022117	0.3067
C(142)	0.192995	0.006288	30.69437	0.0000
C(143)	0.185803	0.006274	29.61339	0.0000
C(144)	-0.049885	0.006277	-7.947110	0.0000
C(145)	0.008133	0.006273	1.296479	0.1948
C(146)	-0.046396	0.006272	-7.396818	0.0000
C(147)	-0.038774	0.006272	-6.182196	0.0000
C(148)	-0.021927	0.006272	-3.496092	0.0005
C(149)	-0.012226	0.006280	-1.946696	0.0516
C(150)	0.023016	0.006274	3.668598	0.0002
C(151)	-0.000126	0.000297	-0.423906	0.6716
C(152)	0.164617	0.005565	29.58264	0.0000
C(153)	0.278503	0.005553	50.15526	0.0000
C(154)	-0.062603	0.005555	-11.26898	0.0000
C(155)	0.113878	0.005552	20.51275	0.0000
C(156)	-0.017378	0.005551	-3.130438	0.0017
C(157)	-0.027908	0.005551	-5.027906	0.0000
C(158)	-0.051477	0.005551	-9.274077	0.0000
C(159)	0.034738	0.005558	6.250065	0.0000
C(160)	0.007384	0.005552	1.329957	0.1835
C(161)	0.000123	0.000305	0.403494	0.6866
C(162)	0.093744	0.005711	16.41613	0.0000
C(163)	0.270249	0.005698	47.42553	0.0000
C(164)	-0.105253	0.005701	-18.46217	0.0000
C(165)	0.258821	0.005697	45.43050	0.0000
C(166)	-0.035683	0.005697	-6.263832	0.0000
C(167)	-0.018184	0.005696	-3.192379	0.0014
C(168)	-0.049580	0.005696	-8.704210	0.0000
C(169)	0.016117	0.005704	2.825801	0.0047

C(170)	0.017564	0.005698	3.082573	0.0021
C(171)	2.90E-05	0.000289	0.100327	0.9201
C(172)	0.320216	0.005416	59.12652	0.0000
C(173)	0.023462	0.005404	4.341314	0.0000
C(174)	-0.003832	0.005407	-0.708814	0.4784
C(175)	0.025863	0.005403	4.786781	0.0000
C(176)	0.040032	0.005403	7.409574	0.0000
C(177)	0.029751	0.005402	5.507198	0.0000
C(178)	0.029971	0.005402	5.548059	0.0000
C(179)	0.012578	0.005409	2.325216	0.0201
C(180)	0.000430	0.005404	0.079532	0.9366
C(181)	-0.000222	0.000372	-0.597889	0.5499
C(182)	0.200712	0.006956	28.85506	0.0000
C(183)	-0.014624	0.006941	-2.106819	0.0351
C(184)	-0.129070	0.006944	-18.58649	0.0000
C(185)	0.007002	0.006940	1.009032	0.3130
C(186)	-0.024943	0.006939	-3.594624	0.0003
C(187)	-0.077354	0.006938	-11.14872	0.0000
C(188)	-0.013593	0.006938	-1.959160	0.0501
C(189)	-0.007589	0.006948	-1.092269	0.2747
C(190)	-0.003813	0.006941	-0.549348	0.5828
C(191)	0.000210	0.000386	0.542788	0.5873
C(192)	0.176324	0.007228	24.39607	0.0000
C(193)	0.105445	0.007212	14.62038	0.0000
C(194)	-0.083850	0.007216	-11.62077	0.0000
C(195)	0.021429	0.007211	2.971926	0.0030
C(196)	-0.062612	0.007210	-8.683964	0.0000
C(197)	-0.013604	0.007209	-1.886963	0.0592
C(198)	-0.030341	0.007209	-4.208595	0.0000
C(199)	-0.043782	0.007219	-6.064959	0.0000
C(200)	0.013085	0.007212	1.814464	0.0696
C(201)	-1.32E-05	0.000130	-0.101702	0.9190
C(202)	0.176618	0.002436	72.49710	0.0000
C(203)	0.090766	0.002431	37.33633	0.0000
C(204)	-0.098348	0.002432	-40.43673	0.0000
C(205)	0.060669	0.002430	24.96188	0.0000
C(206)	-0.386188	0.002430	-158.9034	0.0000
C(207)	0.005209	0.002430	2.143648	0.0321
C(208)	-0.046480	0.002430	-19.12679	0.0000
C(209)	-0.015494	0.002433	-6.367585	0.0000
C(210)	0.000284	0.002431	0.116834	0.9070
C(211)	-8.56E-05	0.000190	-0.450762	0.6522
C(212)	0.099355	0.003553	27.96510	0.0000
C(213)	0.077198	0.003545	21.77489	0.0000
C(214)	-0.348008	0.003547	-98.11603	0.0000
C(215)	0.029199	0.003544	8.237897	0.0000
C(216)	0.026824	0.003544	7.568376	0.0000
C(217)	0.054270	0.003544	15.31375	0.0000
C(218)	-0.027821	0.003544	-7.850302	0.0000
C(219)	0.004425	0.003549	1.246980	0.2124
C(220)	0.011871	0.003545	3.348651	0.0008

Equation: PE_OLES_01=C(1)+C(2)*IC1+C(3)*IC2+C(4)*IC3+C(5)*IC4
+C(6)*IC5+C(7)*IC6+C(8)*IC7+C(9)*IC8+C(10)*IC9
Observations: 1410

R-squared	0.996022	Mean dependent var	0.000805
Adjusted R-squared	0.995997	S.D. dependent var	0.029496
S.E. of regression	0.001866	Sum squared resid	0.004876
Durbin-Watson stat	1.832000		

Equation:
KIMBERA=C(11)+C(12)*IC1+C(13)*IC2+C(14)*IC3+C(15)*IC4
+C(16)*IC5+C(17)*IC6+C(18)*IC7+C(19)*IC8+C(20)*IC9
Observations: 1410

R-squared	0.270711	Mean dependent var	-1.66E-05
Adjusted R-squared	0.266023	S.D. dependent var	0.015126
S.E. of regression	0.012958	Sum squared resid	0.235088
Durbin-Watson stat	1.850781		

Equation: BIMBOA=C(21)+C(22)*IC1+C(23)*IC2+C(24)*IC3+C(25)*IC4
+C(26)*IC5+C(27)*IC6+C(28)*IC7+C(29)*IC8+C(30)*IC9
Observations: 1410

R-squared	0.298515	Mean dependent var	0.000397
Adjusted R-squared	0.294006	S.D. dependent var	0.018665
S.E. of regression	0.015683	Sum squared resid	0.344323
Durbin-Watson stat	1.891197		

Equation: GMODELOC=C(31)+C(32)*IC1+C(33)*IC2+C(34)*IC3+C(35)
*IC4+C(36)*IC5+C(37)*IC6+C(38)*IC7+C(39)*IC8+C(40)*IC9
Observations: 1410

R-squared	0.301844	Mean dependent var	0.000143
Adjusted R-squared	0.297356	S.D. dependent var	0.015787
S.E. of regression	0.013233	Sum squared resid	0.245155
Durbin-Watson stat	2.005582		

Equation: FEMSAUBD=C(41)+C(42)*IC1+C(43)*IC2+C(44)*IC3+C(45)
*IC4+C(46)*IC5+C(47)*IC6+C(48)*IC7+C(49)*IC8+C(50)*IC9
Observations: 1410

R-squared	0.434967	Mean dependent var	0.000231
Adjusted R-squared	0.431335	S.D. dependent var	0.017471
S.E. of regression	0.013175	Sum squared resid	0.243008
Durbin-Watson stat	1.853748		

Equation: CONTAL_01=C(51)+C(52)*IC1+C(53)*IC2+C(54)*IC3+C(55)
*IC4+C(56)*IC5+C(57)*IC6+C(58)*IC7+C(59)*IC8+C(60)*IC9
Observations: 1410

R-squared	0.984905	Mean dependent var	0.000161
Adjusted R-squared	0.984808	S.D. dependent var	0.021112
S.E. of regression	0.002602	Sum squared resid	0.009480
Durbin-Watson stat	1.855626		

Equation: CEMEXCP=C(61)+C(62)*IC1+C(63)*IC2+C(64)*IC3+C(65)
*IC4+C(66)*IC5+C(67)*IC6+C(68)*IC7+C(69)*IC8+C(70)*IC9
Observations: 1410

R-squared	0.391542	Mean dependent var	0.000550
Adjusted R-squared	0.387630	S.D. dependent var	0.016145
S.E. of regression	0.012634	Sum squared resid	0.223463
Durbin-Watson stat	1.873345		

Equation: GEOB=C(71)+C(72)*IC1+C(73)*IC2+C(74)*IC3+C(75)*IC4
+C(76)*IC5+C(77)*IC6+C(78)*IC7+C(79)*IC8+C(80)*IC9
Observations: 1410

R-squared	0.975628	Mean dependent var	0.001474
Adjusted R-squared	0.975472	S.D. dependent var	0.024548
S.E. of regression	0.003845	Sum squared resid	0.020693
Durbin-Watson stat	1.949667		

Equation: ARA_01=C(81)+C(82)*IC1+C(83)*IC2+C(84)*IC3+C(85)*IC4
+C(86)*IC5+C(87)*IC6+C(88)*IC7+C(89)*IC8+C(90)*IC9
Observations: 1410

R-squared	0.416380	Mean dependent var	0.000797
Adjusted R-squared	0.412629	S.D. dependent var	0.018949
S.E. of regression	0.014523	Sum squared resid	0.295265
Durbin-Watson stat	1.904555		

Equation: WALMEXV=C(91)+C(92)*IC1+C(93)*IC2+C(94)*IC3+C(95)
*IC4+C(96)*IC5+C(97)*IC6+C(98)*IC7+C(99)*IC8+C(100)*IC9
Observations: 1410

R-squared	0.508860	Mean dependent var	0.000450
Adjusted R-squared	0.505702	S.D. dependent var	0.018722
S.E. of regression	0.013163	Sum squared resid	0.242561
Durbin-Watson stat	1.942296		

Equation: SORIANAB=C(101)+C(102)*IC1+C(103)*IC2+C(104)*IC3
+C(105)*IC4+C(106)*IC5+C(107)*IC6+C(108)*IC7+C(109)*IC8
+C(110)*IC9
Observations: 1410

R-squared	0.413521	Mean dependent var	-8.42E-05
Adjusted R-squared	0.409751	S.D. dependent var	0.018588
S.E. of regression	0.014281	Sum squared resid	0.285520
Durbin-Watson stat	1.887170		

Equation: COMERUBC=C(111)+C(112)*IC1+C(113)*IC2+C(114)*IC3
+C(115)*IC4+C(116)*IC5+C(117)*IC6+C(118)*IC7+C(119)*IC8
+C(120)*IC9
Observations: 1410

R-squared	0.911199	Mean dependent var	0.000260
Adjusted R-squared	0.910628	S.D. dependent var	0.020449
S.E. of regression	0.006113	Sum squared resid	0.052321
Durbin-Watson stat	1.945908		

Equation: ELEKTRA_01=C(121)+C(122)*IC1+C(123)*IC2+C(124)*IC3
+C(125)*IC4+C(126)*IC5+C(127)*IC6+C(128)*IC7+C(129)*IC8
+C(130)*IC9
Observations: 1410

R-squared	0.923312	Mean dependent var	0.000287
Adjusted R-squared	0.922819	S.D. dependent var	0.024469
S.E. of regression	0.006798	Sum squared resid	0.064697
Durbin-Watson stat	1.943108		

Equation: TELMEXL=C(131)+C(132)*IC1+C(133)*IC2+C(134)*IC3
+C(135)*IC4+C(136)*IC5+C(137)*IC6+C(138)*IC7+C(139)*IC8
+C(140)*IC9
Observations: 1410

R-squared	0.589314	Mean dependent var	-1.50E-07
Adjusted R-squared	0.586674	S.D. dependent var	0.015611
S.E. of regression	0.010036	Sum squared resid	0.141021
Durbin-Watson stat	2.005565		

Equation: TELECOA1=C(141)+C(142)*IC1+C(143)*IC2+C(144)*IC3
+C(145)*IC4+C(146)*IC5+C(147)*IC6+C(148)*IC7+C(149)*IC8
+C(150)*IC9
Observations: 1410

R-squared	0.587807	Mean dependent var	2.74E-05
Adjusted R-squared	0.585157	S.D. dependent var	0.019544
S.E. of regression	0.012588	Sum squared resid	0.221850
Durbin-Watson stat	2.045579		

Equation: TLEVICPO=C(151)+C(152)*IC1+C(153)*IC2+C(154)*IC3
+C(155)*IC4+C(156)*IC5+C(157)*IC6+C(158)*IC7+C(159)*IC8
+C(160)*IC9
Observations: 1410

R-squared	0.744437	Mean dependent var	-5.84E-05
Adjusted R-squared	0.742795	S.D. dependent var	0.021967
S.E. of regression	0.011141	Sum squared resid	0.173763
Durbin-Watson stat	2.001929		

Equation: TVAZTCPO=C(161)+C(162)*IC1+C(163)*IC2+C(164)*IC3
+C(165)*IC4+C(166)*IC5+C(167)*IC6+C(168)*IC7+C(169)*IC8
+C(170)*IC9
Observations: 1410

R-squared	0.782356	Mean dependent var	-0.000324
Adjusted R-squared	0.780957	S.D. dependent var	0.024428
S.E. of regression	0.011433	Sum squared resid	0.182992
Durbin-Watson stat	1.979497		

Equation: GFNORTEO=C(171)+C(172)*IC1+C(173)*IC2+C(174)*IC3
+C(175)*IC4+C(176)*IC5+C(177)*IC6+C(178)*IC7+C(179)*IC8
+C(180)*IC9
Observations: 1410

R-squared	0.721986	Mean dependent var	0.001169
Adjusted R-squared	0.720199	S.D. dependent var	0.020498
S.E. of regression	0.010843	Sum squared resid	0.164591
Durbin-Watson stat	1.878498		

Equation: GFINBURO=C(181)+C(182)*IC1+C(183)*IC2+C(184)*IC3
+C(185)*IC4+C(186)*IC5+C(187)*IC6+C(188)*IC7+C(189)*IC8
+C(190)*IC9
Observations: 1410

R-squared	0.485230	Mean dependent var	0.000276
Adjusted R-squared	0.481921	S.D. dependent var	0.019348
S.E. of regression	0.013926	Sum squared resid	0.271511
Durbin-Watson stat	1.980196		

Equation: GCARSOA1=C(191)+C(192)*IC1+C(193)*IC2+C(194)*IC3
+C(195)*IC4+C(196)*IC5+C(197)*IC6+C(198)*IC7+C(199)*IC8
+C(200)*IC9
Observations: 1410

R-squared	0.436606	Mean dependent var	0.000455
Adjusted R-squared	0.432984	S.D. dependent var	0.019216
S.E. of regression	0.014470	Sum squared resid	0.293134
Durbin-Watson stat	1.900160		

Equation: ALFAA=C(201)+C(202)*IC1+C(203)*IC2+C(204)*IC3+C(205)
*IC4+C(206)*IC5+C(207)*IC6+C(208)*IC7+C(209)*IC8+C(210)*IC9
Observations: 1410

R-squared	0.960834	Mean dependent var	0.000496
Adjusted R-squared	0.960582	S.D. dependent var	0.024567
S.E. of regression	0.004877	Sum squared resid	0.033305
Durbin-Watson stat	1.937013		

Equation: CIEB=C(211)+C(212)*IC1+C(213)*IC2+C(214)*IC3+C(215)
*IC4+C(216)*IC5+C(217)*IC6+C(218)*IC7+C(219)*IC8+C(220)*IC9
Observations: 1410

R-squared	0.889321	Mean dependent var	-0.000633
Adjusted R-squared	0.888610	S.D. dependent var	0.021312
S.E. of regression	0.007113	Sum squared resid	0.070832
Durbin-Watson stat	1.969913		

Appendix_1 (Chapter 6)

Table 13. *Neural Networks Principal Component Analysis. Betas estimation for all the equation system via Seemingly Unrelated Regression. Database of weekly returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.038980	0.005307	-7.345416	0.0000
C(2)	-0.661146	0.067151	-9.845636	0.0000
C(3)	0.404532	0.029816	13.56784	0.0000
C(4)	0.221154	0.038556	5.735842	0.0000
C(5)	-0.348588	0.039660	-8.789495	0.0000
C(6)	-0.212235	0.018520	-11.45980	0.0000
C(7)	0.231895	0.010187	22.76454	0.0000
C(8)	0.070423	0.009890	7.120349	0.0000
C(9)	-0.673661	0.099911	-6.742580	0.0000
C(10)	5.852872	0.697788	8.387748	0.0000
C(11)	-0.068864	0.026749	-2.574463	0.0101
C(12)	-1.018037	0.338478	-3.007694	0.0026
C(13)	-0.400656	0.150286	-2.665960	0.0077
C(14)	0.438115	0.194345	2.254317	0.0242
C(15)	-0.625893	0.199906	-3.130942	0.0018
C(16)	-0.096669	0.093350	-1.035551	0.3005
C(17)	-0.791204	0.051346	-15.40922	0.0000
C(18)	-1.111239	0.049853	-22.29049	0.0000
C(19)	-0.635987	0.503607	-1.262865	0.2067
C(20)	9.654203	3.517222	2.744838	0.0061
C(21)	-0.297804	0.039847	-7.473665	0.0000
C(22)	-3.890342	0.504220	-7.715567	0.0000
C(23)	-1.713984	0.223876	-7.655939	0.0000
C(24)	2.155201	0.289510	7.444305	0.0000
C(25)	-2.288916	0.297793	-7.686261	0.0000
C(26)	-1.123985	0.139061	-8.082677	0.0000
C(27)	-0.286422	0.076489	-3.744623	0.0002
C(28)	0.422383	0.074264	5.687595	0.0000
C(29)	-5.831424	0.750207	-7.773083	0.0000
C(30)	39.52712	5.239499	7.544065	0.0000
C(31)	-0.138861	0.045097	-3.079145	0.0021
C(32)	-1.991500	0.570655	-3.489851	0.0005
C(33)	-0.850115	0.253374	-3.355178	0.0008
C(34)	0.965746	0.327655	2.947445	0.0032
C(35)	-0.961114	0.337030	-2.851719	0.0044
C(36)	-0.477731	0.157383	-3.035458	0.0024
C(37)	-0.274462	0.086567	-3.170523	0.0015
C(38)	-0.286570	0.084049	-3.409563	0.0007
C(39)	-3.042211	0.849053	-3.583063	0.0003
C(40)	18.78646	5.929844	3.168121	0.0015
C(41)	-0.166940	0.032081	-5.203682	0.0000
C(42)	-2.258178	0.405951	-5.562691	0.0000
C(43)	-0.893738	0.180244	-4.958482	0.0000
C(44)	1.203963	0.233086	5.165307	0.0000
C(45)	-1.529109	0.239755	-6.377790	0.0000
C(46)	-0.467717	0.111959	-4.177579	0.0000
C(47)	-1.087118	0.061582	-17.65328	0.0000
C(48)	0.715768	0.059790	11.97129	0.0000
C(49)	-3.867295	0.603997	-6.402839	0.0000

C(50)	22.24885	4.218355	5.274295	0.0000
C(51)	0.072997	0.014648	4.983389	0.0000
C(52)	0.511024	0.185354	2.757020	0.0059
C(53)	0.498312	0.082298	6.054955	0.0000
C(54)	-0.160461	0.106425	-1.507732	0.1317
C(55)	1.147973	0.109470	10.48662	0.0000
C(56)	0.328838	0.051120	6.432732	0.0000
C(57)	-0.153578	0.028118	-5.461969	0.0000
C(58)	-0.183413	0.027300	-6.718466	0.0000
C(59)	1.111378	0.275780	4.029942	0.0001
C(60)	-8.338045	1.926067	-4.329053	0.0000
C(61)	-0.089508	0.047902	-1.868560	0.0617
C(62)	-1.344151	0.606145	-2.217542	0.0266
C(63)	-0.487022	0.269132	-1.809607	0.0704
C(64)	0.738717	0.348033	2.122551	0.0338
C(65)	-0.704364	0.357990	-1.967552	0.0492
C(66)	-0.126022	0.167171	-0.753847	0.4510
C(67)	-0.156074	0.091951	-1.697374	0.0897
C(68)	0.255672	0.089276	2.863837	0.0042
C(69)	-2.395672	0.901857	-2.656377	0.0079
C(70)	12.48928	6.298629	1.982856	0.0474
C(71)	-0.232244	0.043038	-5.396256	0.0000
C(72)	-3.176441	0.544595	-5.832661	0.0000
C(73)	-1.396400	0.241803	-5.774936	0.0000
C(74)	1.689594	0.312693	5.403371	0.0000
C(75)	-1.685988	0.321639	-5.241862	0.0000
C(76)	-0.834470	0.150196	-5.555855	0.0000
C(77)	-0.268451	0.082614	-3.249466	0.0012
C(78)	-0.152103	0.080211	-1.896299	0.0580
C(79)	-3.970040	0.810281	-4.899587	0.0000
C(80)	31.24702	5.659054	5.521596	0.0000
C(81)	-0.198878	0.038280	-5.195337	0.0000
C(82)	-2.760023	0.484391	-5.697930	0.0000
C(83)	-1.198632	0.215072	-5.573164	0.0000
C(84)	1.420615	0.278125	5.107837	0.0000
C(85)	-1.328995	0.286082	-4.645504	0.0000
C(86)	-0.680395	0.133592	-5.093076	0.0000
C(87)	-0.156491	0.073481	-2.129688	0.0332
C(88)	0.461066	0.071343	6.462632	0.0000
C(89)	-2.989794	0.720704	-4.148434	0.0000
C(90)	26.55309	5.033447	5.275330	0.0000
C(91)	0.425291	0.036680	11.59462	0.0000
C(92)	5.139106	0.464144	11.07222	0.0000
C(93)	2.362867	0.206083	11.46563	0.0000
C(94)	-3.117944	0.266500	-11.69962	0.0000
C(95)	3.055385	0.274124	11.14598	0.0000
C(96)	1.485774	0.128008	11.60684	0.0000
C(97)	0.435959	0.070409	6.191768	0.0000
C(98)	0.481870	0.068361	7.048858	0.0000
C(99)	8.626535	0.690581	12.49171	0.0000
C(100)	-55.41998	4.823061	-11.49062	0.0000
C(101)	0.040277	0.032409	1.242759	0.2140
C(102)	0.164280	0.410102	0.400584	0.6887
C(103)	0.198944	0.182087	1.092571	0.2746
C(104)	-0.188980	0.235470	-0.802564	0.4223
C(105)	-0.037455	0.242207	-0.154642	0.8771
C(106)	-0.410214	0.113104	-3.626881	0.0003
C(107)	-0.016089	0.062211	-0.258618	0.7959
C(108)	-0.131377	0.060402	-2.175046	0.0297

C(109)	-0.040359	0.610173	-0.066144	0.9473
C(110)	-4.652279	4.261489	-1.091703	0.2750
C(111)	0.101918	0.032021	3.182842	0.0015
C(112)	1.110381	0.405191	2.740386	0.0062
C(113)	0.512345	0.179907	2.847827	0.0044
C(114)	-0.794749	0.232650	-3.416065	0.0006
C(115)	0.805337	0.239307	3.365289	0.0008
C(116)	0.344741	0.111750	3.084941	0.0020
C(117)	0.364371	0.061466	5.927967	0.0000
C(118)	-0.344495	0.059679	-5.772507	0.0000
C(119)	1.551578	0.602867	2.573665	0.0101
C(120)	-13.07215	4.210464	-3.104682	0.0019
C(121)	0.193988	0.036053	5.380589	0.0000
C(122)	2.214760	0.456214	4.854651	0.0000
C(123)	1.014007	0.202562	5.005921	0.0000
C(124)	-1.487876	0.261946	-5.680079	0.0000
C(125)	1.477933	0.269441	5.485185	0.0000
C(126)	0.712469	0.125821	5.662549	0.0000
C(127)	0.588877	0.069206	8.508987	0.0000
C(128)	-0.645929	0.067193	-9.612979	0.0000
C(129)	3.066804	0.678782	4.518101	0.0000
C(130)	-25.10864	4.740656	-5.296448	0.0000
C(131)	-0.050416	0.044100	-1.143216	0.2530
C(132)	-0.921930	0.558041	-1.652085	0.0986
C(133)	-0.356312	0.247773	-1.438056	0.1505
C(134)	0.318817	0.320412	0.995019	0.3198
C(135)	-0.258356	0.329580	-0.783895	0.4331
C(136)	-0.252440	0.153904	-1.640238	0.1010
C(137)	-0.060988	0.084653	-0.720448	0.4713
C(138)	-0.425646	0.082191	-5.178750	0.0000
C(139)	-0.912894	0.830285	-1.099494	0.2716
C(140)	7.067678	5.798766	1.218824	0.2230
C(141)	0.041687	0.038164	1.092309	0.2747
C(142)	0.217923	0.482925	0.451257	0.6518
C(143)	0.167963	0.214422	0.783329	0.4335
C(144)	-0.268234	0.277283	-0.967364	0.3334
C(145)	0.237500	0.285217	0.832701	0.4050
C(146)	-0.263862	0.133188	-1.981121	0.0476
C(147)	-0.061366	0.073259	-0.837670	0.4023
C(148)	0.036825	0.071128	0.517736	0.6047
C(149)	1.370396	0.718524	1.907236	0.0565
C(150)	-5.149116	5.018222	-1.026084	0.3049
C(151)	-0.219527	0.045532	-4.821419	0.0000
C(152)	-3.074419	0.576151	-5.336135	0.0000
C(153)	-1.340465	0.255814	-5.239993	0.0000
C(154)	1.677342	0.330811	5.070394	0.0000
C(155)	-1.534849	0.340276	-4.510603	0.0000
C(156)	-0.771012	0.158899	-4.852208	0.0000
C(157)	-0.016945	0.087401	-0.193872	0.8463
C(158)	0.581643	0.084858	6.854292	0.0000
C(159)	-3.956530	0.857231	-4.615479	0.0000
C(160)	30.00596	5.986956	5.011889	0.0000
C(161)	0.072054	0.046056	1.564467	0.1178
C(162)	0.699775	0.582790	1.200732	0.2299
C(163)	0.349119	0.258762	1.349190	0.1773
C(164)	-0.542369	0.334623	-1.620838	0.1051
C(165)	0.755233	0.344197	2.194190	0.0283
C(166)	0.441815	0.160730	2.748800	0.0060
C(167)	0.291611	0.088408	3.298479	0.0010

C(168)	-0.141626	0.085836	-1.649953	0.0990
C(169)	0.850592	0.867109	0.980952	0.3267
C(170)	-9.004358	6.055945	-1.486863	0.1371
C(171)	-0.014105	0.044180	-0.319264	0.7495
C(172)	-0.453494	0.559052	-0.811184	0.4173
C(173)	-0.197682	0.248222	-0.796392	0.4258
C(174)	0.061953	0.320993	0.193005	0.8470
C(175)	-0.108553	0.330177	-0.328771	0.7423
C(176)	-0.040953	0.154183	-0.265611	0.7905
C(177)	0.233855	0.084807	2.757504	0.0058
C(178)	0.138577	0.082340	1.682986	0.0924
C(179)	-0.730015	0.831789	-0.877644	0.3802
C(180)	2.539065	5.809272	0.437071	0.6621
C(181)	0.026279	0.017042	1.541977	0.1231
C(182)	-0.052664	0.215653	-0.244206	0.8071
C(183)	0.072603	0.095751	0.758250	0.4483
C(184)	-0.022153	0.123822	-0.178913	0.8580
C(185)	-0.781726	0.127365	-6.137687	0.0000
C(186)	0.395914	0.059476	6.656727	0.0000
C(187)	0.342193	0.032714	10.46016	0.0000
C(188)	-0.212150	0.031762	-6.679302	0.0000
C(189)	0.667970	0.320861	2.081808	0.0374
C(190)	-2.643350	2.240912	-1.179587	0.2382
C(191)	0.073735	0.043280	1.703684	0.0885
C(192)	0.707270	0.547656	1.291449	0.1966
C(193)	0.373413	0.243162	1.535654	0.1247
C(194)	-0.667428	0.314450	-2.122525	0.0338
C(195)	0.733938	0.323447	2.269116	0.0233
C(196)	0.388800	0.151041	2.574145	0.0101
C(197)	-0.168995	0.083078	-2.034170	0.0420
C(198)	0.617267	0.080661	7.652573	0.0000
C(199)	1.192863	0.814834	1.463934	0.1433
C(200)	-9.738467	5.690858	-1.711248	0.0871

Equation: PE_OLES_=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 291

R-squared	0.997509	Mean dependent var	0.004729
Adjusted R-squared	0.997429	S.D. dependent var	0.067404
S.E. of regression	0.003418	Sum squared resid	0.003282
Durbin-Watson stat	1.960664		

Equation: BIMBOA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)*PC4
+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 291

R-squared	0.838351	Mean dependent var	0.003161
Adjusted R-squared	0.833173	S.D. dependent var	0.042175
S.E. of regression	0.017226	Sum squared resid	0.083384
Durbin-Watson stat	1.969302		

Equation: GMODELOC=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)
*PC4+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 291

R-squared	0.382377	Mean dependent var	0.001865
Adjusted R-squared	0.362596	S.D. dependent var	0.032142
S.E. of regression	0.025661	Sum squared resid	0.185039
Durbin-Watson stat	2.351086		

Equation: FEMSAUBD=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 291

R-squared	0.544425	Mean dependent var	0.002358
Adjusted R-squared	0.529833	S.D. dependent var	0.042355
S.E. of regression	0.029042	Sum squared resid	0.237012
Durbin-Watson stat	2.279936		

Equation: CONTAL_=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 291

R-squared	0.784818	Mean dependent var	0.002039
Adjusted R-squared	0.777926	S.D. dependent var	0.043841
S.E. of regression	0.020660	Sum squared resid	0.119941
Durbin-Watson stat	1.878161		

Equation: GEOB=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)*PC4
+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 291

R-squared	0.978180	Mean dependent var	0.008191
Adjusted R-squared	0.977482	S.D. dependent var	0.062862
S.E. of regression	0.009433	Sum squared resid	0.025005
Durbin-Watson stat	2.072245		

Equation: ARA_=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)*PC4
+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 291

R-squared	0.440728	Mean dependent var	0.004898
Adjusted R-squared	0.422815	S.D. dependent var	0.040605
S.E. of regression	0.030849	Sum squared resid	0.267408
Durbin-Watson stat	1.998635		

Equation: WALMEXV=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)
*PC4+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 291

R-squared	0.530918	Mean dependent var	0.003334
Adjusted R-squared	0.515894	S.D. dependent var	0.039835
S.E. of regression	0.027716	Sum squared resid	0.215859
Durbin-Watson stat	2.362696		

Equation: SORIANAB=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)
*PC4+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 291

R-squared	0.693511	Mean dependent var	0.000746
Adjusted R-squared	0.683695	S.D. dependent var	0.043833
S.E. of regression	0.024652	Sum squared resid	0.170771
Durbin-Watson stat	2.311981		

Equation: COMERUBC=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 291

R-squared	0.737809	Mean dependent var	0.002256
Adjusted R-squared	0.729411	S.D. dependent var	0.045411
S.E. of regression	0.023622	Sum squared resid	0.156794
Durbin-Watson stat	2.034560		

Equation: ELEKTRA_=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 291

R-squared	0.869497	Mean dependent var	0.002654
Adjusted R-squared	0.865318	S.D. dependent var	0.056871
S.E. of regression	0.020871	Sum squared resid	0.122407
Durbin-Watson stat	2.077531		

Equation: TELMEXL=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 291

R-squared	0.631299	Mean dependent var	0.001198
Adjusted R-squared	0.619491	S.D. dependent var	0.033430
S.E. of regression	0.020621	Sum squared resid	0.119493
Durbin-Watson stat	1.975485		

Equation: TELECOA1=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 291

R-squared	0.735504	Mean dependent var	0.001320
Adjusted R-squared	0.727032	S.D. dependent var	0.044440
S.E. of regression	0.023218	Sum squared resid	0.151482
Durbin-Watson stat	2.136120		

Equation: TLEVICPO=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 291

R-squared	0.653287	Mean dependent var	0.000899
Adjusted R-squared	0.642182	S.D. dependent var	0.047478
S.E. of regression	0.028400	Sum squared resid	0.226649
Durbin-Watson stat	2.099857		

Equation: TVAZTCPO=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 291

R-squared	0.789657	Mean dependent var	-0.000334
Adjusted R-squared	0.782920	S.D. dependent var	0.052751
S.E. of regression	0.024578	Sum squared resid	0.169739
Durbin-Watson stat	2.071429		

Equation: GFNORTEO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 291

R-squared	0.562437	Mean dependent var	0.006851
Adjusted R-squared	0.548422	S.D. dependent var	0.043634
S.E. of regression	0.029322	Sum squared resid	0.241599
Durbin-Watson stat	2.241876		

Equation: GFINBURO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 291

R-squared	0.530141	Mean dependent var	0.002456
Adjusted R-squared	0.515092	S.D. dependent var	0.042593
S.E. of regression	0.029660	Sum squared resid	0.247199
Durbin-Watson stat	2.060965		

Equation: GCARSOA1=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 291

R-squared	0.603628	Mean dependent var	0.003413
Adjusted R-squared	0.590933	S.D. dependent var	0.044485
S.E. of regression	0.028452	Sum squared resid	0.227471
Durbin-Watson stat	2.190921		

Equation: ALFAA=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3+C(185)
*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8+C(190)
*PC9
Observations: 291

R-squared	0.969531	Mean dependent var	0.003559
Adjusted R-squared	0.968555	S.D. dependent var	0.061893
S.E. of regression	0.010975	Sum squared resid	0.033848
Durbin-Watson stat	2.059566		

Equation: CIEB=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3+C(195)
*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8+C(200)
*PC9
Observations: 291

R-squared	0.705015	Mean dependent var	-0.001948
Adjusted R-squared	0.695567	S.D. dependent var	0.050515
S.E. of regression	0.027872	Sum squared resid	0.218292
Durbin-Watson stat	2.043159		

Table 14. *Neural Networks Principal Component Analysis. Betas estimation for all the equation system via Seemingly Unrelated Regression. Database of weekly excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.001219	0.000210	5.816567	0.0000
C(2)	-0.043163	0.005096	-8.469813	0.0000
C(3)	0.486162	0.001853	262.4244	0.0000
C(4)	0.121661	0.002177	55.88483	0.0000
C(5)	0.004812	0.002726	1.765012	0.0776
C(6)	-0.499104	0.047689	-10.46583	0.0000
C(7)	-0.086944	0.006015	-14.45413	0.0000
C(8)	-0.030139	0.017609	-1.711597	0.0870
C(9)	0.230848	0.020857	11.06816	0.0000
C(10)	1.280904	0.178775	7.164915	0.0000
C(11)	0.002893	0.000732	3.948999	0.0001
C(12)	0.153674	0.017817	8.625089	0.0000
C(13)	0.045729	0.006477	7.060157	0.0000
C(14)	0.147311	0.007611	19.35417	0.0000
C(15)	0.014452	0.009532	1.516092	0.1296
C(16)	-1.668440	0.166732	-10.00671	0.0000
C(17)	0.461090	0.021031	21.92475	0.0000
C(18)	1.513013	0.061565	24.57585	0.0000
C(19)	1.654952	0.072921	22.69513	0.0000
C(20)	8.051806	0.625040	12.88207	0.0000
C(21)	-0.001067	0.001573	-0.678399	0.4975
C(22)	0.004531	0.038271	0.118389	0.9058
C(23)	-0.007567	0.013913	-0.543853	0.5866
C(24)	0.047386	0.016349	2.898381	0.0038
C(25)	-0.010580	0.020476	-0.516724	0.6054
C(26)	-0.797574	0.358142	-2.226975	0.0260
C(27)	-0.000274	0.045174	-0.006075	0.9952
C(28)	-0.186712	0.132242	-1.411896	0.1580
C(29)	0.074784	0.156635	0.477443	0.6331
C(30)	2.403672	1.342592	1.790321	0.0735
C(31)	-0.002657	0.001887	-1.408226	0.1591
C(32)	-0.078199	0.045889	-1.704079	0.0884
C(33)	-0.025567	0.016682	-1.532607	0.1254
C(34)	0.068588	0.019604	3.498759	0.0005
C(35)	0.082091	0.024552	3.343599	0.0008
C(36)	-0.528778	0.429433	-1.231341	0.2182
C(37)	0.036231	0.054166	0.668878	0.5036
C(38)	0.271890	0.158566	1.714682	0.0865
C(39)	0.186012	0.187814	0.990404	0.3220
C(40)	1.987517	1.609844	1.234602	0.2170
C(41)	-0.004596	0.001495	-3.075207	0.0021
C(42)	-0.220585	0.036354	-6.067714	0.0000
C(43)	0.010571	0.013216	0.799898	0.4238
C(44)	-0.020720	0.015530	-1.334154	0.1822
C(45)	-0.122170	0.019450	-6.281239	0.0000
C(46)	2.065821	0.340200	6.072374	0.0000
C(47)	0.195926	0.042911	4.565881	0.0000
C(48)	-0.630877	0.125617	-5.022219	0.0000
C(49)	-0.927799	0.148788	-6.235718	0.0000
C(50)	-4.671980	1.275330	-3.663349	0.0003
C(51)	-0.001445	0.000648	-2.230661	0.0257
C(52)	-0.148365	0.015760	-9.413988	0.0000
C(53)	0.129246	0.005729	22.55888	0.0000

C(54)	-0.222991	0.006733	-33.12129	0.0000
C(55)	0.327174	0.008432	38.80197	0.0000
C(56)	-0.461602	0.147482	-3.129887	0.0018
C(57)	0.100265	0.018603	5.389879	0.0000
C(58)	0.218690	0.054457	4.015817	0.0001
C(59)	0.283212	0.064502	4.390754	0.0000
C(60)	1.990332	0.552876	3.599961	0.0003
C(61)	-0.004872	0.001634	-2.982419	0.0029
C(62)	-0.447752	0.039735	-11.26835	0.0000
C(63)	-0.033100	0.014445	-2.291464	0.0220
C(64)	-0.158602	0.016975	-9.343463	0.0000
C(65)	-0.070679	0.021259	-3.324622	0.0009
C(66)	3.722934	0.371843	10.01210	0.0000
C(67)	-0.335731	0.046902	-7.158122	0.0000
C(68)	-0.714461	0.137301	-5.203595	0.0000
C(69)	-1.644692	0.162627	-10.11325	0.0000
C(70)	-12.18471	1.393955	-8.741110	0.0000
C(71)	-0.003170	0.001571	-2.017917	0.0436
C(72)	-0.271972	0.038208	-7.118109	0.0000
C(73)	-0.085520	0.013890	-6.156920	0.0000
C(74)	-0.029591	0.016322	-1.812942	0.0699
C(75)	0.009086	0.020442	0.444475	0.6567
C(76)	1.198038	0.357555	3.350644	0.0008
C(77)	-0.235595	0.045100	-5.223869	0.0000
C(78)	-0.772432	0.132025	-5.850634	0.0000
C(79)	-0.216296	0.156378	-1.383163	0.1667
C(80)	-5.406945	1.340389	-4.033863	0.0001
C(81)	-0.005481	0.001649	-3.323942	0.0009
C(82)	-0.204700	0.040112	-5.103227	0.0000
C(83)	-0.066497	0.014582	-4.560257	0.0000
C(84)	0.013455	0.017135	0.785226	0.4324
C(85)	0.074716	0.021461	3.481536	0.0005
C(86)	0.466036	0.375366	1.241551	0.2145
C(87)	-0.052683	0.047346	-1.112706	0.2659
C(88)	-0.601527	0.138602	-4.339956	0.0000
C(89)	0.106980	0.164168	0.651652	0.5147
C(90)	-2.186891	1.407161	-1.554116	0.1202
C(91)	-0.007892	0.001650	-4.782822	0.0000
C(92)	-0.549244	0.040136	-13.68449	0.0000
C(93)	-0.097007	0.014591	-6.648507	0.0000
C(94)	-0.095963	0.017146	-5.596865	0.0000
C(95)	-0.127488	0.021474	-5.936963	0.0000
C(96)	4.095215	0.375595	10.90328	0.0000
C(97)	-0.195747	0.047375	-4.131846	0.0000
C(98)	-1.466123	0.138687	-10.57149	0.0000
C(99)	-1.380805	0.164268	-8.405809	0.0000
C(100)	-14.65570	1.408017	-10.40875	0.0000
C(101)	-0.005943	0.000953	-6.238753	0.0000
C(102)	-0.174958	0.023173	-7.549985	0.0000
C(103)	0.015274	0.008424	1.813112	0.0699
C(104)	-0.041840	0.009899	-4.226515	0.0000
C(105)	-0.219799	0.012398	-17.72838	0.0000
C(106)	-1.255692	0.216856	-5.790455	0.0000
C(107)	0.202962	0.027353	7.420152	0.0000
C(108)	0.551251	0.080073	6.884372	0.0000
C(109)	-0.204423	0.094843	-2.155392	0.0312
C(110)	1.131834	0.812941	1.392271	0.1639
C(111)	-0.004715	0.001235	-3.819317	0.0001
C(112)	-0.205931	0.030031	-6.857246	0.0000

C(113)	-0.052827	0.010917	-4.838848	0.0000
C(114)	0.018535	0.012829	1.444775	0.1486
C(115)	0.007397	0.016067	0.460373	0.6453
C(116)	0.785378	0.281031	2.794630	0.0052
C(117)	-0.247164	0.035448	-6.972656	0.0000
C(118)	-0.118289	0.103769	-1.139925	0.2544
C(119)	-0.486135	0.122910	-3.955207	0.0001
C(120)	-3.474624	1.053520	-3.298109	0.0010
C(121)	-0.006383	0.001373	-4.647959	0.0000
C(122)	-0.289263	0.033403	-8.659679	0.0000
C(123)	-0.068546	0.012143	-5.644798	0.0000
C(124)	0.021333	0.014270	1.494975	0.1350
C(125)	-0.005011	0.017871	-0.280369	0.7792
C(126)	1.249064	0.312589	3.995868	0.0001
C(127)	-0.375073	0.039428	-9.512833	0.0000
C(128)	0.008123	0.115422	0.070377	0.9439
C(129)	-0.714292	0.136712	-5.224791	0.0000
C(130)	-4.933621	1.171823	-4.210209	0.0000
C(131)	-0.006880	0.001747	-3.937234	0.0001
C(132)	-0.277070	0.042503	-6.518869	0.0000
C(133)	-0.064901	0.015451	-4.200445	0.0000
C(134)	0.015916	0.018157	0.876597	0.3807
C(135)	0.042153	0.022740	1.853697	0.0638
C(136)	0.694879	0.397741	1.747067	0.0807
C(137)	-0.152665	0.050169	-3.043034	0.0024
C(138)	-0.366217	0.146864	-2.493583	0.0127
C(139)	-0.261792	0.173954	-1.504955	0.1324
C(140)	-3.654387	1.491037	-2.450903	0.0143
C(141)	-0.005123	0.001410	-3.634614	0.0003
C(142)	0.052864	0.034287	1.541812	0.1232
C(143)	0.011772	0.012464	0.944424	0.3450
C(144)	0.077374	0.014647	5.282574	0.0000
C(145)	-0.007142	0.018344	-0.389321	0.6971
C(146)	-3.159456	0.320857	-9.846928	0.0000
C(147)	0.414829	0.040471	10.25004	0.0000
C(148)	0.426167	0.118475	3.597104	0.0003
C(149)	1.222152	0.140328	8.709241	0.0000
C(150)	8.869991	1.202818	7.374339	0.0000
C(151)	0.000549	0.002010	0.273094	0.7848
C(152)	-0.162738	0.048894	-3.328353	0.0009
C(153)	-0.050966	0.017775	-2.867317	0.0042
C(154)	-0.028292	0.020887	-1.354492	0.1756
C(155)	0.066173	0.026159	2.529593	0.0114
C(156)	0.181307	0.457554	0.396252	0.6919
C(157)	-0.118540	0.057713	-2.053955	0.0400
C(158)	-0.375837	0.168949	-2.224555	0.0262
C(159)	-0.099638	0.200113	-0.497911	0.6186
C(160)	-1.109637	1.715262	-0.646920	0.5177
C(161)	-5.06E-05	0.001501	-0.033737	0.9731
C(162)	0.194463	0.036510	5.326277	0.0000
C(163)	0.046816	0.013273	3.527265	0.0004
C(164)	0.132634	0.015597	8.503938	0.0000
C(165)	0.215212	0.019534	11.01759	0.0000
C(166)	-2.595970	0.341661	-7.598096	0.0000
C(167)	0.177413	0.043095	4.116780	0.0000
C(168)	1.423572	0.126157	11.28417	0.0000
C(169)	0.891450	0.149427	5.965801	0.0000
C(170)	11.35731	1.280806	8.867314	0.0000
C(171)	-0.004942	0.001691	-2.921814	0.0035

C(172)	-0.340196	0.041139	-8.269338	0.0000
C(173)	-0.105147	0.014955	-7.030650	0.0000
C(174)	-0.010619	0.017574	-0.604256	0.5457
C(175)	-0.024488	0.022010	-1.112573	0.2659
C(176)	1.698205	0.384982	4.411124	0.0000
C(177)	-0.305285	0.048559	-6.286836	0.0000
C(178)	-0.456768	0.142153	-3.213215	0.0013
C(179)	-0.916672	0.168374	-5.444270	0.0000
C(180)	-6.726470	1.443210	-4.660771	0.0000
C(181)	-0.004826	0.000648	-7.448784	0.0000
C(182)	-0.088369	0.015760	-5.607029	0.0000
C(183)	-0.000211	0.005729	-0.036860	0.9706
C(184)	-0.036272	0.006733	-5.387430	0.0000
C(185)	-0.326857	0.008432	-38.76330	0.0000
C(186)	-0.395250	0.147486	-2.679904	0.0074
C(187)	-0.147516	0.018603	-7.929667	0.0000
C(188)	0.252845	0.054459	4.642871	0.0000
C(189)	0.685454	0.064504	10.62657	0.0000
C(190)	5.094150	0.552892	9.213637	0.0000
C(191)	-0.004416	0.001349	-3.274211	0.0011
C(192)	0.216224	0.032806	6.590920	0.0000
C(193)	0.042960	0.011926	3.602146	0.0003
C(194)	0.230983	0.014015	16.48153	0.0000
C(195)	0.222422	0.017552	12.67219	0.0000
C(196)	-3.062860	0.307002	-9.976672	0.0000
C(197)	0.562687	0.038723	14.53093	0.0000
C(198)	0.988704	0.113359	8.721871	0.0000
C(199)	1.233040	0.134269	9.183370	0.0000
C(200)	13.61141	1.150880	11.82696	0.0000

Equation: PE_OLES_=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 291

R-squared	0.997463	Mean dependent var	0.003041
Adjusted R-squared	0.997382	S.D. dependent var	0.067481
S.E. of regression	0.003453	Sum squared resid	0.003350
Durbin-Watson stat	2.206805		

Equation: BIMBOA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)*PC4
+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 291

R-squared	0.920768	Mean dependent var	0.001472
Adjusted R-squared	0.918230	S.D. dependent var	0.042216
S.E. of regression	0.012072	Sum squared resid	0.040950
Durbin-Watson stat	2.241646		

Equation: GMODELOC=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)
*PC4+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 291

R-squared	0.370326	Mean dependent var	0.000176
Adjusted R-squared	0.350158	S.D. dependent var	0.032167
S.E. of regression	0.025930	Sum squared resid	0.188942
Durbin-Watson stat	2.238772		

Equation: FEMSAUBD=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 291

R-squared	0.479059	Mean dependent var	0.000669
Adjusted R-squared	0.462374	S.D. dependent var	0.042404
S.E. of regression	0.031092	Sum squared resid	0.271649
Durbin-Watson stat	2.267884		

Equation: CONTAL_=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 291

R-squared	0.694061	Mean dependent var	0.000350
Adjusted R-squared	0.684262	S.D. dependent var	0.043836
S.E. of regression	0.024631	Sum squared resid	0.170485
Durbin-Watson stat	2.022975		

Equation: GEOB=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)*PC4
+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 291

R-squared	0.972148	Mean dependent var	0.006502
Adjusted R-squared	0.971256	S.D. dependent var	0.062982
S.E. of regression	0.010678	Sum squared resid	0.032040
Durbin-Watson stat	2.065596		

Equation: ARA_=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)*PC4
+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 291

R-squared	0.574842	Mean dependent var	0.003209
Adjusted R-squared	0.561225	S.D. dependent var	0.040644
S.E. of regression	0.026923	Sum squared resid	0.203675
Durbin-Watson stat	2.247096		

Equation: WALMEXV=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)
*PC4+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 291

R-squared	0.591074	Mean dependent var	0.001645
Adjusted R-squared	0.577977	S.D. dependent var	0.039850
S.E. of regression	0.025888	Sum squared resid	0.188322
Durbin-Watson stat	2.395548		

Equation: SORIANAB=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)
*PC4+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 291

R-squared	0.629443	Mean dependent var	-0.000943
Adjusted R-squared	0.617575	S.D. dependent var	0.043948
S.E. of regression	0.027178	Sum squared resid	0.207552
Durbin-Watson stat	2.419533		

Equation: COMERUBC=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 291

R-squared	0.653721	Mean dependent var	0.000568
Adjusted R-squared	0.642631	S.D. dependent var	0.045490
S.E. of regression	0.027194	Sum squared resid	0.207805
Durbin-Watson stat	2.309825		

Equation: ELEKTRA_=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 291

R-squared	0.926350	Mean dependent var	0.000965
Adjusted R-squared	0.923991	S.D. dependent var	0.056950
S.E. of regression	0.015701	Sum squared resid	0.069272
Durbin-Watson stat	2.014486		

Equation: TELMEXL=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 291

R-squared	0.641779	Mean dependent var	-0.000491
Adjusted R-squared	0.630306	S.D. dependent var	0.033465
S.E. of regression	0.020347	Sum squared resid	0.116339
Durbin-Watson stat	2.021183		

Equation: TELECOA1=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 291

R-squared	0.749422	Mean dependent var	-0.000369
Adjusted R-squared	0.741397	S.D. dependent var	0.044505
S.E. of regression	0.022632	Sum squared resid	0.143934
Durbin-Watson stat	2.136762		

Equation: TLEVICPO=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 291

R-squared	0.644957	Mean dependent var	-0.000790
Adjusted R-squared	0.633586	S.D. dependent var	0.047574
S.E. of regression	0.028798	Sum squared resid	0.233033
Durbin-Watson stat	2.144234		

Equation: TVAZTCPO=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 291

R-squared	0.812758	Mean dependent var	-0.002023
Adjusted R-squared	0.806761	S.D. dependent var	0.052847
S.E. of regression	0.023231	Sum squared resid	0.151649
Durbin-Watson stat	1.949979		

Equation: GFNORTEO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 291

R-squared	0.442085	Mean dependent var	0.005163
Adjusted R-squared	0.424216	S.D. dependent var	0.043658
S.E. of regression	0.033128	Sum squared resid	0.308390
Durbin-Watson stat	2.086308		

Equation: GFINBURO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 291

R-squared	0.673783	Mean dependent var	0.000767
Adjusted R-squared	0.663334	S.D. dependent var	0.042633
S.E. of regression	0.024737	Sum squared resid	0.171952
Durbin-Watson stat	2.221252		

Equation: GCARSOA1=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 291

R-squared	0.621039	Mean dependent var	0.001724
Adjusted R-squared	0.608901	S.D. dependent var	0.044571
S.E. of regression	0.027874	Sum squared resid	0.218323
Durbin-Watson stat	2.233078		

Equation: ALFAA=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3+C(185)
*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8+C(190)
*PC9
Observations: 291

R-squared	0.971251	Mean dependent var	0.001871
Adjusted R-squared	0.970330	S.D. dependent var	0.061994
S.E. of regression	0.010678	Sum squared resid	0.032042
Durbin-Watson stat	1.910017		

Equation: CIEB=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3+C(195)
*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8+C(200)
*PC9
Observations: 291

R-squared	0.812707	Mean dependent var	-0.003637
Adjusted R-squared	0.806708	S.D. dependent var	0.050558
S.E. of regression	0.022228	Sum squared resid	0.138835
Durbin-Watson stat	2.024732		

Table 15. *Neural Networks Principal Component Analysis. Betas estimation for all the equation system via Seemingly Unrelated Regression. Database of daily returns.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.001083	3.21E-05	33.72380	0.0000
C(2)	-0.038338	0.001965	-19.51268	0.0000
C(3)	-0.442438	0.000438	-1009.385	0.0000
C(4)	0.030615	0.000587	52.17144	0.0000
C(5)	-0.046444	0.001441	-32.21937	0.0000
C(6)	0.129480	0.001275	101.5129	0.0000
C(7)	0.003988	0.003222	1.237927	0.2158
C(8)	-0.014879	0.001601	-9.293047	0.0000
C(9)	0.006439	0.001535	4.194359	0.0000
C(10)	1.019991	0.082563	12.35414	0.0000
C(11)	-0.000902	0.000416	-2.168032	0.0302
C(12)	0.077976	0.025449	3.063982	0.0022
C(13)	-0.014725	0.005678	-2.593560	0.0095
C(14)	-0.028925	0.007601	-3.805394	0.0001
C(15)	-0.013048	0.018671	-0.698842	0.4847
C(16)	-0.010713	0.016521	-0.648454	0.5167
C(17)	0.203777	0.041732	4.882986	0.0000
C(18)	-0.119361	0.020739	-5.755452	0.0000
C(19)	0.053778	0.019885	2.704462	0.0068
C(20)	6.114341	1.069422	5.717427	0.0000
C(21)	0.005498	0.000427	12.87284	0.0000
C(22)	-0.573015	0.026130	-21.92903	0.0000
C(23)	0.023321	0.005829	4.000550	0.0001
C(24)	0.086986	0.007804	11.14580	0.0000
C(25)	0.431654	0.019171	22.51593	0.0000
C(26)	-0.091011	0.016964	-5.365093	0.0000
C(27)	-0.674661	0.042849	-15.74508	0.0000
C(28)	0.415778	0.021294	19.52573	0.0000
C(29)	-0.475327	0.020417	-23.28075	0.0000
C(30)	-20.77902	1.098043	-18.92368	0.0000
C(31)	-0.001114	0.000425	-2.619359	0.0088
C(32)	0.116145	0.026018	4.463976	0.0000
C(33)	-0.019705	0.005804	-3.394843	0.0007
C(34)	-0.003043	0.007771	-0.391532	0.6954
C(35)	-0.091161	0.019089	-4.775658	0.0000
C(36)	-0.012834	0.016891	-0.759801	0.4474
C(37)	0.305166	0.042665	7.152608	0.0000
C(38)	-0.170306	0.021202	-8.032382	0.0000
C(39)	0.223829	0.020330	11.01007	0.0000
C(40)	8.025039	1.093329	7.340002	0.0000
C(41)	-0.000117	0.000423	-0.275854	0.7827
C(42)	-0.001580	0.025858	-0.061097	0.9513
C(43)	0.010911	0.005769	1.891473	0.0586
C(44)	-0.006309	0.007723	-0.816937	0.4140
C(45)	-0.051264	0.018971	-2.702227	0.0069
C(46)	0.048139	0.016786	2.867711	0.0041
C(47)	0.084701	0.042402	1.997568	0.0458
C(48)	-0.106962	0.021072	-5.076122	0.0000
C(49)	0.081577	0.020204	4.037624	0.0001
C(50)	4.653299	1.086585	4.282498	0.0000
C(51)	0.000241	0.000151	1.596360	0.1104
C(52)	-0.047465	0.009230	-5.142274	0.0000
C(53)	-0.055500	0.002059	-26.95190	0.0000

C(54)	0.011448	0.002757	4.152434	0.0000
C(55)	0.129665	0.006772	19.14724	0.0000
C(56)	-0.757126	0.005992	-126.3515	0.0000
C(57)	0.237908	0.015136	15.71794	0.0000
C(58)	-0.092710	0.007522	-12.32539	0.0000
C(59)	0.143984	0.007212	19.96402	0.0000
C(60)	1.110448	0.387875	2.862902	0.0042
C(61)	9.65E-05	0.000400	0.241336	0.8093
C(62)	0.010020	0.024461	0.409646	0.6821
C(63)	-0.000139	0.005457	-0.025473	0.9797
C(64)	-0.016461	0.007306	-2.253149	0.0243
C(65)	-0.060534	0.017946	-3.373101	0.0007
C(66)	-0.012478	0.015880	-0.785768	0.4320
C(67)	0.156311	0.040111	3.896941	0.0001
C(68)	-0.096419	0.019933	-4.837064	0.0000
C(69)	0.133969	0.019113	7.009455	0.0000
C(70)	4.755374	1.027885	4.626368	0.0000
C(71)	0.002372	0.000139	17.01476	0.0000
C(72)	-0.160941	0.008530	-18.86851	0.0000
C(73)	-0.022096	0.001903	-11.61158	0.0000
C(74)	-0.315774	0.002548	-123.9521	0.0000
C(75)	-0.088388	0.006258	-14.12420	0.0000
C(76)	-0.080340	0.005537	-14.50883	0.0000
C(77)	-0.113839	0.013987	-8.138967	0.0000
C(78)	-0.029102	0.006951	-4.186885	0.0000
C(79)	-0.003862	0.006665	-0.579424	0.5623
C(80)	-1.311625	0.358428	-3.659382	0.0003
C(81)	0.003924	0.000493	7.952236	0.0000
C(82)	-0.367559	0.030189	-12.17542	0.0000
C(83)	0.022457	0.006735	3.334522	0.0009
C(84)	-0.022127	0.009016	-2.454024	0.0141
C(85)	0.222848	0.022148	10.06159	0.0000
C(86)	0.031997	0.019598	1.632673	0.1025
C(87)	-0.470141	0.049504	-9.497099	0.0000
C(88)	0.233205	0.024601	9.479528	0.0000
C(89)	-0.236326	0.023588	-10.01889	0.0000
C(90)	-11.65902	1.268575	-9.190643	0.0000
C(91)	0.002558	0.000416	6.144541	0.0000
C(92)	-0.278230	0.025465	-10.92584	0.0000
C(93)	0.023390	0.005681	4.117157	0.0000
C(94)	0.053996	0.007606	7.099357	0.0000
C(95)	0.138225	0.018683	7.398397	0.0000
C(96)	0.090822	0.016532	5.493817	0.0000
C(97)	-0.308476	0.041758	-7.387164	0.0000
C(98)	0.085523	0.020752	4.121237	0.0000
C(99)	0.013762	0.019897	0.691660	0.4892
C(100)	-6.415841	1.070096	-5.995575	0.0000
C(101)	0.001581	0.000440	3.589718	0.0003
C(102)	-0.223950	0.026947	-8.310825	0.0000
C(103)	0.013078	0.006012	2.175433	0.0296
C(104)	0.026909	0.008048	3.343492	0.0008
C(105)	0.115123	0.019770	5.823093	0.0000
C(106)	0.051610	0.017493	2.950263	0.0032
C(107)	-0.232138	0.044188	-5.253467	0.0000
C(108)	0.073207	0.021959	3.333779	0.0009
C(109)	-0.031040	0.021055	-1.474226	0.1404
C(110)	-4.269208	1.132348	-3.770225	0.0002
C(111)	-0.001851	0.000438	-4.224699	0.0000
C(112)	0.192156	0.026806	7.168507	0.0000

C(113)	-0.027502	0.005980	-4.598919	0.0000
C(114)	-0.080978	0.008006	-10.11459	0.0000
C(115)	-0.152992	0.019666	-7.779360	0.0000
C(116)	-0.013513	0.017402	-0.776545	0.4374
C(117)	0.647395	0.043956	14.72818	0.0000
C(118)	-0.166292	0.021844	-7.612669	0.0000
C(119)	0.444057	0.020945	21.20137	0.0000
C(120)	12.80431	1.126417	11.36730	0.0000
C(121)	0.002150	0.000228	9.443108	0.0000
C(122)	-0.278237	0.013931	-19.97308	0.0000
C(123)	0.023310	0.003108	7.500369	0.0000
C(124)	0.064610	0.004161	15.52868	0.0000
C(125)	-0.136506	0.010220	-13.35621	0.0000
C(126)	-0.301085	0.009044	-33.29276	0.0000
C(127)	-0.119005	0.022844	-5.209557	0.0000
C(128)	0.248398	0.011352	21.88116	0.0000
C(129)	-0.087945	0.010885	-8.079603	0.0000
C(130)	-4.765151	0.585387	-8.140174	0.0000
C(131)	0.002027	0.000317	6.391681	0.0000
C(132)	-0.257093	0.019397	-13.25436	0.0000
C(133)	0.028976	0.004327	6.696150	0.0000
C(134)	0.062086	0.005793	10.71699	0.0000
C(135)	0.128207	0.014231	9.009081	0.0000
C(136)	0.113123	0.012592	8.983596	0.0000
C(137)	-0.327997	0.031807	-10.31204	0.0000
C(138)	0.074919	0.015807	4.739755	0.0000
C(139)	-0.005984	0.015156	-0.394815	0.6930
C(140)	-6.331497	0.815087	-7.767876	0.0000
C(141)	0.005179	0.000330	15.70067	0.0000
C(142)	-0.607666	0.020180	-30.11302	0.0000
C(143)	0.056768	0.004502	12.60981	0.0000
C(144)	0.126594	0.006027	21.00437	0.0000
C(145)	0.373054	0.014805	25.19772	0.0000
C(146)	0.205238	0.013100	15.66669	0.0000
C(147)	-0.810291	0.033091	-24.48703	0.0000
C(148)	0.333888	0.016444	20.30401	0.0000
C(149)	-0.190420	0.015767	-12.07686	0.0000
C(150)	-19.75610	0.847976	-23.29794	0.0000
C(151)	-0.003575	0.000324	-11.04619	0.0000
C(152)	0.292525	0.019796	14.77667	0.0000
C(153)	-0.001613	0.004416	-0.365309	0.7149
C(154)	-0.045446	0.005913	-7.686319	0.0000
C(155)	-0.367921	0.014524	-25.33190	0.0000
C(156)	-0.019137	0.012852	-1.489062	0.1365
C(157)	0.532455	0.032462	16.40219	0.0000
C(158)	-0.437547	0.016132	-27.12253	0.0000
C(159)	0.312110	0.015468	20.17773	0.0000
C(160)	19.54631	0.831878	23.49660	0.0000
C(161)	0.001220	0.000344	3.550705	0.0004
C(162)	-0.258728	0.021022	-12.30772	0.0000
C(163)	0.040846	0.004690	8.709544	0.0000
C(164)	0.122455	0.006279	19.50371	0.0000
C(165)	-0.126184	0.015423	-8.181623	0.0000
C(166)	-0.169337	0.013647	-12.40846	0.0000
C(167)	-0.333002	0.034471	-9.660214	0.0000
C(168)	0.018069	0.017131	1.054780	0.2915
C(169)	-0.161110	0.016425	-9.808615	0.0000
C(170)	-3.467456	0.883363	-3.925292	0.0001
C(171)	5.84E-05	0.000416	0.140428	0.8883

C(172)	0.085617	0.025462	3.362593	0.0008
C(173)	0.009229	0.005680	1.624707	0.1042
C(174)	-0.089211	0.007605	-11.73109	0.0000
C(175)	-0.097295	0.018680	-5.208412	0.0000
C(176)	0.168555	0.016529	10.19734	0.0000
C(177)	0.305925	0.041752	7.327140	0.0000
C(178)	-0.078290	0.020749	-3.773215	0.0002
C(179)	0.365721	0.019895	18.38293	0.0000
C(180)	8.760370	1.069940	8.187719	0.0000
C(181)	0.002309	0.000474	4.867762	0.0000
C(182)	-0.247660	0.029017	-8.535076	0.0000
C(183)	0.035318	0.006473	5.455917	0.0000
C(184)	0.018683	0.008666	2.155734	0.0311
C(185)	0.210425	0.021289	9.884376	0.0000
C(186)	0.093254	0.018837	4.950509	0.0000
C(187)	-0.207238	0.047582	-4.355391	0.0000
C(188)	0.186200	0.023646	7.874524	0.0000
C(189)	-0.095708	0.022672	-4.221355	0.0000
C(190)	-6.225637	1.219330	-5.105785	0.0000
C(191)	0.002824	0.000440	6.413533	0.0000
C(192)	-0.297732	0.026939	-11.05192	0.0000
C(193)	0.028970	0.006010	4.820303	0.0000
C(194)	0.069805	0.008046	8.675765	0.0000
C(195)	0.198131	0.019765	10.02456	0.0000
C(196)	0.122770	0.017489	7.019952	0.0000
C(197)	-0.273227	0.044176	-6.185024	0.0000
C(198)	0.144487	0.021953	6.581616	0.0000
C(199)	-0.075135	0.021049	-3.569497	0.0004
C(200)	-7.335534	1.132039	-6.479932	0.0000
C(201)	0.000514	7.86E-05	6.531099	0.0000
C(202)	-0.083280	0.004810	-17.31300	0.0000
C(203)	0.020138	0.001073	18.76543	0.0000
C(204)	0.006525	0.001437	4.541536	0.0000
C(205)	-0.146136	0.003529	-41.40845	0.0000
C(206)	0.298487	0.003123	95.58472	0.0000
C(207)	0.711866	0.007888	90.24777	0.0000
C(208)	-0.129479	0.003920	-33.03118	0.0000
C(209)	-0.124208	0.003759	-33.04719	0.0000
C(210)	3.158050	0.202135	15.62351	0.0000
C(211)	-0.004072	0.000211	-19.25567	0.0000
C(212)	0.309391	0.012936	23.91720	0.0000
C(213)	-0.034740	0.002886	-12.03779	0.0000
C(214)	-0.113025	0.003864	-29.25383	0.0000
C(215)	-0.145258	0.009491	-15.30535	0.0000
C(216)	-0.059051	0.008398	-7.031757	0.0000
C(217)	0.582030	0.021212	27.43813	0.0000
C(218)	-0.305708	0.010542	-29.00029	0.0000
C(219)	-0.208520	0.010108	-20.63014	0.0000
C(220)	18.57913	0.543588	34.17868	0.0000

Equation: PE_OLES_=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 1410

R-squared	0.998867	Mean dependent var	0.001028
Adjusted R-squared	0.998860	S.D. dependent var	0.029462
S.E. of regression	0.000995	Sum squared resid	0.001385
Durbin-Watson stat	1.996303		

Equation: KIMBERA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)
*PC4+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 1410

R-squared	0.279140	Mean dependent var	0.000209
Adjusted R-squared	0.274506	S.D. dependent var	0.015126
S.E. of regression	0.012884	Sum squared resid	0.232389
Durbin-Watson stat	1.860410		

Equation: BIMBOA=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)*PC4
+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 1410

R-squared	0.500695	Mean dependent var	0.000650
Adjusted R-squared	0.497485	S.D. dependent var	0.018661
S.E. of regression	0.013229	Sum squared resid	0.244994
Durbin-Watson stat	1.911890		

Equation: GMODELOC=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 1410

R-squared	0.308155	Mean dependent var	0.000384
Adjusted R-squared	0.303708	S.D. dependent var	0.015785
S.E. of regression	0.013172	Sum squared resid	0.242895
Durbin-Watson stat	2.007770		

Equation: FEMSAUBD=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 1410

R-squared	0.442405	Mean dependent var	0.000500
Adjusted R-squared	0.438820	S.D. dependent var	0.017475
S.E. of regression	0.013091	Sum squared resid	0.239908
Durbin-Watson stat	1.853306		

Equation: CONTAL_=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)
*PC4+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 1410

R-squared	0.951317	Mean dependent var	0.000405
Adjusted R-squared	0.951004	S.D. dependent var	0.021111
S.E. of regression	0.004673	Sum squared resid	0.030570
Durbin-Watson stat	1.917350		

Equation: CEMEXCP=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)
*PC4+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 1410

R-squared	0.416169	Mean dependent var	0.000771
Adjusted R-squared	0.412415	S.D. dependent var	0.016155
S.E. of regression	0.012383	Sum squared resid	0.214687
Durbin-Watson stat	1.863187		

Equation: GEOB=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)*PC4
+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 1410

R-squared	0.969212	Mean dependent var	0.001662
Adjusted R-squared	0.969014	S.D. dependent var	0.024531
S.E. of regression	0.004318	Sum squared resid	0.026105
Durbin-Watson stat	1.929200		

Equation: ARA_=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)*PC4
+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 1410

R-squared	0.353528	Mean dependent var	0.001007
Adjusted R-squared	0.349372	S.D. dependent var	0.018947
S.E. of regression	0.015283	Sum squared resid	0.327001
Durbin-Watson stat	1.916651		

Equation: WALMEXV=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 1410

R-squared	0.529431	Mean dependent var	0.000655
Adjusted R-squared	0.526406	S.D. dependent var	0.018733
S.E. of regression	0.012892	Sum squared resid	0.232682
Durbin-Watson stat	1.902735		

Equation: SORIANAB=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 1410

R-squared	0.464936	Mean dependent var	0.000171
Adjusted R-squared	0.461496	S.D. dependent var	0.018590
S.E. of regression	0.013642	Sum squared resid	0.260542
Durbin-Watson stat	1.842921		

Equation: COMERUBC=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 1410

R-squared	0.562203	Mean dependent var	0.000498
Adjusted R-squared	0.559388	S.D. dependent var	0.020444
S.E. of regression	0.013570	Sum squared resid	0.257819
Durbin-Watson stat	1.992373		

Equation: ELEKTRA_=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 1410

R-squared	0.917431	Mean dependent var	0.000526
Adjusted R-squared	0.916900	S.D. dependent var	0.024465
S.E. of regression	0.007052	Sum squared resid	0.069631
Durbin-Watson stat	1.977398		

Equation: TELMEXL=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 1410

R-squared	0.607454	Mean dependent var	0.000215
Adjusted R-squared	0.604931	S.D. dependent var	0.015623
S.E. of regression	0.009820	Sum squared resid	0.134997
Durbin-Watson stat	2.046099		

Equation: TELECOA1=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 1410

R-squared	0.728350	Mean dependent var	0.000252
Adjusted R-squared	0.726604	S.D. dependent var	0.019538
S.E. of regression	0.010216	Sum squared resid	0.146112
Durbin-Watson stat	2.110332		

Equation: TLEVICPO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 1410

R-squared	0.793194	Mean dependent var	0.000171
Adjusted R-squared	0.791864	S.D. dependent var	0.021968
S.E. of regression	0.010022	Sum squared resid	0.140617
Durbin-Watson stat	1.928299		

Equation: TVAZTCPO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 1410

R-squared	0.811268	Mean dependent var	-7.68E-05
Adjusted R-squared	0.810054	S.D. dependent var	0.024418
S.E. of regression	0.010642	Sum squared resid	0.158561
Durbin-Watson stat	1.977403		

Equation: GFNORTEO=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 1410

R-squared	0.607135	Mean dependent var	0.001415
Adjusted R-squared	0.604609	S.D. dependent var	0.020499
S.E. of regression	0.012890	Sum squared resid	0.232614
Durbin-Watson stat	1.921999		

Equation: GFINBURO=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3
+C(185)*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8
+C(190)*PC9
Observations: 1410

R-squared	0.428121	Mean dependent var	0.000502
Adjusted R-squared	0.424445	S.D. dependent var	0.019363
S.E. of regression	0.014690	Sum squared resid	0.302106
Durbin-Watson stat	1.962358		

Equation: GCARSOA1=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3
+C(195)*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8
+C(200)*PC9
Observations: 1410

R-squared	0.499126	Mean dependent var	0.000711
Adjusted R-squared	0.495906	S.D. dependent var	0.019209
S.E. of regression	0.013638	Sum squared resid	0.260399
Durbin-Watson stat	1.939402		

Equation: ALFAA=C(201)+C(202)*PC1+C(203)*PC2+C(204)*PC3+C(205)
*PC4+C(206)*PC5+C(207)*PC6+C(208)*PC7+C(209)*PC8+C(210)
*PC9
Observations: 1410

R-squared	0.990238	Mean dependent var	0.000723
Adjusted R-squared	0.990176	S.D. dependent var	0.024569
S.E. of regression	0.002435	Sum squared resid	0.008302
Durbin-Watson stat	1.971607		

Equation: CIEB=C(211)+C(212)*PC1+C(213)*PC2+C(214)*PC3+C(215)
*PC4+C(216)*PC5+C(217)*PC6+C(218)*PC7+C(219)*PC8+C(220)
*PC9
Observations: 1410

R-squared	0.906255	Mean dependent var	-0.000376
Adjusted R-squared	0.905653	S.D. dependent var	0.021321
S.E. of regression	0.006549	Sum squared resid	0.060042
Durbin-Watson stat	1.948649		

Table 16. *Neural Networks Principal Component Analysis. Betas estimation for all the equation system via Seemingly Unrelated Regression. Database of daily excesses.*

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.009501	0.001815	5.235693	0.0000
C(2)	-0.097772	0.020310	-4.813884	0.0000
C(3)	0.533503	0.005340	99.91115	0.0000
C(4)	-0.041415	0.001191	-34.76147	0.0000
C(5)	0.001193	0.002640	0.451810	0.6514
C(6)	0.043114	0.001549	27.83342	0.0000
C(7)	0.077819	0.010028	7.760557	0.0000
C(8)	-0.061091	0.048294	-1.264980	0.2059
C(9)	-0.044924	0.074491	-0.603083	0.5465
C(10)	0.292448	0.250479	1.167554	0.2430
C(11)	-0.172948	0.014765	-11.71352	0.0000
C(12)	1.934205	0.165255	11.70440	0.0000
C(13)	0.527653	0.043447	12.14482	0.0000
C(14)	0.100114	0.009694	10.32777	0.0000
C(15)	-0.234403	0.021478	-10.91374	0.0000
C(16)	0.030347	0.012603	2.407846	0.0161
C(17)	-0.999937	0.081589	-12.25586	0.0000
C(18)	4.600877	0.392944	11.70875	0.0000
C(19)	6.940297	0.606089	11.45095	0.0000
C(20)	-24.65667	2.038007	-12.09843	0.0000
C(21)	-0.154369	0.019068	-8.095752	0.0000
C(22)	1.731509	0.213416	8.113291	0.0000
C(23)	0.485822	0.056109	8.658575	0.0000
C(24)	0.089567	0.012519	7.154566	0.0000
C(25)	-0.211853	0.027737	-7.637849	0.0000
C(26)	0.012837	0.016276	0.788683	0.4303
C(27)	-1.064735	0.105367	-10.10504	0.0000
C(28)	4.533703	0.507463	8.934057	0.0000
C(29)	6.768506	0.782728	8.647334	0.0000
C(30)	-22.28061	2.631963	-8.465396	0.0000
C(31)	0.213255	0.017070	12.49313	0.0000
C(32)	-2.387162	0.191053	-12.49479	0.0000
C(33)	-0.601416	0.050229	-11.97343	0.0000
C(34)	-0.140141	0.011207	-12.50482	0.0000
C(35)	0.308304	0.024831	12.41626	0.0000
C(36)	0.054216	0.014571	3.720889	0.0002
C(37)	1.124880	0.094325	11.92553	0.0000
C(38)	-5.666746	0.454286	-12.47396	0.0000
C(39)	-8.652569	0.700706	-12.34836	0.0000
C(40)	28.59507	2.356161	12.13629	0.0000
C(41)	-0.065694	0.016932	-3.879861	0.0001
C(42)	0.737080	0.189512	3.889351	0.0001
C(43)	0.186177	0.049824	3.736666	0.0002
C(44)	0.016741	0.011117	1.505918	0.1321
C(45)	-0.094387	0.024630	-3.832135	0.0001
C(46)	0.006069	0.014453	0.419894	0.6746
C(47)	-0.372734	0.093565	-3.983689	0.0001
C(48)	1.877825	0.450624	4.167165	0.0000
C(49)	3.257826	0.695058	4.687130	0.0000
C(50)	-10.30515	2.337169	-4.409243	0.0000
C(51)	0.153269	0.007382	20.76295	0.0000
C(52)	-1.715419	0.082621	-20.76242	0.0000
C(53)	-0.373859	0.021722	-17.21126	0.0000

C(54)	-0.066750	0.004846	-13.77293	0.0000
C(55)	0.241707	0.010738	22.50924	0.0000
C(56)	-0.316650	0.006301	-50.25278	0.0000
C(57)	0.280945	0.040791	6.887360	0.0000
C(58)	-3.978198	0.196458	-20.24964	0.0000
C(59)	-5.931457	0.303023	-19.57429	0.0000
C(60)	20.28601	1.018930	19.90912	0.0000
C(61)	-0.055276	0.014586	-3.789648	0.0002
C(62)	0.624589	0.163253	3.825898	0.0001
C(63)	0.170146	0.042920	3.964223	0.0001
C(64)	0.019648	0.009576	2.051789	0.0402
C(65)	-0.083074	0.021218	-3.915332	0.0001
C(66)	-0.004646	0.012451	-0.373130	0.7091
C(67)	-0.369818	0.080600	-4.588301	0.0000
C(68)	1.779183	0.388184	4.583350	0.0000
C(69)	3.036110	0.598748	5.070768	0.0000
C(70)	-8.783847	2.013321	-4.362864	0.0000
C(71)	-0.107838	0.004493	-23.99890	0.0000
C(72)	1.223633	0.050293	24.33010	0.0000
C(73)	0.389409	0.013222	29.45071	0.0000
C(74)	0.479473	0.002950	162.5255	0.0000
C(75)	-0.189436	0.006536	-28.98142	0.0000
C(76)	-0.125639	0.003836	-32.75600	0.0000
C(77)	-0.628082	0.024830	-25.29495	0.0000
C(78)	2.993219	0.119587	25.02964	0.0000
C(79)	4.886910	0.184455	26.49380	0.0000
C(80)	-16.42512	0.620239	-26.48190	0.0000
C(81)	0.415727	0.017420	23.86507	0.0000
C(82)	-4.645785	0.194972	-23.82800	0.0000
C(83)	-1.187565	0.051260	-23.16766	0.0000
C(84)	-0.110229	0.011437	-9.638039	0.0000
C(85)	0.602297	0.025340	23.76861	0.0000
C(86)	0.083047	0.014870	5.585036	0.0000
C(87)	2.257217	0.096260	23.44910	0.0000
C(88)	-10.66053	0.463605	-22.99485	0.0000
C(89)	-16.90248	0.715080	-23.63719	0.0000
C(90)	56.29629	2.404495	23.41294	0.0000
C(91)	0.017755	0.017314	1.025504	0.3051
C(92)	-0.195449	0.193782	-1.008602	0.3132
C(93)	-0.040656	0.050947	-0.798012	0.4249
C(94)	-0.032522	0.011367	-2.861061	0.0042
C(95)	0.026580	0.025185	1.055361	0.2913
C(96)	0.057711	0.014779	3.904961	0.0001
C(97)	0.081098	0.095673	0.847662	0.3966
C(98)	-0.393842	0.460777	-0.854735	0.3927
C(99)	-0.320910	0.710718	-0.451529	0.6516
C(100)	0.990996	2.389826	0.414673	0.6784
C(101)	-0.034321	0.017951	-1.911993	0.0559
C(102)	0.381649	0.200911	1.899590	0.0575
C(103)	0.118982	0.052821	2.252542	0.0243
C(104)	0.018920	0.011785	1.605425	0.1084
C(105)	-0.046906	0.026112	-1.796335	0.0725
C(106)	0.013540	0.015323	0.883684	0.3769
C(107)	-0.199454	0.099193	-2.010766	0.0444
C(108)	1.042065	0.477729	2.181290	0.0292
C(109)	1.666630	0.736865	2.261786	0.0237
C(110)	-6.095472	2.477748	-2.460086	0.0139
C(111)	-0.215799	0.020998	-10.27718	0.0000
C(112)	2.416777	0.235018	10.28336	0.0000

C(113)	0.660070	0.061788	10.68280	0.0000
C(114)	0.136078	0.013786	9.870796	0.0000
C(115)	-0.316441	0.030545	-10.35990	0.0000
C(116)	0.032710	0.017924	1.824936	0.0680
C(117)	-1.263438	0.116032	-10.88872	0.0000
C(118)	6.099257	0.558828	10.91437	0.0000
C(119)	8.910342	0.861955	10.33736	0.0000
C(120)	-31.05827	2.898370	-10.71577	0.0000
C(121)	0.033825	0.010704	3.160019	0.0016
C(122)	-0.376405	0.119806	-3.141781	0.0017
C(123)	-0.081354	0.031498	-2.582843	0.0098
C(124)	-0.056572	0.007028	-8.049821	0.0000
C(125)	-0.023416	0.015571	-1.503831	0.1326
C(126)	-0.393025	0.009137	-43.01431	0.0000
C(127)	0.245721	0.059150	4.154199	0.0000
C(128)	-0.069912	0.284876	-0.245411	0.8061
C(129)	-1.245614	0.439402	-2.834794	0.0046
C(130)	2.832206	1.477513	1.916874	0.0553
C(131)	0.058336	0.013082	4.459203	0.0000
C(132)	-0.654118	0.146421	-4.467368	0.0000
C(133)	-0.172661	0.038495	-4.485244	0.0000
C(134)	-0.068693	0.008589	-7.997859	0.0000
C(135)	0.081955	0.019030	4.306622	0.0000
C(136)	0.066340	0.011167	5.940747	0.0000
C(137)	0.296039	0.072290	4.095142	0.0000
C(138)	-1.474741	0.348162	-4.235794	0.0000
C(139)	-1.779940	0.537016	-3.314500	0.0009
C(140)	6.893578	1.805746	3.817580	0.0001
C(141)	0.133602	0.015381	8.686057	0.0000
C(142)	-1.496942	0.172154	-8.695364	0.0000
C(143)	-0.385918	0.045261	-8.526574	0.0000
C(144)	-0.110092	0.010098	-10.90195	0.0000
C(145)	0.192542	0.022374	8.605461	0.0000
C(146)	0.166826	0.013129	12.70630	0.0000
C(147)	0.698404	0.084995	8.217011	0.0000
C(148)	-3.384455	0.409349	-8.267892	0.0000
C(149)	-4.728460	0.631394	-7.488926	0.0000
C(150)	16.91207	2.123095	7.965764	0.0000
C(151)	0.282807	0.014493	19.51397	0.0000
C(152)	-3.168261	0.162207	-19.53222	0.0000
C(153)	-0.840688	0.042645	-19.71341	0.0000
C(154)	-0.179648	0.009515	-18.88064	0.0000
C(155)	0.386420	0.021082	18.32967	0.0000
C(156)	-0.082192	0.012371	-6.644045	0.0000
C(157)	1.544202	0.080084	19.28231	0.0000
C(158)	-7.463439	0.385697	-19.35053	0.0000
C(159)	-11.00434	0.594912	-18.49743	0.0000
C(160)	37.22989	2.000423	18.61102	0.0000
C(161)	-0.248089	0.014267	-17.38873	0.0000
C(162)	2.772315	0.159685	17.36110	0.0000
C(163)	0.706448	0.041983	16.82717	0.0000
C(164)	0.020152	0.009367	2.151339	0.0315
C(165)	-0.415274	0.020754	-20.00941	0.0000
C(166)	-0.371423	0.012178	-30.49834	0.0000
C(167)	-1.350791	0.078839	-17.13354	0.0000
C(168)	6.806987	0.379701	17.92721	0.0000
C(169)	10.82161	0.585664	18.47751	0.0000
C(170)	-36.12472	1.969326	-18.34369	0.0000
C(171)	0.243728	0.017704	13.76668	0.0000

C(172)	-2.715507	0.198154	-13.70405	0.0000
C(173)	-0.713770	0.052096	-13.70103	0.0000
C(174)	-0.071300	0.011624	-6.134151	0.0000
C(175)	0.355004	0.025754	13.78465	0.0000
C(176)	0.119207	0.015112	7.888105	0.0000
C(177)	1.417318	0.097831	14.48737	0.0000
C(178)	-5.889119	0.471171	-12.49890	0.0000
C(179)	-9.371779	0.726750	-12.89547	0.0000
C(180)	32.22665	2.443735	13.18745	0.0000
C(181)	-0.157590	0.018276	-8.622632	0.0000
C(182)	1.766658	0.204558	8.636487	0.0000
C(183)	0.450304	0.053780	8.373119	0.0000
C(184)	0.079845	0.011999	6.654233	0.0000
C(185)	-0.211588	0.026586	-7.958685	0.0000
C(186)	0.101461	0.015601	6.503649	0.0000
C(187)	-0.926617	0.100993	-9.175069	0.0000
C(188)	4.722877	0.486398	9.709894	0.0000
C(189)	7.065137	0.750237	9.417208	0.0000
C(190)	-22.86206	2.522712	-9.062493	0.0000
C(191)	-0.004312	0.016810	-0.256510	0.7976
C(192)	0.050808	0.188148	0.270041	0.7871
C(193)	0.019478	0.049465	0.393767	0.6938
C(194)	-0.034159	0.011037	-3.095109	0.0020
C(195)	-0.003266	0.024453	-0.133577	0.8937
C(196)	0.118251	0.014349	8.240955	0.0000
C(197)	-0.043357	0.092891	-0.466752	0.6407
C(198)	0.282761	0.447379	0.632040	0.5274
C(199)	0.198584	0.690052	0.287782	0.7735
C(200)	-2.065460	2.320336	-0.890156	0.3734
C(201)	0.030593	0.005679	5.387106	0.0000
C(202)	-0.341686	0.063562	-5.375622	0.0000
C(203)	-0.086610	0.016711	-5.182838	0.0000
C(204)	-0.022527	0.003728	-6.041827	0.0000
C(205)	-0.050329	0.008261	-6.092386	0.0000
C(206)	0.486563	0.004848	100.3722	0.0000
C(207)	-0.126613	0.031381	-4.034652	0.0001
C(208)	-0.465215	0.151138	-3.078074	0.0021
C(209)	-0.755529	0.233121	-3.240932	0.0012
C(210)	2.507180	0.783881	3.198418	0.0014
C(211)	-0.070576	0.018261	-3.864835	0.0001
C(212)	0.781452	0.204387	3.823389	0.0001
C(213)	0.232376	0.053735	4.324483	0.0000
C(214)	0.060058	0.011989	5.009333	0.0000
C(215)	-0.061175	0.026564	-2.302965	0.0213
C(216)	0.026148	0.015588	1.677493	0.0935
C(217)	-0.423187	0.100909	-4.193749	0.0000
C(218)	2.274551	0.485994	4.680206	0.0000
C(219)	2.986473	0.749613	3.984019	0.0001
C(220)	-11.11594	2.520614	-4.410012	0.0000

Equation: PE_OLES_=C(1)+C(2)*PC1+C(3)*PC2+C(4)*PC3+C(5)*PC4
+C(6)*PC5+C(7)*PC6+C(8)*PC7+C(9)*PC8+C(10)*PC9
Observations: 1410

R-squared	0.997902	Mean dependent var	0.000805
Adjusted R-squared	0.997888	S.D. dependent var	0.029496
S.E. of regression	0.001356	Sum squared resid	0.002572
Durbin-Watson stat	2.014164		

Equation: KIMBERA=C(11)+C(12)*PC1+C(13)*PC2+C(14)*PC3+C(15)
*PC4+C(16)*PC5+C(17)*PC6+C(18)*PC7+C(19)*PC8+C(20)*PC9
Observations: 1410

R-squared	0.471715	Mean dependent var	-1.66E-05
Adjusted R-squared	0.468319	S.D. dependent var	0.015126
S.E. of regression	0.011029	Sum squared resid	0.170294
Durbin-Watson stat	1.856582		

Equation: BIMBOA=C(21)+C(22)*PC1+C(23)*PC2+C(24)*PC3+C(25)*PC4
+C(26)*PC5+C(27)*PC6+C(28)*PC7+C(29)*PC8+C(30)*PC9
Observations: 1410

R-squared	0.421372	Mean dependent var	0.000397
Adjusted R-squared	0.417653	S.D. dependent var	0.018665
S.E. of regression	0.014243	Sum squared resid	0.284019
Durbin-Watson stat	1.882480		

Equation: GMODELOC=C(31)+C(32)*PC1+C(33)*PC2+C(34)*PC3+C(35)
*PC4+C(36)*PC5+C(37)*PC6+C(38)*PC7+C(39)*PC8+C(40)*PC9
Observations: 1410

R-squared	0.351799	Mean dependent var	0.000143
Adjusted R-squared	0.347632	S.D. dependent var	0.015787
S.E. of regression	0.012751	Sum squared resid	0.227613
Durbin-Watson stat	2.043201		

Equation: FEMSAUBD=C(41)+C(42)*PC1+C(43)*PC2+C(44)*PC3+C(45)
*PC4+C(46)*PC5+C(47)*PC6+C(48)*PC7+C(49)*PC8+C(50)*PC9
Observations: 1410

R-squared	0.479260	Mean dependent var	0.000231
Adjusted R-squared	0.475913	S.D. dependent var	0.017471
S.E. of regression	0.012648	Sum squared resid	0.223959
Durbin-Watson stat	1.833759		

Equation: CONTAL_=C(51)+C(52)*PC1+C(53)*PC2+C(54)*PC3+C(55)
*PC4+C(56)*PC5+C(57)*PC6+C(58)*PC7+C(59)*PC8+C(60)*PC9
Observations: 1410

R-squared	0.932216	Mean dependent var	0.000161
Adjusted R-squared	0.931780	S.D. dependent var	0.021112
S.E. of regression	0.005514	Sum squared resid	0.042567
Durbin-Watson stat	1.905602		

Equation: CEMEXCP=C(61)+C(62)*PC1+C(63)*PC2+C(64)*PC3+C(65)
*PC4+C(66)*PC5+C(67)*PC6+C(68)*PC7+C(69)*PC8+C(70)*PC9
Observations: 1410

R-squared	0.547478	Mean dependent var	0.000550
Adjusted R-squared	0.544569	S.D. dependent var	0.016145
S.E. of regression	0.010895	Sum squared resid	0.166193
Durbin-Watson stat	1.896656		

Equation: GEOB=C(71)+C(72)*PC1+C(73)*PC2+C(74)*PC3+C(75)*PC4
+C(76)*PC5+C(77)*PC6+C(78)*PC7+C(79)*PC8+C(80)*PC9
Observations: 1410

R-squared	0.981423	Mean dependent var	0.001474
Adjusted R-squared	0.981304	S.D. dependent var	0.024548
S.E. of regression	0.003357	Sum squared resid	0.015773
Durbin-Watson stat	1.885705		

Equation: ARA_=C(81)+C(82)*PC1+C(83)*PC2+C(84)*PC3+C(85)*PC4
+C(86)*PC5+C(87)*PC6+C(88)*PC7+C(89)*PC8+C(90)*PC9
Observations: 1410

R-squared	0.531453	Mean dependent var	0.000797
Adjusted R-squared	0.528441	S.D. dependent var	0.018949
S.E. of regression	0.013012	Sum squared resid	0.237048
Durbin-Watson stat	1.947513		

Equation: WALMEXV=C(91)+C(92)*PC1+C(93)*PC2+C(94)*PC3+C(95)
*PC4+C(96)*PC5+C(97)*PC6+C(98)*PC7+C(99)*PC8+C(100)*PC9
Observations: 1410

R-squared	0.525863	Mean dependent var	0.000450
Adjusted R-squared	0.522815	S.D. dependent var	0.018722
S.E. of regression	0.012933	Sum squared resid	0.234164
Durbin-Watson stat	1.881621		

Equation: SORIANAB=C(101)+C(102)*PC1+C(103)*PC2+C(104)*PC3
+C(105)*PC4+C(106)*PC5+C(107)*PC6+C(108)*PC7+C(109)*PC8
+C(110)*PC9
Observations: 1410

R-squared	0.482967	Mean dependent var	-8.42E-05
Adjusted R-squared	0.479644	S.D. dependent var	0.018588
S.E. of regression	0.013409	Sum squared resid	0.251711
Durbin-Watson stat	1.896770		

Equation: COMERUBC=C(111)+C(112)*PC1+C(113)*PC2+C(114)*PC3
+C(115)*PC4+C(116)*PC5+C(117)*PC6+C(118)*PC7+C(119)*PC8
+C(120)*PC9
Observations: 1410

R-squared	0.415427	Mean dependent var	0.000260
Adjusted R-squared	0.411669	S.D. dependent var	0.020449
S.E. of regression	0.015685	Sum squared resid	0.344426
Durbin-Watson stat	2.054896		

Equation: ELEKTRA_=C(121)+C(122)*PC1+C(123)*PC2+C(124)*PC3
+C(125)*PC4+C(126)*PC5+C(127)*PC6+C(128)*PC7+C(129)*PC8
+C(130)*PC9
Observations: 1410

R-squared	0.893906	Mean dependent var	0.000287
Adjusted R-squared	0.893224	S.D. dependent var	0.024469
S.E. of regression	0.007996	Sum squared resid	0.089506
Durbin-Watson stat	1.985367		

Equation: TELMEXL=C(131)+C(132)*PC1+C(133)*PC2+C(134)*PC3
+C(135)*PC4+C(136)*PC5+C(137)*PC6+C(138)*PC7+C(139)*PC8
+C(140)*PC9
Observations: 1410

R-squared	0.610662	Mean dependent var	-1.50E-07
Adjusted R-squared	0.608159	S.D. dependent var	0.015611
S.E. of regression	0.009772	Sum squared resid	0.133691
Durbin-Watson stat	1.986439		

Equation: TELECOA1=C(141)+C(142)*PC1+C(143)*PC2+C(144)*PC3
+C(145)*PC4+C(146)*PC5+C(147)*PC6+C(148)*PC7+C(149)*PC8
+C(150)*PC9
Observations: 1410

R-squared	0.656626	Mean dependent var	2.74E-05
Adjusted R-squared	0.654418	S.D. dependent var	0.019544
S.E. of regression	0.011489	Sum squared resid	0.184810
Durbin-Watson stat	2.007262		

Equation: TLEVICPO=C(151)+C(152)*PC1+C(153)*PC2+C(154)*PC3
+C(155)*PC4+C(156)*PC5+C(157)*PC6+C(158)*PC7+C(159)*PC8
+C(160)*PC9
Observations: 1410

R-squared	0.758693	Mean dependent var	-5.84E-05
Adjusted R-squared	0.757142	S.D. dependent var	0.021967
S.E. of regression	0.010826	Sum squared resid	0.164071
Durbin-Watson stat	2.004222		

Equation: TVAZTCPO=C(161)+C(162)*PC1+C(163)*PC2+C(164)*PC3
+C(165)*PC4+C(166)*PC5+C(167)*PC6+C(168)*PC7+C(169)*PC8
+C(170)*PC9
Observations: 1410

R-squared	0.810880	Mean dependent var	-0.000324
Adjusted R-squared	0.809664	S.D. dependent var	0.024428
S.E. of regression	0.010657	Sum squared resid	0.159009
Durbin-Watson stat	2.030441		

Equation: GFNORTEO=C(171)+C(172)*PC1+C(173)*PC2+C(174)*PC3
+C(175)*PC4+C(176)*PC5+C(177)*PC6+C(178)*PC7+C(179)*PC8
+C(180)*PC9
Observations: 1410

R-squared	0.586423	Mean dependent var	0.001169
Adjusted R-squared	0.583764	S.D. dependent var	0.020498
S.E. of regression	0.013225	Sum squared resid	0.244848
Durbin-Watson stat	1.854986		

Equation: GFINBURO=C(181)+C(182)*PC1+C(183)*PC2+C(184)*PC3
+C(185)*PC4+C(186)*PC5+C(187)*PC6+C(188)*PC7+C(189)*PC8
+C(190)*PC9
Observations: 1410

R-squared	0.505292	Mean dependent var	0.000276
Adjusted R-squared	0.502112	S.D. dependent var	0.019348
S.E. of regression	0.013652	Sum squared resid	0.260929
Durbin-Watson stat	1.966729		

Equation: GCARSOA1=C(191)+C(192)*PC1+C(193)*PC2+C(194)*PC3
+C(195)*PC4+C(196)*PC5+C(197)*PC6+C(198)*PC7+C(199)*PC8
+C(200)*PC9
Observations: 1410

R-squared	0.575737	Mean dependent var	0.000455
Adjusted R-squared	0.573009	S.D. dependent var	0.019216
S.E. of regression	0.012557	Sum squared resid	0.220744
Durbin-Watson stat	1.851959		

Equation: ALFAA=C(201)+C(202)*PC1+C(203)*PC2+C(204)*PC3+C(205)
*PC4+C(206)*PC5+C(207)*PC6+C(208)*PC7+C(209)*PC8+C(210)
*PC9
Observations: 1410

R-squared	0.970373	Mean dependent var	0.000496
Adjusted R-squared	0.970183	S.D. dependent var	0.024567
S.E. of regression	0.004242	Sum squared resid	0.025193
Durbin-Watson stat	1.870912		

Equation: CIEB=C(211)+C(212)*PC1+C(213)*PC2+C(214)*PC3+C(215)
*PC4+C(216)*PC5+C(217)*PC6+C(218)*PC7+C(219)*PC8+C(220)
*PC9
Observations: 1410

R-squared	0.592962	Mean dependent var	-0.000633
Adjusted R-squared	0.590346	S.D. dependent var	0.021312
S.E. of regression	0.013641	Sum squared resid	0.260496
Durbin-Watson stat	1.998047		

Appendix_2 (Chapter 3)

Table 1. *Correlation matrix. Database of weekly returns.*

	PE_OLES_	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
PE_OLES_	1.00000																			

BIMBOA	0.07160	1.00000																		
	1.22033	-----																		
	0.22334	-----																		
GMODELOC	0.06507	0.00913	1.00000																	
	1.10845	0.15517	-----																	
	0.26859	0.87680	-----																	
FEMSAUBD	0.08579	0.27110	0.28842	1.00000																
	1.46384	4.78795	5.12080	-----																
	0.14433	0.00000	0.00000	-----																
CONTAL_	0.16487	0.17577	0.13083	0.23985	1.00000															
	2.84169	3.03535	2.24345	4.20007	-----															
	0.00481	0.00262	0.02563	0.00004	-----															
GEOB	0.23308	0.11829	0.12743	0.30987	0.20383	1.00000														
	4.07454	2.02519	2.18414	5.54045	3.53949	-----														
	0.00006	0.04377	0.02976	0.00000	0.00047	-----														
ARA_	0.17673	0.15213	0.10574	0.26653	0.21005	0.35963	1.00000													
	3.05246	2.61669	1.80766	4.70106	3.65224	6.55207	-----													
	0.00248	0.00935	0.07170	0.00000	0.00031	0.00000	-----													
WALMEXV	0.04167	0.18173	0.24122	0.47716	0.19367	0.29463	0.20703	1.00000												
	0.70894	3.14167	4.22560	9.23020	3.35593	5.24130	3.59749	-----												
	0.47893	0.00185	0.00003	0.00000	0.00090	0.00000	0.00038	-----												
SORIANAB	0.06163	0.17411	0.31288	0.42109	0.15854	0.34235	0.24598	0.45702	1.00000											
	1.04972	3.00585	5.60017	7.89245	2.72965	6.19426	4.31415	8.73500	-----											
	0.29472	0.00288	0.00000	0.00000	0.00673	0.00000	0.00002	0.00000	-----											
COMERUBC	0.14205	0.24945	0.21091	0.33519	0.25727	0.26923	0.31794	0.33046	0.46159	1.00000										
	2.43960	4.37902	3.66793	6.04807	4.52597	4.75235	5.70083	5.95217	8.84581	-----										
	0.01530	0.00002	0.00029	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	-----										
ELEKTRA_	0.15410	0.19459	0.26054	0.40156	0.23546	0.38490	0.31358	0.33890	0.35987	0.38125	1.00000									
	2.65133	3.37247	4.58764	7.45399	4.11854	7.08939	5.61406	6.12374	6.55710	7.01077	-----									
	0.00846	0.00085	0.00001	0.00000	0.00005	0.00000	0.00000	0.00000	0.00000	0.00000	-----									

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 2. *Correlation matrix. Database of weekly returns. (Cont.)*

	PE_OLES_	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
TELMEXL	0.10121	0.23865	0.30597	0.43269	0.17032	0.25268	0.32043	0.44907	0.40268	0.34737	0.37171	1.00000								
	1.72951	4.17774	5.46360	8.15911	2.93841	4.43954	5.75056	8.54418	7.47880	6.29745	6.80679	-----								
	0.08479	0.00004	0.00000	0.00000	0.00356	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	-----								
TELECOA1	0.11165	0.29981	0.29228	0.41168	0.19353	0.27031	0.31239	0.43129	0.42532	0.34095	0.40650	0.77490	1.00000							
	1.90999	5.34245	5.19558	7.67944	3.35342	4.77303	5.59033	8.12664	7.98902	6.16560	7.56363	20.84120	-----							
	0.05712	0.00000	0.00000	0.00000	0.00090	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----							
TLEVICPO	0.11177	0.26536	0.31520	0.54566	0.25062	0.36695	0.31108	0.57354	0.48750	0.40360	0.43641	0.57384	0.55380	1.00000						
	1.91202	4.67878	5.64615	11.06949	4.40091	6.70601	5.56440	11.90251	9.49187	7.49904	8.24572	11.91177	11.30677	-----						
	0.05686	0.00000	0.00000	0.00000	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----						
TVAZTCPO	0.10197	0.21638	0.33823	0.38286	0.23856	0.39465	0.23297	0.45461	0.50050	0.41831	0.57978	0.46107	0.41017	0.57219	1.00000					
	1.74255	3.76776	6.11003	7.04536	4.17612	7.30172	4.07264	8.67677	9.82812	7.82913	12.09707	8.83323	7.64564	11.86057	-----					
	0.08248	0.00020	0.00000	0.00000	0.00004	0.00000	0.00006	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----					
GFNORTEO	0.05191	0.09805	0.21834	0.34300	0.14836	0.35688	0.25108	0.38794	0.39837	0.38561	0.36933	0.37716	0.36502	0.40078	0.39888	1.00000				
	0.88371	1.67498	3.80349	6.20760	2.55033	6.49453	4.40969	7.15527	7.38353	7.10489	6.75622	6.92293	6.66531	7.43669	7.39464	-----				
	0.37759	0.09502	0.00017	0.00000	0.01128	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----				
GFINBURO	0.08642	0.20161	0.10648	0.37731	0.14639	0.33591	0.29816	0.28320	0.38300	0.31851	0.29902	0.36044	0.42775	0.38861	0.28989	0.34252	1.00000			
	1.47466	3.49919	1.82055	6.92629	2.51571	6.06280	5.31020	5.01993	7.04844	5.71216	5.32715	6.56913	8.04494	7.16996	5.14929	6.19779	-----			
	0.14139	0.00054	0.06971	0.00000	0.01242	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----			
GCARSOA1	0.04721	0.18904	0.28712	0.43812	0.24883	0.26558	0.30650	0.42767	0.47723	0.39753	0.41881	0.52828	0.58335	0.48159	0.46175	0.42422	0.45257	1.00000		
	0.80345	3.27260	5.09553	8.28553	4.36741	4.68308	5.47403	8.04312	9.23192	7.36505	7.84050	10.57711	12.20968	9.34168	8.84971	7.96385	8.62791	-----		
	0.42237	0.00119	0.00000	0.00000	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----		
ALFAA	0.10033	0.20587	0.25928	0.37517	0.28111	0.34774	0.33542	0.37606	0.38041	0.37290	0.45565	0.36030	0.39664	0.41717	0.43759	0.36150	0.33307	0.40389	1.00000	
	1.71431	3.57643	4.56383	6.88037	4.97974	6.30505	6.05285	6.89956	6.99278	6.83213	8.70178	6.56618	7.34543	7.80339	8.27318	6.59129	6.00510	7.50550	-----	
	0.08754	0.00041	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----	
CIEB	0.11736	0.28604	0.25577	0.45957	0.29705	0.30342	0.28940	0.35581	0.51093	0.44318	0.34534	0.38954	0.38559	0.45473	0.45034	0.38074	0.47448	0.45742	0.36780	1.00000
	2.00894	5.07474	4.49766	8.79673	5.28856	5.41342	5.13974	6.47226	10.10411	8.40455	6.25555	7.19008	7.10441	8.67972	8.57449	6.99970	9.16344	8.74466	6.72392	-----
	0.04547	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 3. *Descriptive statistics. Database of weekly excesses.*

	PE_OLES	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
Mean	0.00304	0.00147	0.00018	0.00067	0.00035	0.00650	0.00321	0.00165	-0.00094	0.00057	0.00097	-0.00049	-0.00037	-0.00079	-0.00202	0.00516	0.00077	0.00172	0.00187	-0.00364
Median	-0.00171	0.00016	0.00014	0.00033	-0.00175	0.01030	0.00446	0.00162	-0.00097	-0.00053	0.00170	-0.00150	0.00064	0.00072	-0.00090	0.00615	0.00150	0.00516	0.00302	-0.00101
Maximum	0.26081	0.17076	0.14537	0.14565	0.16682	0.24075	0.13863	0.12968	0.18103	0.17202	0.20134	0.10083	0.15032	0.16109	0.17026	0.19913	0.11071	0.12978	0.18671	0.13679
Minimum	-0.20082	-0.15340	-0.11759	-0.16931	-0.16156	-0.23987	-0.13210	-0.13975	-0.18046	-0.15102	-0.20866	-0.21005	-0.16157	-0.22510	-0.17371	-0.12899	-0.21499	-0.16054	-0.36257	-0.26460
Std. Dev.	0.06748	0.04222	0.03217	0.04240	0.04384	0.06298	0.04064	0.03985	0.04395	0.04549	0.05695	0.03346	0.04451	0.04757	0.05285	0.04366	0.04263	0.04457	0.06199	0.05056
Skewness	0.33157	0.06986	0.28733	-0.27229	0.05970	-0.28474	-0.14225	-0.06265	-0.07206	0.12747	-0.25002	-0.60626	-0.14578	-0.41347	-0.36505	0.23791	-0.35555	-0.40089	-0.67092	-0.78742
Kurtosis	4.38012	4.78357	5.22716	4.73558	4.64723	5.11601	3.53187	4.58449	4.77665	4.43347	4.34816	7.82378	3.74615	5.76030	4.46368	4.47594	5.33539	4.33932	7.37421	6.19422
Jarque-Bera	28.42667	38.80787	64.14730	40.11908	33.07250	58.22178	4.41149	30.63142	38.52444	25.70275	25.06947	299.96063	7.78122	100.67490	32.43913	29.15816	72.26142	29.54416	253.82792	153.78293
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.11017	0.00000	0.00000	0.00000	0.00000	0.00000	0.02043	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291	291

Table 4. *Correlation matrix. Database of weekly excesses.*

	PE_OLES_	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
PE_OLES_	1.00000																			

BIMBOA	0.07388	1.00000																		
	1.25934	-----																		
	0.20892	-----																		
GMODELOC	0.06770	0.01098	1.00000																	
	1.15351	0.18661	-----																	
	0.24965	0.85210	-----																	
FEMSAUBD	0.08813	0.27265	0.28998	1.00000																
	1.50414	4.81761	5.15102	-----																
	0.13364	0.00000	0.00000	-----																
CONTAL_	0.16637	0.17642	0.13114	0.24059	1.00000															
	2.86830	3.04697	2.24879	4.21384	-----															
	0.00443	0.00253	0.02528	0.00003	-----															
GEOB	0.23536	0.12144	0.13121	0.31252	0.20611	1.00000														
	4.11680	2.07984	2.24994	5.59303	3.58078	-----														
	0.00005	0.03842	0.02521	0.00000	0.00040	-----														
ARA_	0.17883	0.15377	0.10738	0.26810	0.21062	0.36216	1.00000													
	3.08988	2.64558	1.83608	4.73082	3.66271	6.60519	-----													
	0.00220	0.00860	0.06737	0.00000	0.00030	0.00000	-----													
WALMEXV	0.04376	0.18287	0.24205	0.47802	0.19383	0.29720	0.20811	1.00000												
	0.74461	3.16218	4.24092	9.25176	3.35878	5.29148	3.61709	-----												
	0.45711	0.00173	0.00003	0.00000	0.00089	0.00000	0.00035	-----												
SORIANAB	0.06485	0.17714	0.31596	0.42333	0.16063	0.34535	0.24881	0.45888	1.00000											
	1.10474	3.05978	5.66125	7.94351	2.76664	6.25584	4.36709	8.77996	-----											
	0.27019	0.00242	0.00000	0.00000	0.00603	0.00000	0.00002	0.00000	-----											
COMERUBC	0.14451	0.25155	0.21339	0.33717	0.25854	0.27214	0.31989	0.33208	0.46391	1.00000										
	2.48268	4.41846	3.71321	6.08839	4.54991	4.80779	5.73981	5.98509	8.90238	-----										
	0.01361	0.00001	0.00025	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	-----										
ELEKTRA_	0.15622	0.19671	0.26286	0.40326	0.23685	0.38698	0.31547	0.34054	0.36223	0.38318	1.00000									
	2.68879	3.41072	4.63145	7.49157	4.14441	7.13454	5.65149	6.15729	6.60667	7.05233	-----									
	0.00759	0.00074	0.00001	0.00000	0.00004	0.00000	0.00000	0.00000	0.00000	0.00000	-----									

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 5. *Correlation matrix. Database of weekly excesses. (Cont.)*

	PE_OLES_	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
TELMEXL	0.10380	0.24022	0.30725	0.43403	0.17079	0.25606	0.32181	0.44976	0.40543	0.34954	0.37377	1.00000								
	1.77426	4.20691	5.48868	8.19023	2.94674	4.50316	5.77823	8.56070	7.53988	6.34228	6.85057	-----								
	0.07707	0.00003	0.00000	0.00000	0.00347	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	-----								
TELECOA1	0.11406	0.30155	0.29422	0.41324	0.19464	0.27313	0.31412	0.43248	0.42765	0.34308	0.40826	0.77570	1.00000							
	1.95169	5.37659	5.23335	7.71470	3.37336	4.82676	5.62467	8.15419	8.04261	6.20921	7.60282	20.89476	-----							
	0.05194	0.00000	0.00000	0.00000	0.00084	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----							
TLEVICPO	0.11445	0.26769	0.31782	0.54722	0.25221	0.36955	0.31333	0.57489	0.48984	0.40585	0.43827	0.57568	0.55540	1.00000						
	1.95850	4.72319	5.69837	11.11467	4.43076	6.76100	5.60905	11.94433	9.55168	7.54923	8.28899	11.96889	11.35396	-----						
	0.05113	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----						
TVAZTCPO	0.10454	0.21883	0.34081	0.38491	0.24024	0.39697	0.23543	0.45631	0.50264	0.42043	0.58110	0.46329	0.41222	0.57382	1.00000					
	1.78705	3.81252	6.16276	7.08976	4.20733	7.35269	4.11806	8.71771	9.88432	7.87739	12.13860	8.88715	7.69163	11.91120	-----					
	0.07498	0.00017	0.00000	0.00000	0.00003	0.00000	0.00005	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----					
GFNORTEO	0.05394	0.09941	0.21936	0.34411	0.14871	0.35912	0.25219	0.38853	0.40029	0.38707	0.37083	0.37807	0.36633	0.40245	0.40059	1.00000				
	0.91833	1.69843	3.82230	6.23032	2.55656	6.54145	4.43043	7.16813	7.42576	7.13656	6.78818	6.94253	6.69277	7.47367	7.43238	-----				
	0.35921	0.09050	0.00016	0.00000	0.01108	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----				
GFINBURO	0.08864	0.20314	0.10813	0.37862	0.14705	0.33840	0.29950	0.28420	0.38524	0.32040	0.30088	0.36175	0.42916	0.39056	0.29211	0.34350	1.00000			
	1.51281	3.52687	1.84913	6.95435	2.52739	6.11352	5.33637	5.03910	7.09693	5.74994	5.36344	6.59648	8.07739	7.21224	5.19227	6.21776	-----			
	0.13142	0.00049	0.06546	0.00000	0.01202	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----			
GCARSOA1	0.05006	0.19144	0.28957	0.43990	0.25021	0.26862	0.30861	0.42919	0.47959	0.39975	0.42070	0.53006	0.58477	0.48365	0.46380	0.42568	0.45419	1.00000		
	0.85214	3.31589	5.14310	8.32723	4.39336	4.74070	5.51560	8.07798	9.29128	7.41380	7.88339	10.62673	12.25478	9.39376	8.89980	7.99724	8.66681	-----		
	0.39484	0.00103	0.00000	0.00000	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----		
ALFAA	0.10279	0.20839	0.26220	0.37730	0.28291	0.35005	0.33767	0.37809	0.38295	0.37515	0.45732	0.36292	0.39874	0.41932	0.43954	0.36342	0.33523	0.40611	1.00000	
	1.75678	3.62219	4.61902	6.92592	5.01423	6.35270	6.09862	6.94292	7.04740	6.87996	8.74210	6.62115	7.39161	7.85215	8.31894	6.63149	6.04902	7.55483	-----	
	0.08001	0.00034	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----	
CIEB	0.11928	0.28735	0.25718	0.46064	0.29770	0.30564	0.29071	0.35675	0.51240	0.44455	0.34687	0.39077	0.38696	0.45623	0.45185	0.38166	0.47544	0.45882	0.36958	1.00000
	2.04233	5.10003	4.52427	8.82255	5.30132	5.45697	5.16506	6.49191	10.14373	8.43681	6.28721	7.21701	7.13402	8.71575	8.61064	7.01963	9.18721	8.77840	6.76160	-----
	0.04203	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

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Figure 1. *Box plots. Database of weekly excesses.*

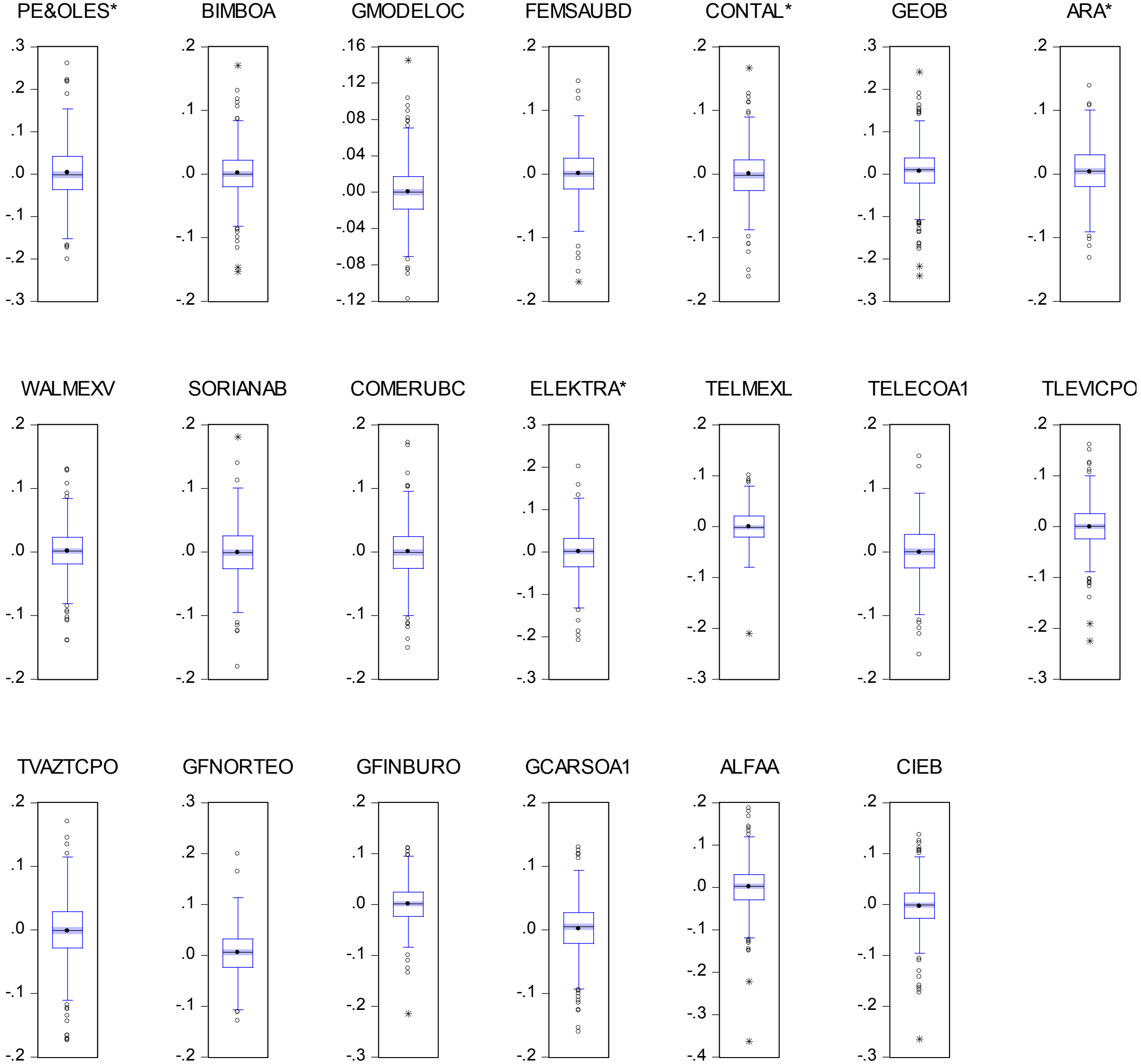


Figure 2. *Histograms. Database of weekly excesses.*

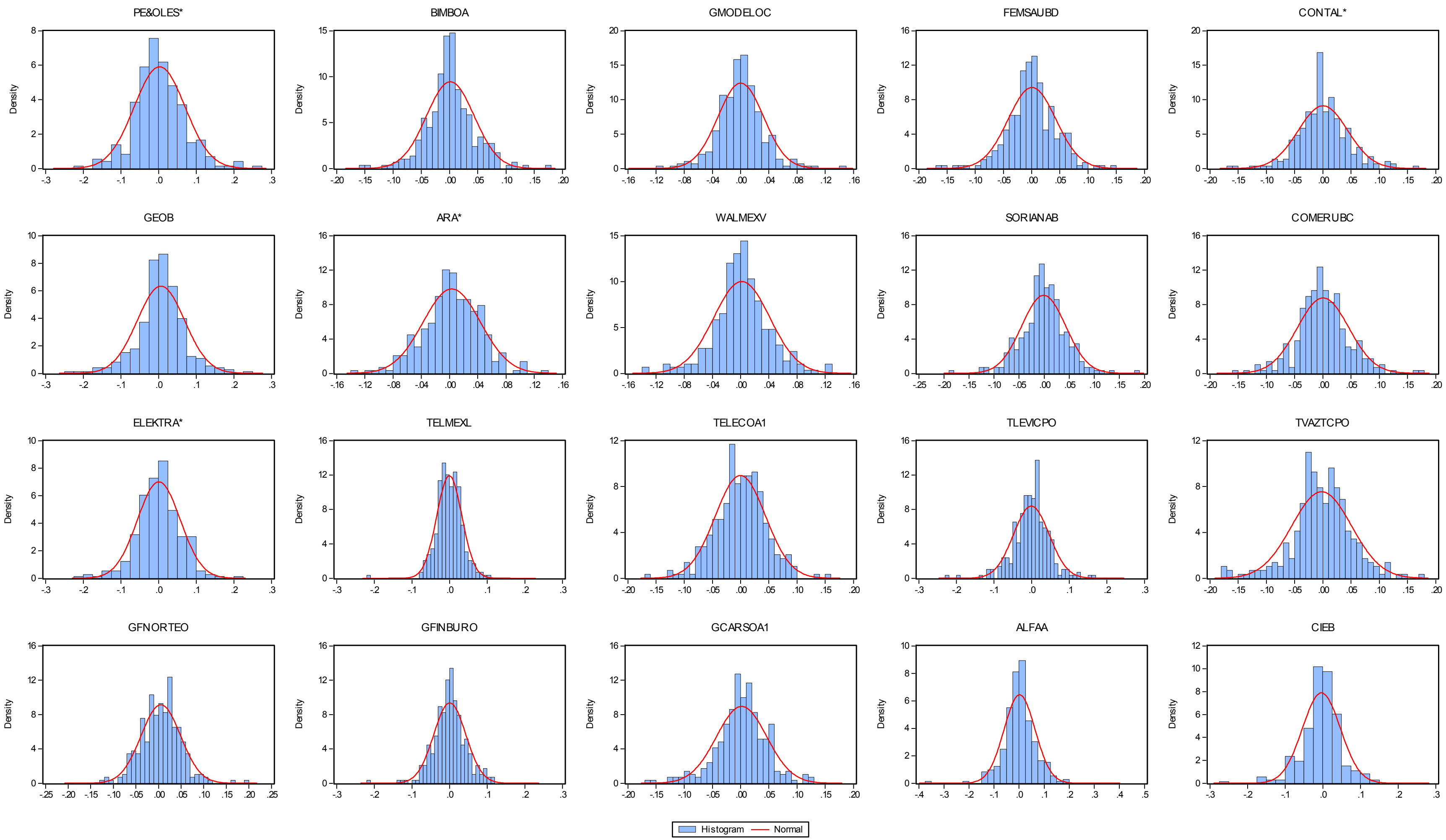


Figure 3. *Line plots (Multiple Graph). Database of weekly excesses.*

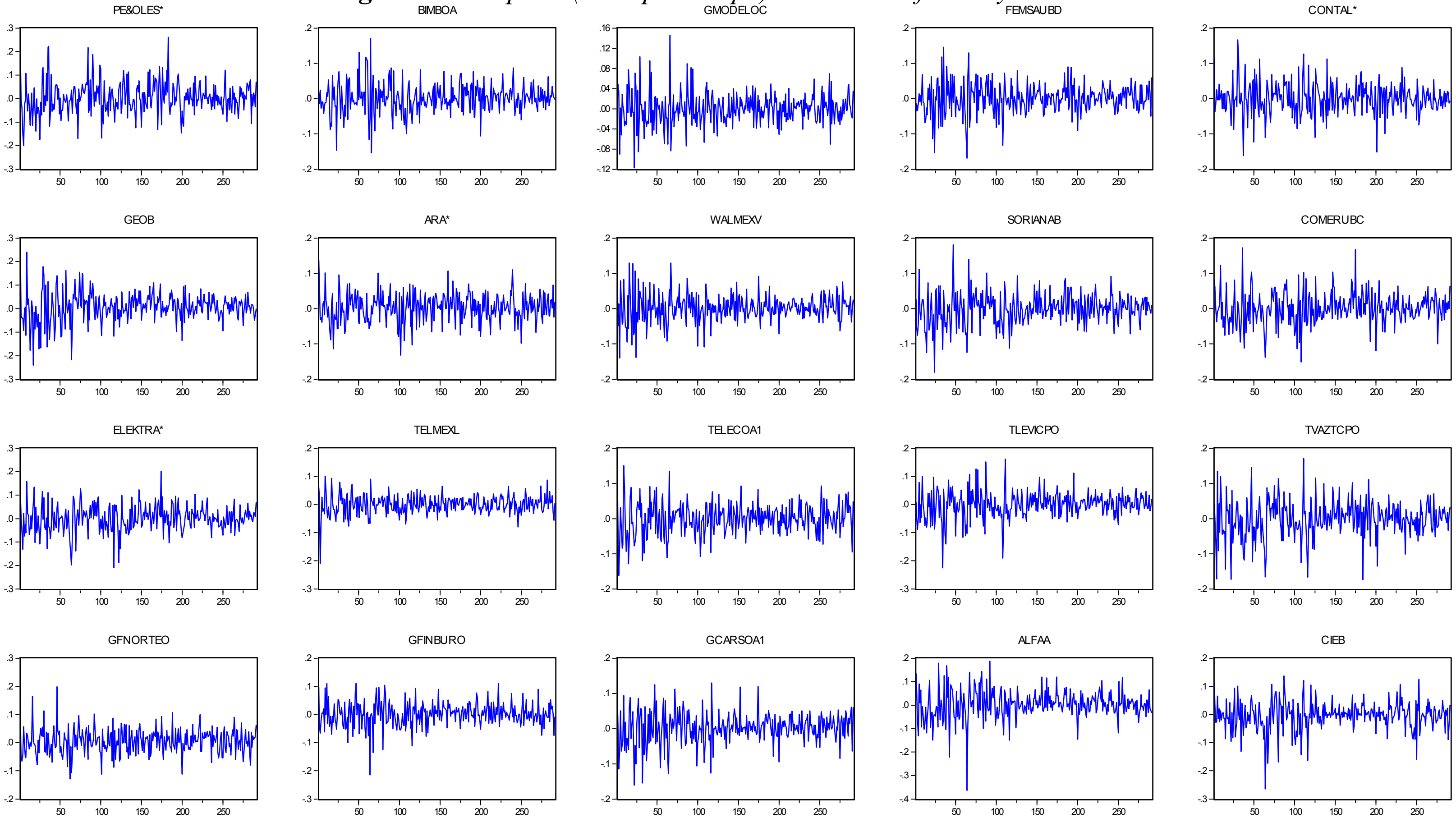


Table 6. *Correlation matrix. Database of daily returns.*

	PE_OLES_	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	CEMEXCP	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
PE_OLES_	1.00000																					

KIMBERA	0.08800	1.00000																				
	3.31490	-----																				
	0.00094	-----																				
BIMBOA	0.11619	0.22692	1.00000																			
	4.38967	8.74302	-----																			
	0.00001	0.00000	-----																			
GMODELOC	0.10568	0.25877	0.15813	1.00000																		
	3.98767	10.05224	6.00909	-----																		
	0.00007	0.00000	0.00000	-----																		
FEMSAUBD	0.07556	0.26340	0.25771	0.30200	1.00000																	
	2.84340	10.24561	10.00809	11.88727	-----																	
	0.00453	0.00000	0.00000	0.00000	-----																	
CONTAL_	0.14488	0.18280	0.21139	0.19981	0.16677	1.00000																
	5.49435	6.97699	8.11553	7.65168	6.34651	-----																
	0.00000	0.00000	0.00000	0.00000	0.00000	-----																
CEMEXCP	0.10004	0.27512	0.26690	0.26662	0.46625	0.22258	1.00000															
	3.77267	10.73778	10.39190	10.38022	19.77653	8.56687	-----															
	0.00017	0.00000	0.00000	0.00000	0.00000	0.00000	-----															
GEOB	0.12631	0.18008	0.19929	0.15316	0.27131	0.15258	0.27935	1.00000														
	4.77778	6.86934	7.63126	5.81577	10.57703	5.79313	10.91679	-----														
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----														
ARA_	0.09329	0.19280	0.21364	0.15923	0.27106	0.15208	0.29798	0.29579	1.00000													
	3.51582	7.37298	8.20601	6.05213	10.56673	5.77388	11.71338	11.61898	-----													
	0.00045	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----													
WALMEXV	0.11131	0.29997	0.26303	0.36804	0.41829	0.20364	0.40155	0.28896	0.27398	1.00000												
	4.20273	11.79911	10.22993	14.85276	17.27979	7.80482	16.45232	11.32590	10.68979	-----												
	0.00003	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----												
SORIANAB	0.12055	0.28190	0.27005	0.30735	0.42666	0.19807	0.37946	0.30203	0.25609	0.45892	1.00000											
	4.55661	11.02489	10.52406	12.11959	17.70184	7.58242	15.38969	11.88858	9.94089	19.38156	-----											
	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----											

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 7. *Correlation matrix. Database of daily returns. (Cont.)*

	PE_OLES	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	CEMEXCP	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
COMERUBC	0.10643	0.21505	0.21352	0.23462	0.30643	0.18424	0.32365	0.24512	0.22847	0.30638	0.35744	1.00000										
	4.01651	8.26276	8.20103	9.05664	12.07939	7.03373	12.83547	9.48700	8.80600	12.07706	14.36106	-----										
	0.00006	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----										
ELEKTRA_	0.11521	0.21654	0.26344	0.26775	0.36937	0.19128	0.38246	0.30006	0.27216	0.37468	0.36831	0.32306	1.00000									
	4.35196	8.32282	10.24707	10.42779	14.91472	7.31254	15.53207	11.80317	10.61296	15.16405	14.86513	12.80915	-----									
	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----									
TELMEXL	0.09541	0.29710	0.27497	0.31962	0.45830	0.19003	0.46224	0.27167	0.28747	0.45122	0.40081	0.30219	0.35920	1.00000								
	3.59658	11.67533	10.73125	12.65696	19.34864	7.26308	19.55988	10.59253	11.26208	18.97253	16.41603	11.89547	14.44233	-----								
	0.00033	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----								
TELECOA1	0.10918	0.28945	0.29815	0.32544	0.42856	0.19149	0.40761	0.29011	0.30208	0.48384	0.44978	0.32916	0.38772	0.70269	1.00000							
	4.12127	11.34705	11.72047	12.91461	17.79810	7.32062	16.74925	11.37525	11.89069	20.74524	18.89677	13.07990	15.78305	37.05900	-----							
	0.00004	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----							
TLEVICPO	0.08346	0.29138	0.25926	0.31792	0.49344	0.21484	0.48566	0.32879	0.35003	0.51154	0.45026	0.32101	0.45866	0.57431	0.52748	1.00000						
	3.14284	11.42943	10.07288	12.58225	21.28731	8.25406	20.84746	13.06381	14.02130	22.33863	18.92175	12.71851	19.36772	26.32407	23.29726	-----						
	0.00171	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----						
TVAZTCPO	0.09362	0.23334	0.24327	0.28623	0.40879	0.20146	0.40042	0.27509	0.27216	0.43415	0.44161	0.30922	0.51318	0.46555	0.46083	0.59328	1.00000					
	3.52832	9.00409	9.41093	11.20911	16.80745	7.71751	16.39717	10.73659	10.61309	18.08381	18.46898	12.20087	22.43568	19.73839	19.48428	27.65428	-----					
	0.00043	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----					
GFNORTEO	0.06104	0.26444	0.19913	0.26685	0.32858	0.12297	0.36597	0.29668	0.28942	0.36894	0.35861	0.32853	0.35744	0.35913	0.39230	0.38421	0.33491	1.00000				
	2.29479	10.28880	7.62469	10.38983	13.05425	4.64955	14.75589	11.65730	11.34564	14.89474	14.41518	13.05204	14.36126	14.43893	16.00348	15.61518	13.33698	-----				
	0.02189	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----				
GFINBURO	0.04817	0.19056	0.23913	0.18532	0.27382	0.16145	0.30868	0.21541	0.26688	0.31389	0.31417	0.24294	0.29839	0.31931	0.37673	0.33153	0.28831	0.30653	1.00000			
	1.80971	7.28404	9.24094	7.07656	10.68306	6.13855	12.17719	8.27742	10.39093	12.40532	12.41743	9.39736	11.73114	12.64367	15.26051	13.18570	11.29813	12.08393	-----			
	0.07055	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----			
GCARSOA1	0.09785	0.29793	0.25616	0.28991	0.39377	0.19723	0.33744	0.23906	0.25608	0.45260	0.44163	0.31062	0.37943	0.43384	0.49344	0.43584	0.39107	0.33434	0.37255	1.00000		
	3.68918	11.71131	9.94369	11.36634	16.07445	7.54919	13.45086	9.23802	9.94056	19.04557	18.47020	12.26186	15.38812	18.06794	21.28739	18.17064	15.94383	13.31152	15.06390	-----		
	0.00023	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----		
ALFAA	0.08635	0.22497	0.25787	0.26824	0.33961	0.16109	0.35772	0.27827	0.26275	0.37500	0.34911	0.31172	0.38543	0.37914	0.42423	0.41191	0.40359	0.31176	0.28687	0.37604	1.00000	
	3.25230	8.66385	10.01471	10.44813	13.54856	6.12460	14.37403	10.87080	10.21808	15.17886	13.97910	12.31011	15.67368	15.37441	17.57886	16.96192	16.55182	12.31194	11.23665	15.22777	-----	
	0.00117	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----	
CIEB	0.11027	0.34282	0.29633	0.24188	0.36495	0.20954	0.32736	0.26959	0.29054	0.34551	0.39214	0.29370	0.33657	0.33713	0.38692	0.37881	0.36338	0.32331	0.32958	0.38282	0.29236	1.00000
	4.16307	13.69348	11.64216	9.35372	14.70861	8.04115	12.99991	10.50488	11.39365	13.81530	15.99566	11.52918	13.41149	13.43692	15.74475	15.35903	14.63563	12.82015	13.09883	15.54928	11.47147	-----
	0.00003	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 8 *Descriptive statistics. Database of daily excesses.*

	PE_OLES_	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	CEMEXCP	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
Mean	0.00080	-0.00002	0.00040	0.00014	0.00023	0.00016	0.00055	0.00147	0.00080	0.00045	-0.00008	0.00026	0.00029	-0.00000	0.00003	-0.00006	-0.00032	0.00117	0.00028	0.00046	0.00050	-0.00063
Median	-0.00021	-0.00016	-0.00020	-0.00020	-0.00021	-0.00021	-0.00015	-0.00012	-0.00021	0.00039	-0.00019	-0.00024	-0.00003	-0.00017	0.00047	0.00044	-0.00023	-0.00014	-0.00020	-0.00012	-0.00014	-0.00022
Maximum	0.17239	0.07119	0.13392	0.08276	0.08348	0.10427	0.07044	0.13464	0.07363	0.10401	0.07475	0.12593	0.12917	0.09005	0.09407	0.11882	0.10065	0.12945	0.10831	0.08819	0.11830	0.09282
Minimum	-0.21392	-0.12370	-0.09798	-0.07766	-0.13401	-0.12475	-0.07485	-0.20780	-0.10847	-0.08897	-0.08545	-0.08636	-0.13929	-0.10024	-0.08464	-0.15498	-0.19479	-0.09729	-0.09904	-0.10502	-0.12970	-0.17657
Std. Dev.	0.02950	0.01513	0.01866	0.01579	0.01747	0.02111	0.01614	0.02455	0.01895	0.01872	0.01859	0.02045	0.02447	0.01561	0.01954	0.02197	0.02443	0.02050	0.01935	0.01922	0.02457	0.02131
Skewness	-0.36953	-0.56206	0.37445	0.16696	-0.25673	-0.19616	0.13159	-0.11444	-0.04955	0.11425	-0.08832	0.42730	-0.12661	-0.11298	-0.12422	-0.11223	-0.50827	0.27160	0.22082	-0.23650	-0.12146	-0.66967
Kurtosis	10.13262	9.03499	7.62115	5.64060	7.20681	6.79993	4.21518	10.19755	5.94021	5.94647	4.62252	6.44672	6.48541	6.05595	4.78902	6.66666	8.02482	6.77663	5.05710	6.17743	6.39550	9.97069
Jarque-Bera	3020.95408	2213.97563	1287.55675	416.20179	1055.20377	857.36127	90.82310	3046.60283	508.46176	513.11548	156.49754	740.85038	717.46530	551.65619	191.66132	792.82003	1544.07832	855.28213	260.06846	606.28756	680.81895	2960.07901
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 9. *Correlation matrix. Database of daily excesses.*

	PE_OLES_	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	CEMEXCP	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
PE_OLES_	1.000000																					

KIMBERA	0.089879	1.000000																				
	3.386251	-----																				
	0.0007	-----																				
BIMBOA	0.114996	0.227198	1.000000																			
	4.343832	8.754162	-----																			
	0.0000	0.0000	-----																			
GMODELOC	0.105648	0.258953	0.158338	1.000000																		
	3.986583	10.05993	6.017273	-----																		
	0.0001	0.0000	0.0000	-----																		
FEMSAUBD	0.072823	0.264251	0.257976	0.302320	1.000000																	
	2.739824	10.28102	10.01927	11.90095	-----																	
	0.0062	0.0000	0.0000	0.0000	-----																	
CONTAL_	0.144354	0.182615	0.211647	0.199843	0.167337	1.000000																
	5.473973	6.969537	8.125780	7.653154	6.368857	-----																
	0.0000	0.0000	0.0000	0.0000	0.0000	-----																
CEMEXCP	0.102073	0.274756	0.267749	0.267085	0.468444	0.222634	1.000000															
	3.850232	10.72241	10.42754	10.39969	19.89556	8.569026	-----															
	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	-----															
GEOB	0.130537	0.180426	0.199452	0.153612	0.272029	0.152246	0.278698	1.000000														
	4.940465	6.883151	7.637541	5.833252	10.60743	5.780147	10.88913	-----														
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----														
ARA_	0.096402	0.192777	0.213770	0.159417	0.271811	0.151719	0.297309	0.296325	1.000000													
	3.634240	7.371924	8.211188	6.059366	10.59829	5.759694	11.68435	11.64196	-----													
	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----													
WALMEXV	0.114736	0.299690	0.263458	0.368378	0.419870	0.203328	0.400557	0.288991	0.273703	1.000000												
	4.333914	11.78713	10.24787	14.86835	17.35918	7.792300	16.40366	11.32722	10.67798	-----												
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----												
SORIANAB	0.119704	0.283219	0.270183	0.307852	0.426170	0.198510	0.381626	0.303794	0.257612	0.461111	1.000000											
	4.524242	11.08102	10.52976	12.14128	17.67691	7.600006	15.49238	11.96485	10.00412	19.49912	-----											
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----											

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 10. *Correlation matrix. Database of daily excesses. (Cont.)*

	PE_OLES_	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL_	CEMEXCP	GEOB	ARA_	WALMEXV	SORIANAB	COMERUBC	ELEKTRA_	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB
COMERUBC	0.107086	0.215941	0.213334	0.234814	0.305778	0.184219	0.324848	0.246816	0.229732	0.307891	0.357506	1.000000										
	4.041459	8.298626	8.193622	9.064459	12.05100	7.032867	12.88838	9.557021	8.857188	12.14299	14.36414	-----										
	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----										
ELEKTRA_	0.114912	0.216045	0.264377	0.268160	0.371371	0.191644	0.381988	0.298412	0.270986	0.373428	0.369628	0.323294	1.000000									
	4.340638	8.302796	10.28628	10.44480	15.00839	7.326909	15.50960	11.73196	10.56355	15.10497	14.92679	12.81950	-----									
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----									
TELMEXL	0.098336	0.296805	0.275706	0.320095	0.460398	0.189914	0.461438	0.271397	0.286996	0.450402	0.403186	0.303680	0.358347	1.000000								
	3.707868	11.66267	10.76255	12.67808	19.46090	7.258297	19.51671	10.58084	11.24196	18.92930	16.53216	11.95990	14.40289	-----								
	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----								
TELECOA1	0.110840	0.289755	0.298177	0.325601	0.428795	0.191336	0.407781	0.290893	0.302537	0.484273	0.450605	0.329859	0.387250	0.703195	1.000000							
	4.184857	11.35989	11.72182	12.92179	17.81026	7.314687	16.75789	11.40863	11.91033	20.76941	18.94003	13.11123	15.76063	37.11153	-----							
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----							
TLEVICPO	0.084321	0.291223	0.260098	0.318426	0.495236	0.215103	0.485437	0.327976	0.349440	0.510898	0.451810	0.321704	0.458615	0.573985	0.527425	1.000000						
	3.175298	11.42279	10.10760	12.60448	21.39016	8.264846	20.83475	13.02735	13.99438	22.30071	19.00363	12.74913	19.36539	26.30202	23.29412	-----						
	0.0015	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----						
TVAZTCPO	0.092981	0.233320	0.243894	0.286567	0.409884	0.201807	0.400688	0.274362	0.271713	0.433842	0.442281	0.309249	0.513620	0.465630	0.460564	0.593561	1.000000					
	3.504144	9.003422	9.436698	11.22366	16.86175	7.731529	16.41006	10.70578	10.59413	18.06816	18.50408	12.20218	22.46193	19.74284	19.46980	27.67479	-----					
	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----					
GFNORTEO	0.060855	0.264988	0.199044	0.266935	0.328200	0.123000	0.367033	0.297676	0.290164	0.370055	0.358609	0.328560	0.357966	0.360329	0.392666	0.384951	0.335139	1.000000				
	2.287710	10.31187	7.621306	10.39342	13.03734	4.650685	14.80560	11.70018	11.37742	14.94678	14.41496	13.05337	14.38533	14.49441	16.02092	15.65075	13.34744	-----				
	0.0223	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----				
GFINBURO	0.049076	0.189660	0.240386	0.185800	0.276709	0.161711	0.307449	0.213420	0.265284	0.311900	0.316445	0.243771	0.298252	0.317654	0.376395	0.331166	0.288902	0.307594	1.000000			
	1.843729	7.248240	9.292565	7.095384	10.80492	6.148851	12.12374	8.197100	10.32426	12.31801	12.51731	9.431630	11.72506	12.57051	15.24468	13.16958	11.32342	12.13004	-----			
	0.0654	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----			
GCARSOA1	0.096486	0.298240	0.256582	0.290193	0.394233	0.197624	0.338384	0.239018	0.256143	0.453029	0.441794	0.310373	0.380440	0.434666	0.493308	0.436684	0.391703	0.334280	0.374020	1.000000		
	3.637433	11.72452	9.961275	11.37867	16.09660	7.564716	13.49329	9.236475	9.943045	19.06815	18.47875	12.25126	15.43609	18.11043	21.28008	18.21426	15.97450	13.30891	15.13283	-----		
	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----		
ALFAA	0.087169	0.224747	0.258863	0.268838	0.341698	0.161445	0.357305	0.277188	0.261985	0.374068	0.350819	0.312465	0.385429	0.378501	0.424166	0.411854	0.404027	0.312617	0.286409	0.377078	1.000000	
	3.283371	8.654651	10.05620	10.47327	13.64279	6.138476	14.35488	10.82520	10.18633	15.13505	14.05731	12.34274	15.67355	15.34423	17.57554	16.95929	16.57334	12.34940	11.21694	15.27696	-----	
	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----	
CIEB	0.109251	0.343902	0.296261	0.242113	0.364232	0.209810	0.329255	0.271180	0.291865	0.347446	0.391805	0.293582	0.337753	0.339216	0.387578	0.380199	0.363939	0.323136	0.331699	0.382818	0.293897	1.000000
	4.124163	13.74258	11.63921	9.363457	14.67525	8.051978	13.08429	10.57169	11.45029	13.90352	15.97940	11.52399	13.46486	13.53079	15.77635	15.42466	14.66167	12.81250	13.19339	15.54909	11.53753	-----
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Figure 4. *Box plots. Database of daily excesses.*

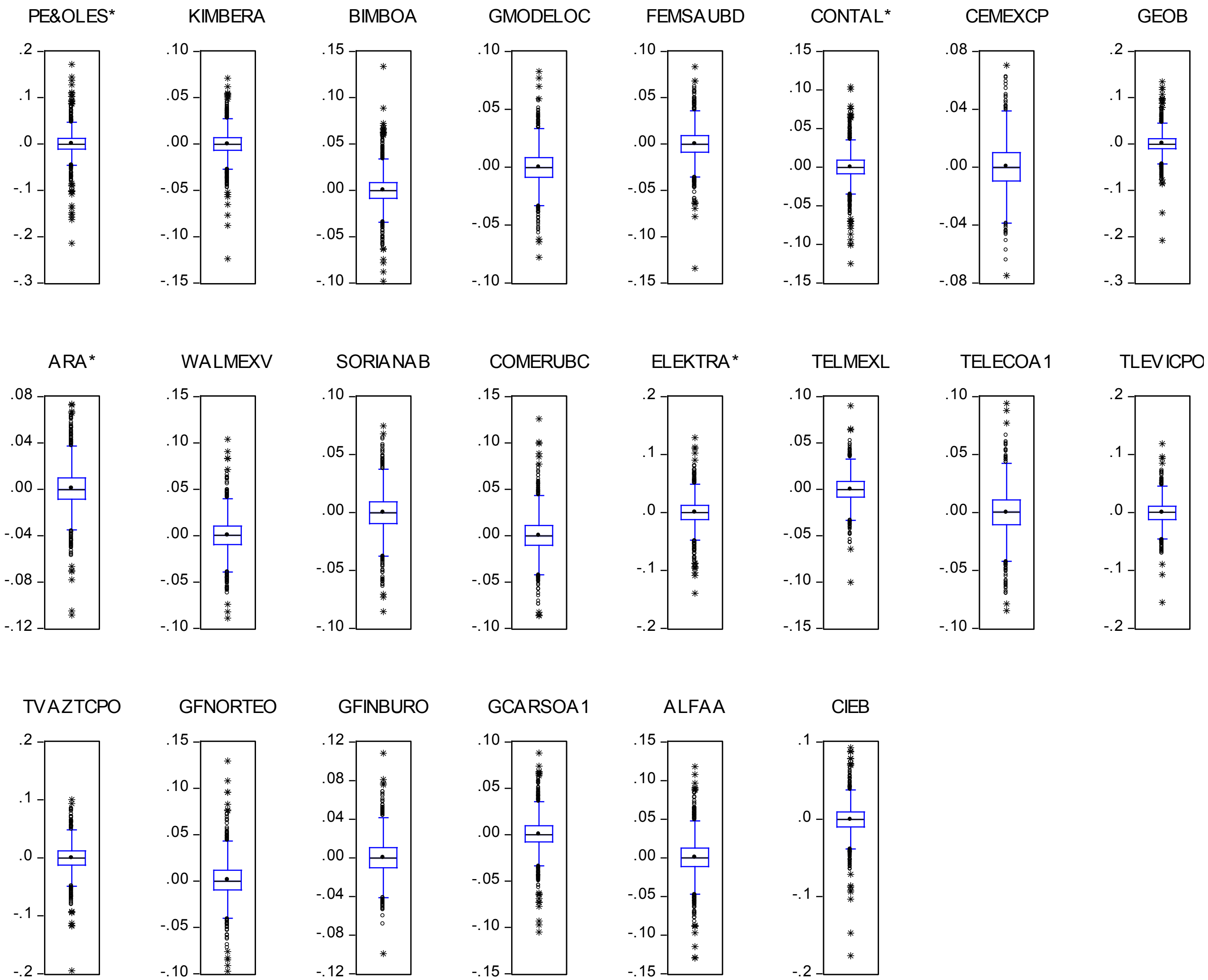


Figure 5. *Histograms. Database of daily excesses.*

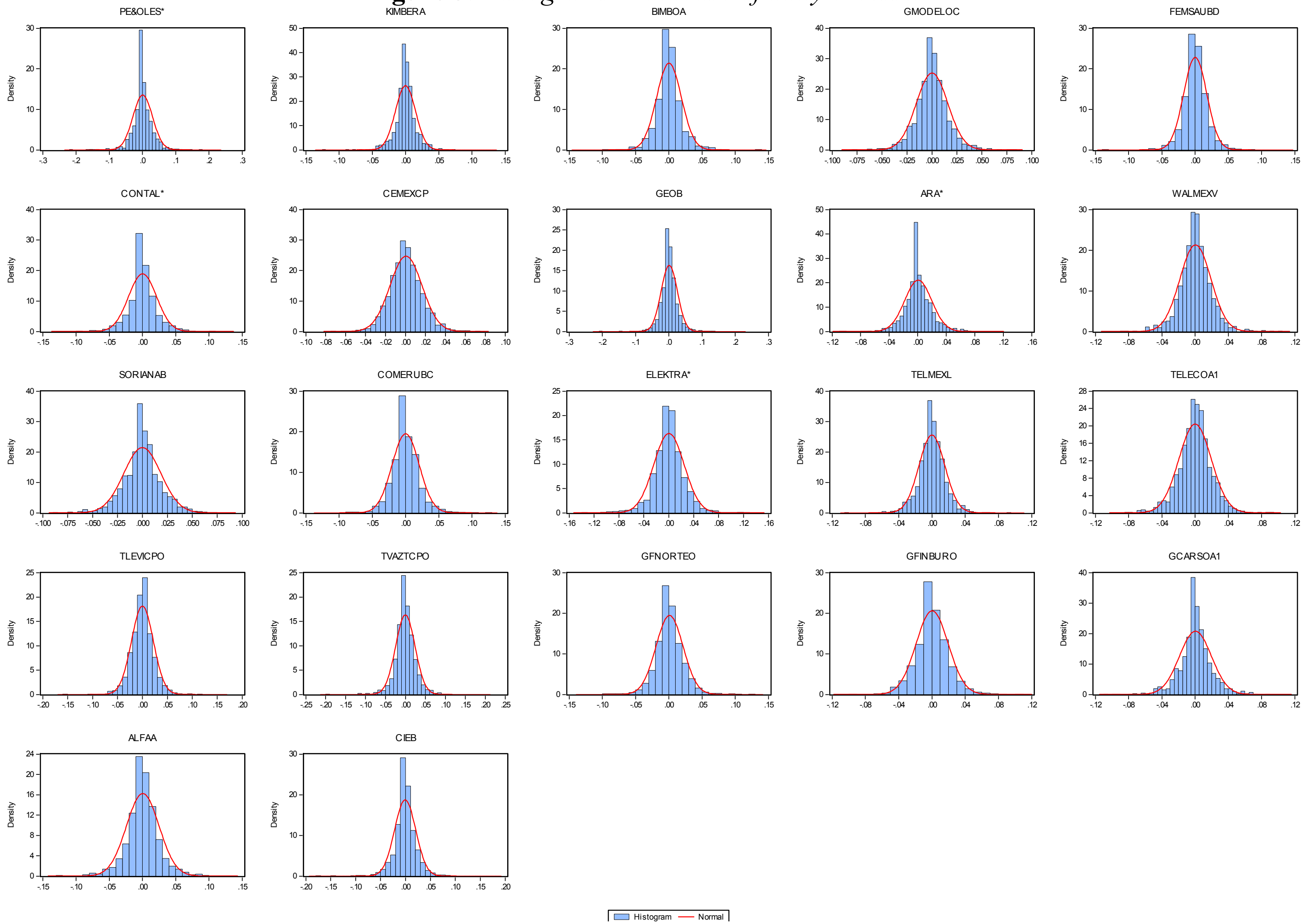
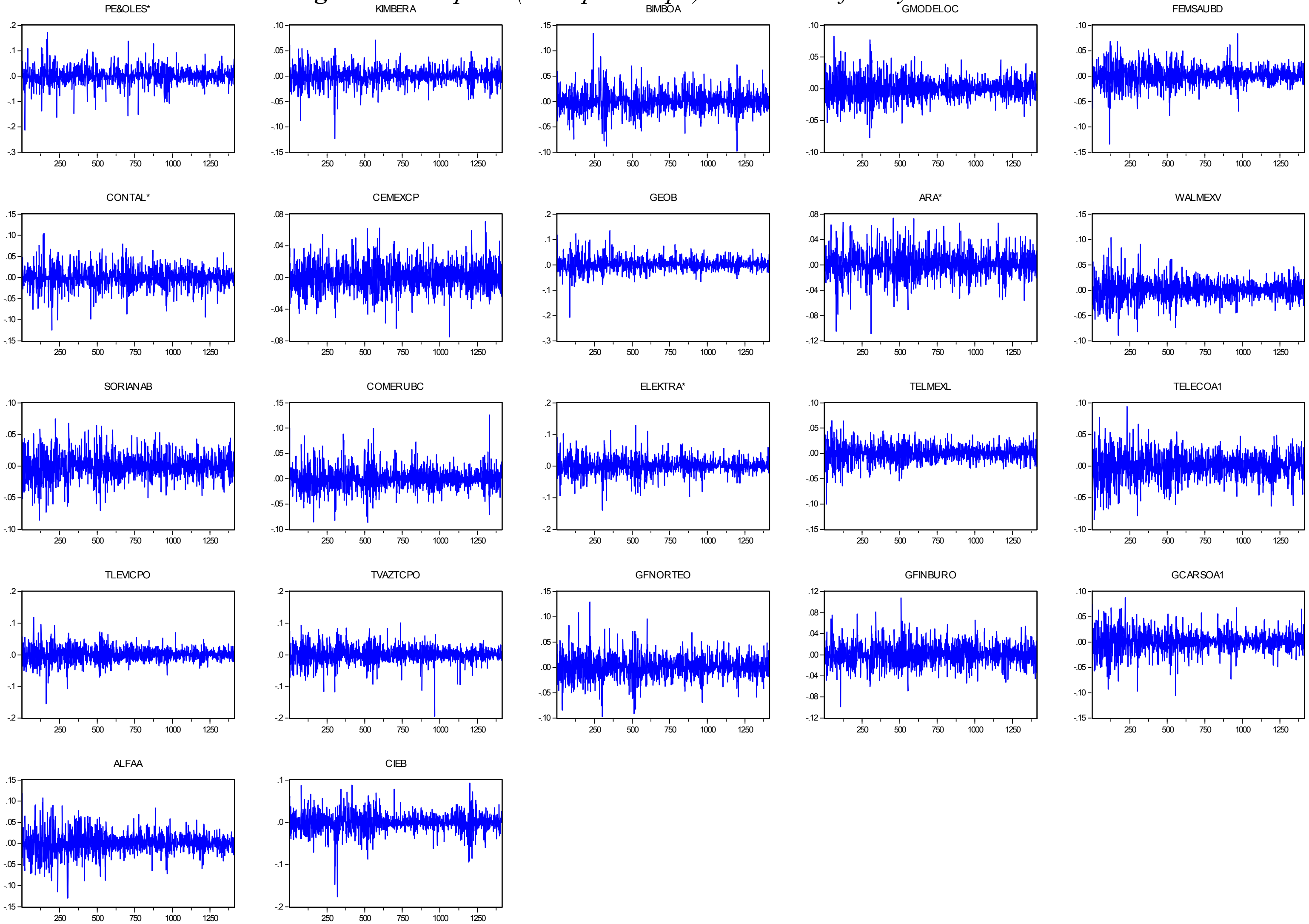
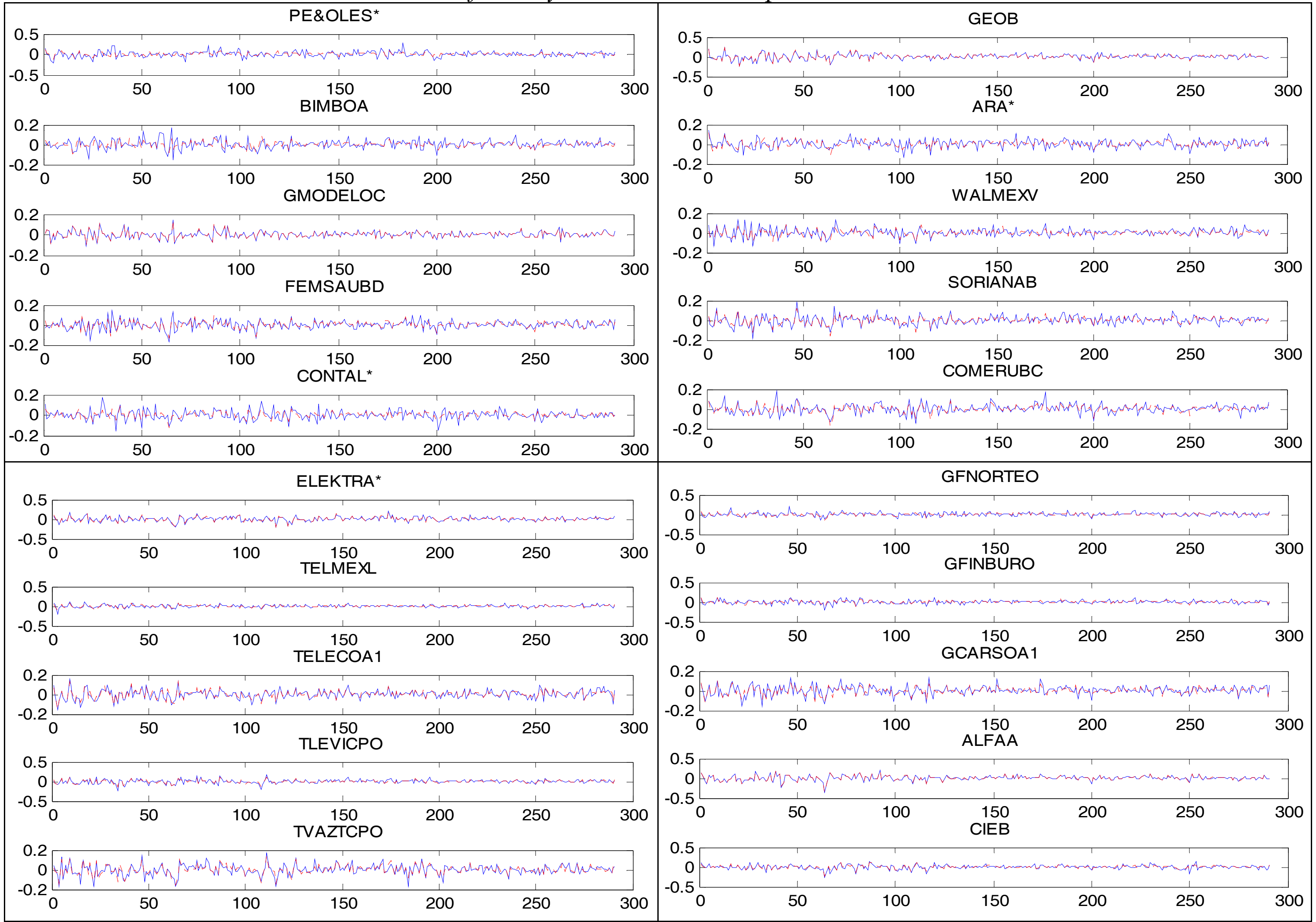


Figure 6. *Line plots (Multiple Graph). Database of daily excesses.*

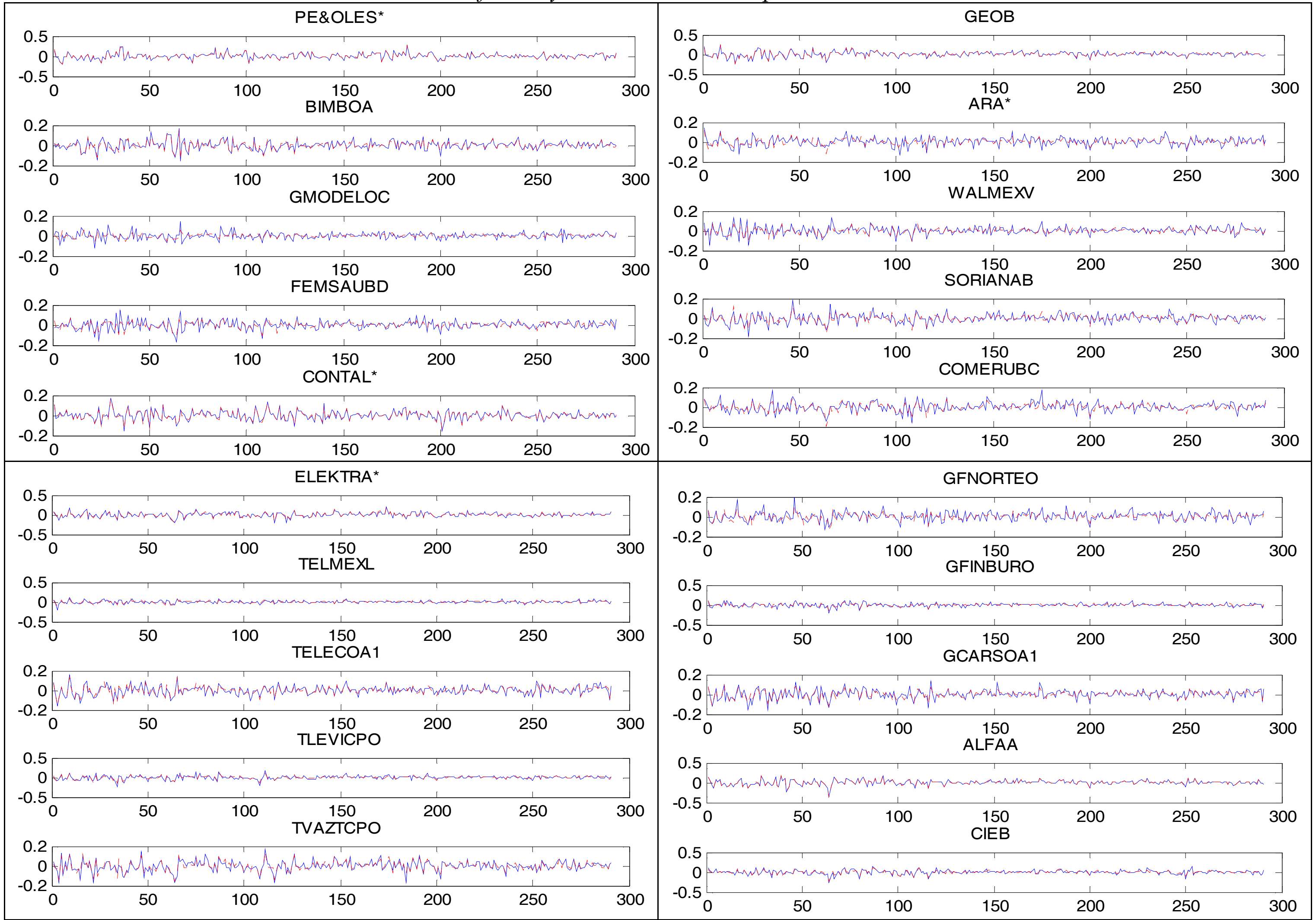


Appendix_2 (Chapter 4) **Figure 1.** *Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of weekly returns. Nine components extracted.*



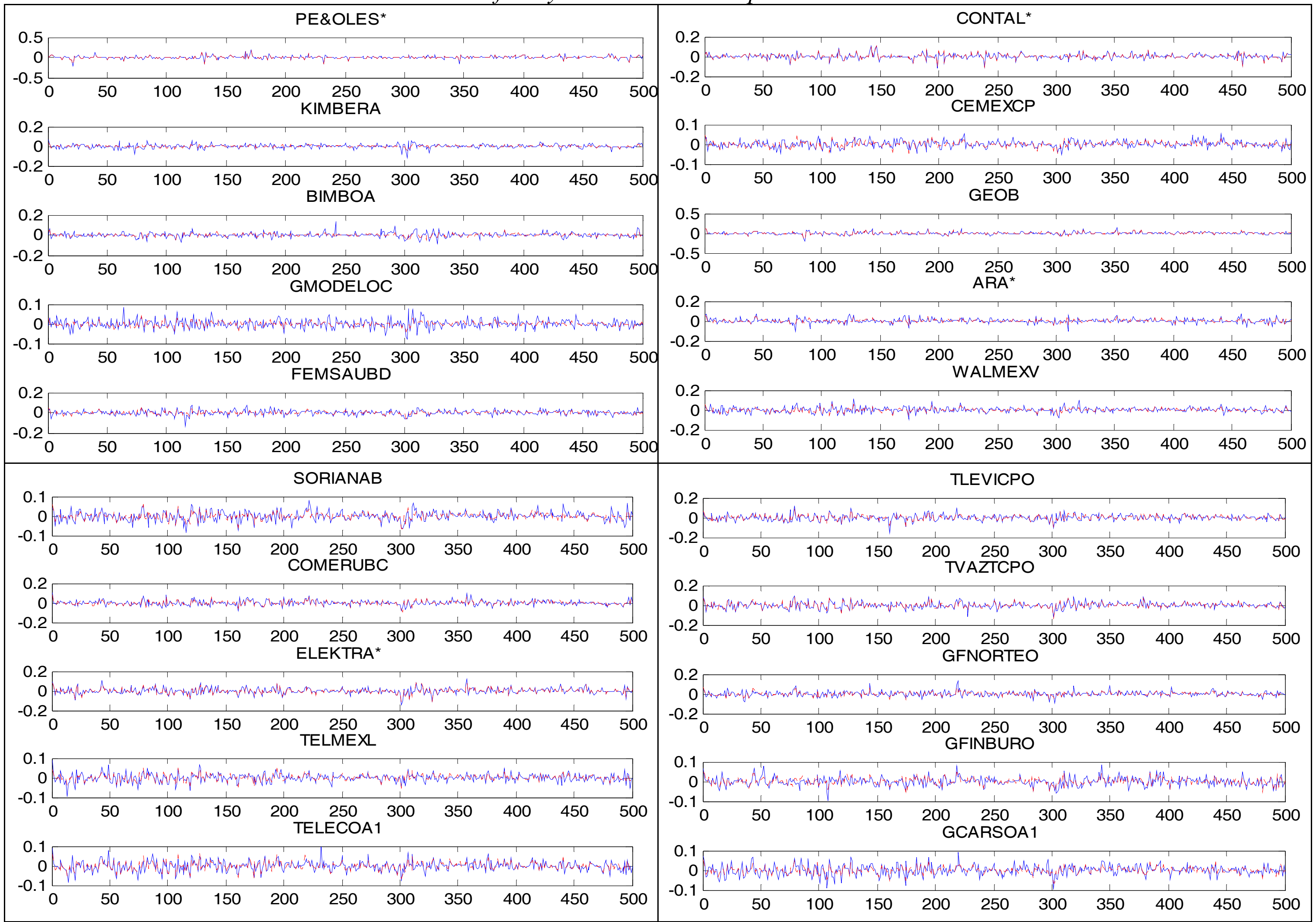
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 2. *Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of weekly excesses. Nine components extracted.*



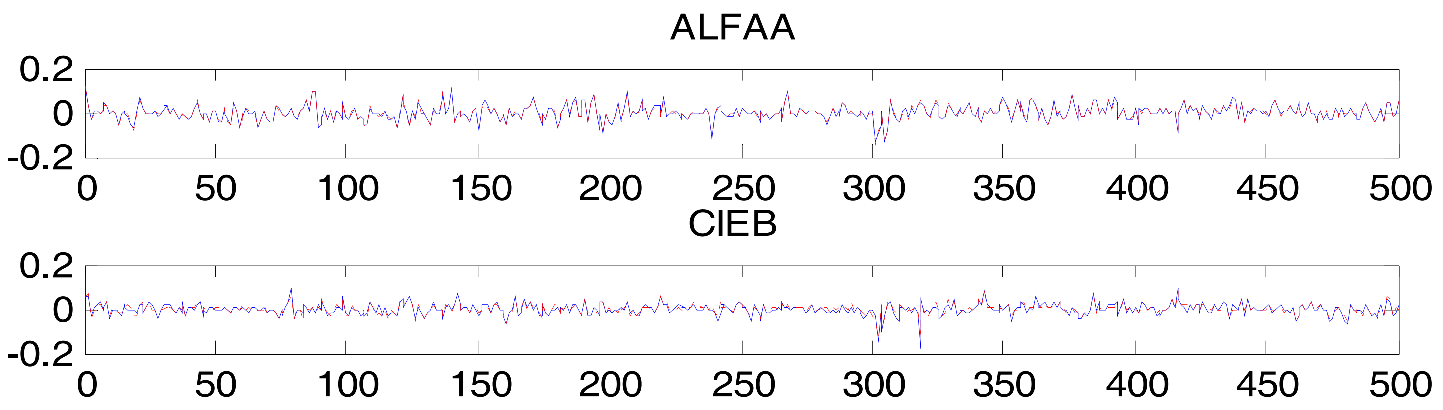
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 3. *Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine components extracted.*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 4. *Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine components extracted. (Cont.)*

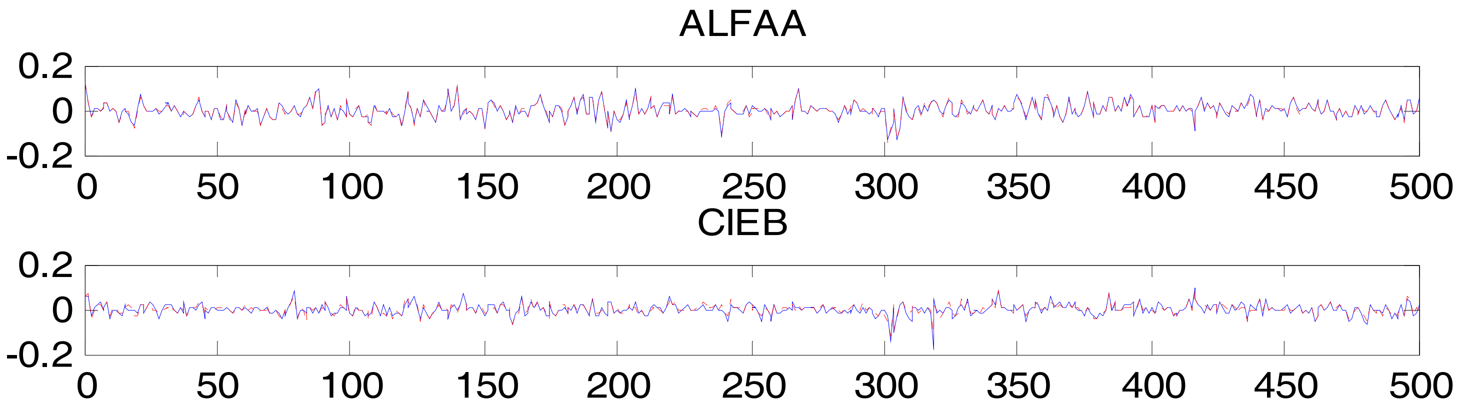


Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 5. *Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine components extracted.*

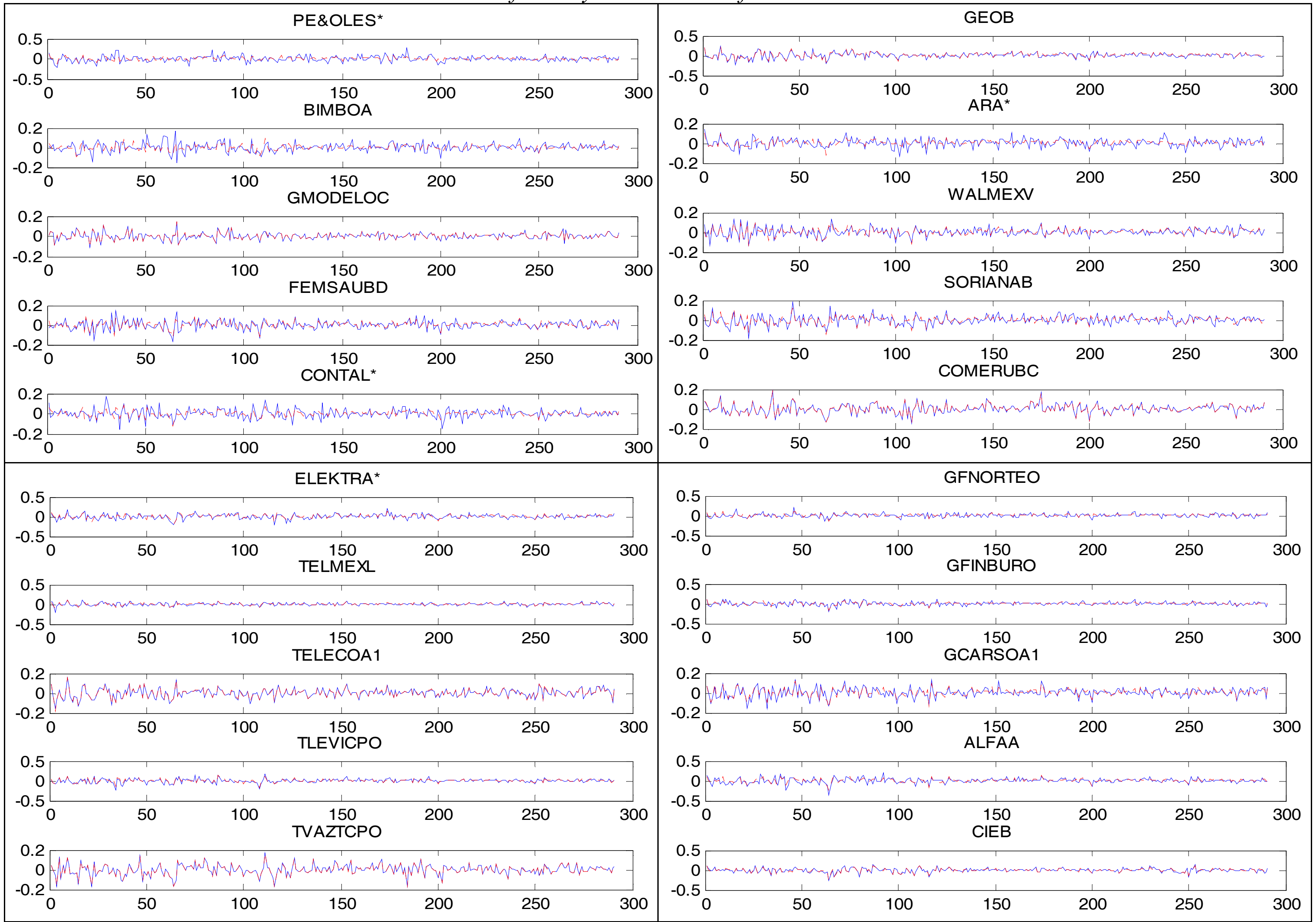
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 6. *Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine components extracted. (Cont.)*



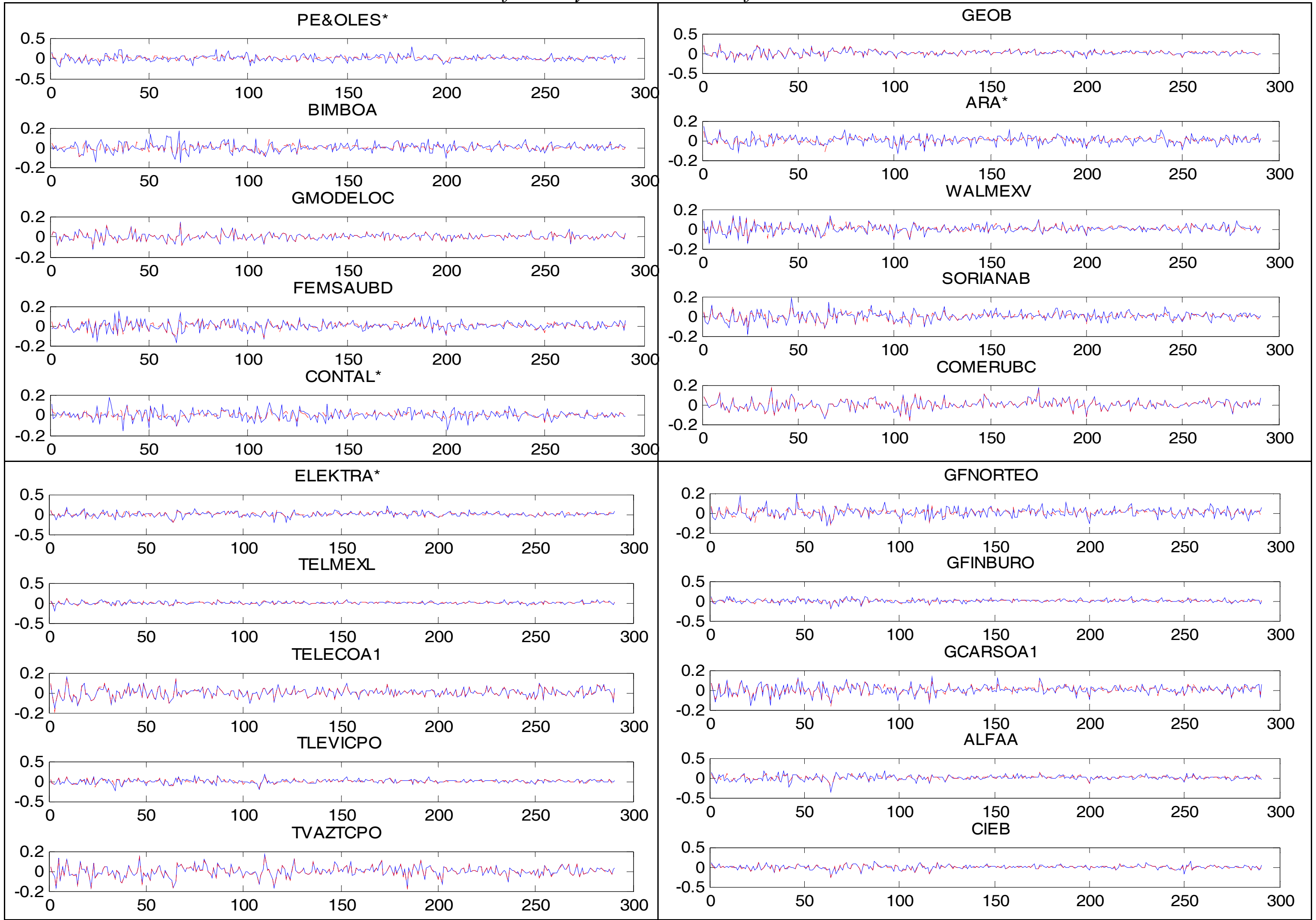
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 7. *Factor Analysis. Observed and reproduced variables. Line Plots.*
Database of weekly returns. Nine factors extracted.



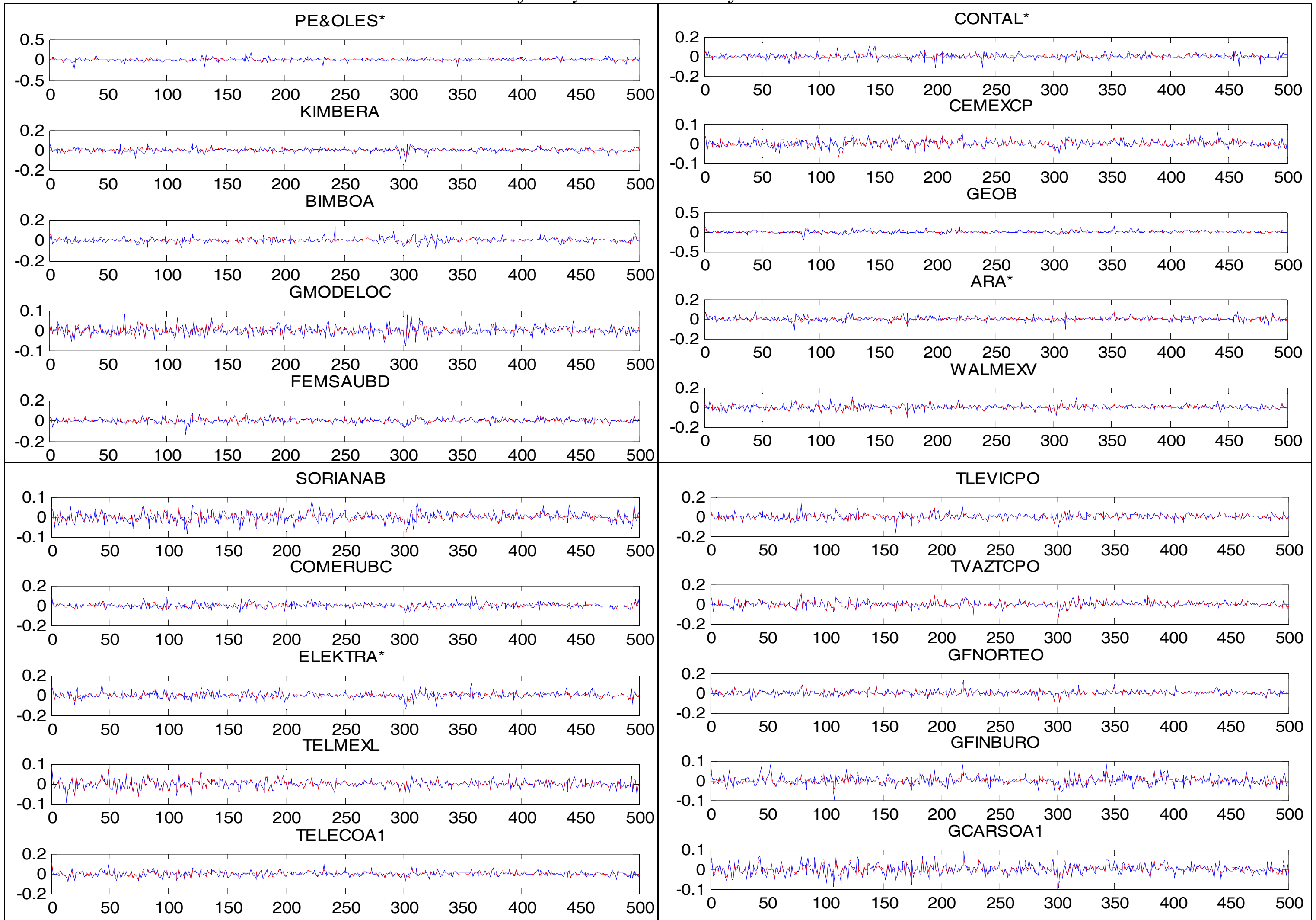
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 8. *Factor Analysis. Observed and reproduced variables. Line Plots. Database of weekly excesses. Nine factors extracted.*



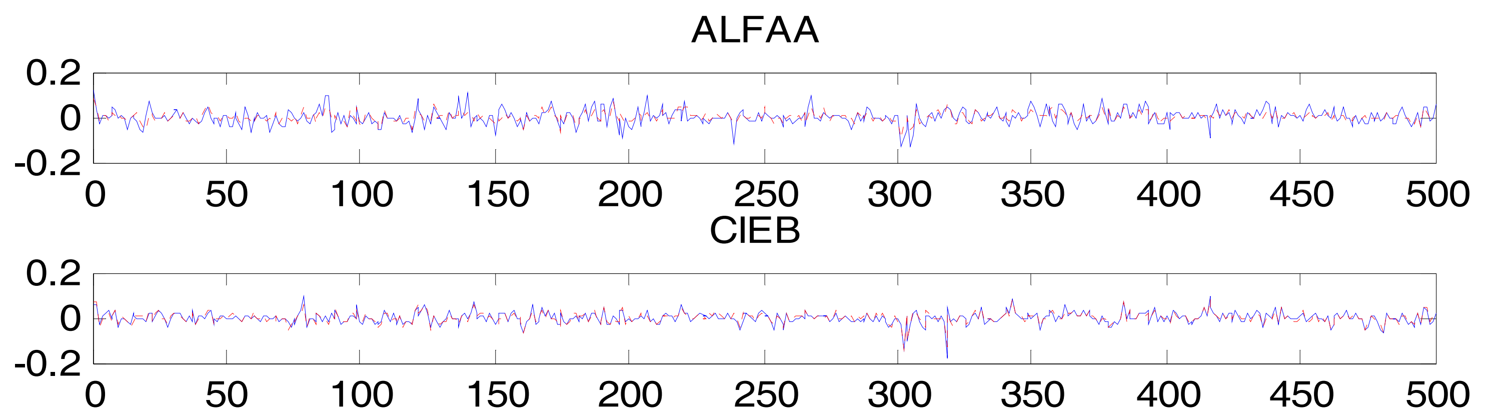
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 9. *Factor Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine factors extracted.*



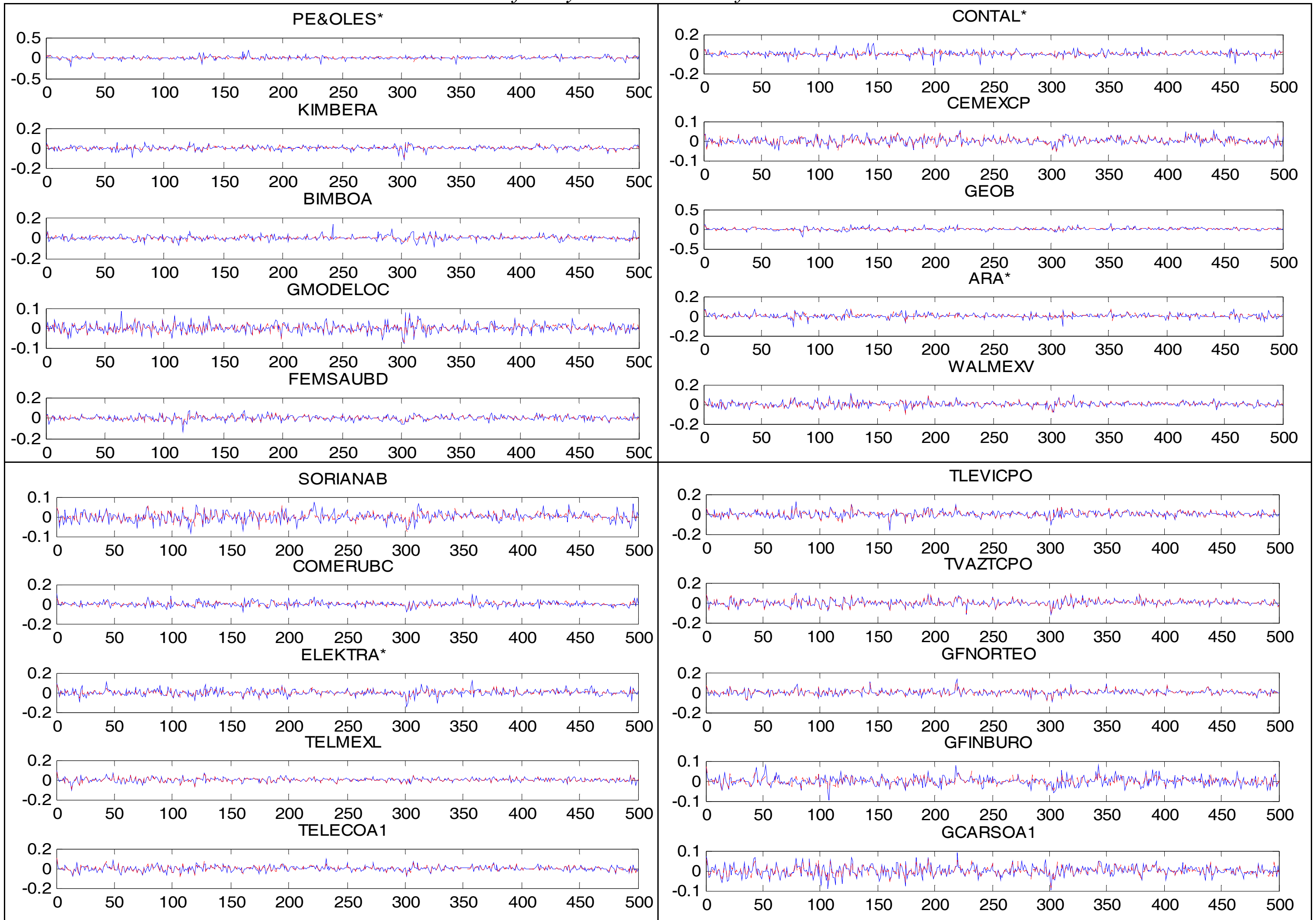
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 10. *Factor Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine factors extracted. (Cont.)*



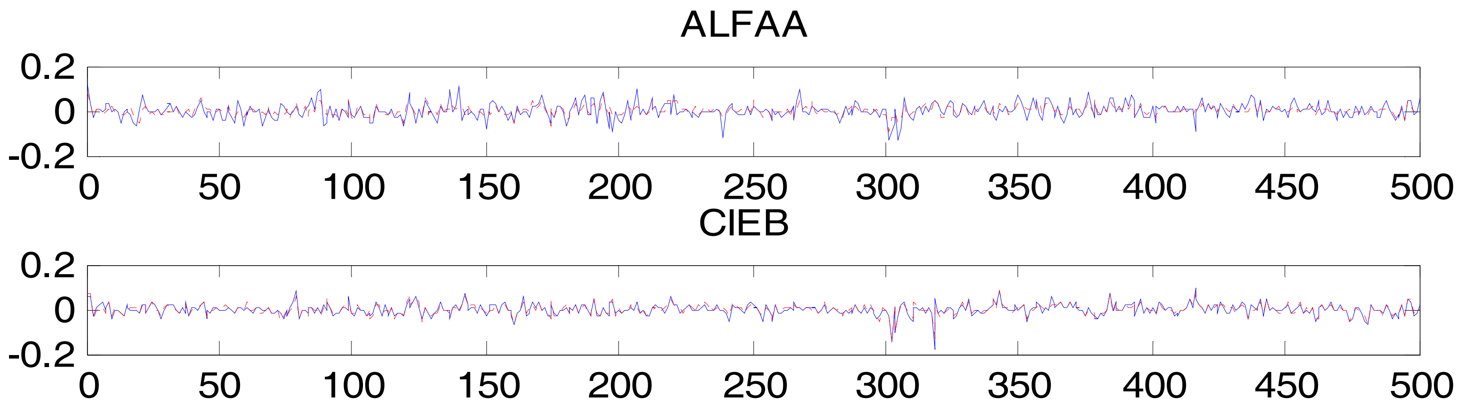
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 11. *Factor Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine factors extracted.*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 12. *Factor Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine factors extracted. (Cont.)*

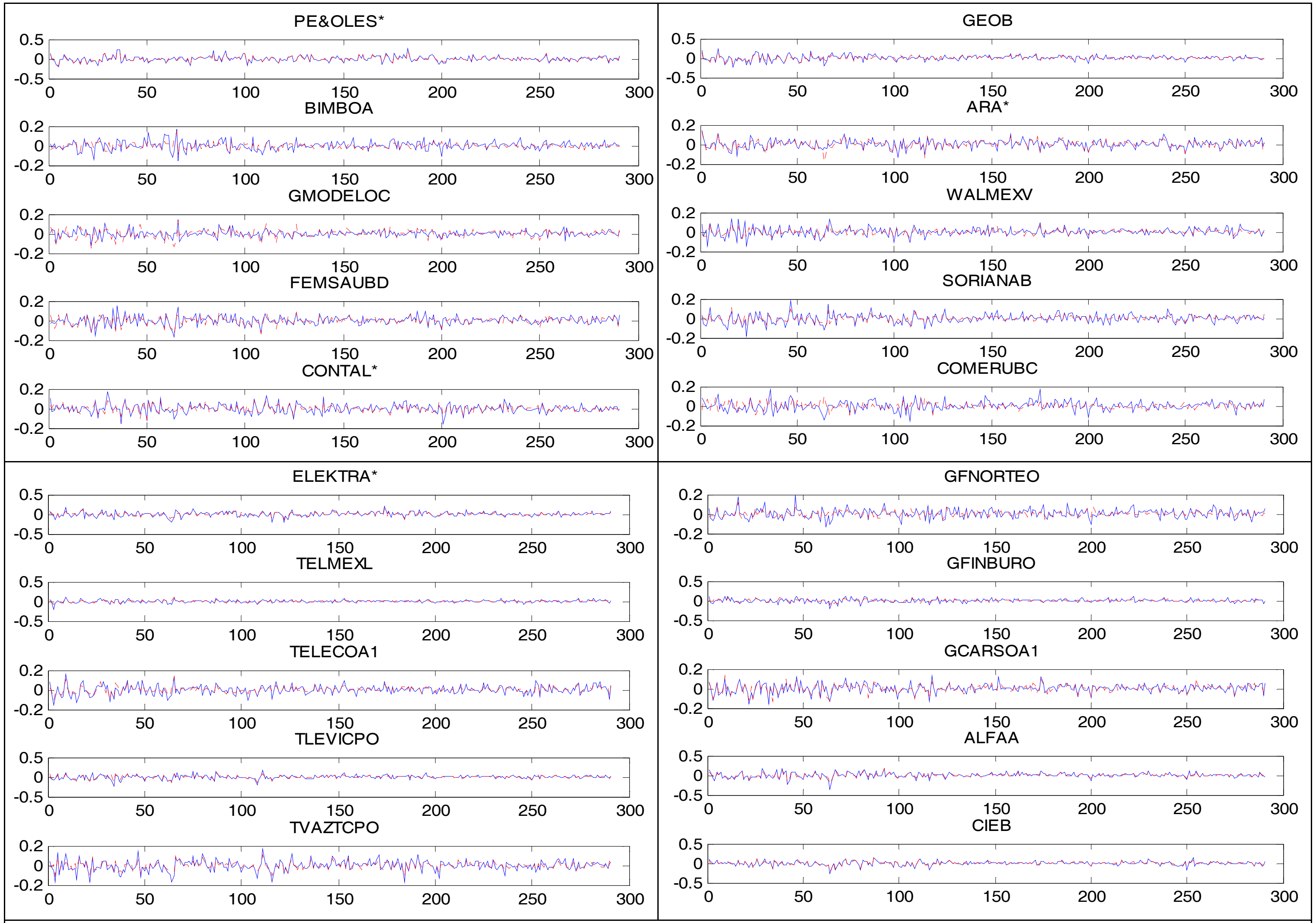


Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Appendix_2 (Chapter 5) **Figure 1.** *Independent Component Analysis. Observed and reproduced variables. Line Plots. Database of weekly returns. Nine components extracted.*

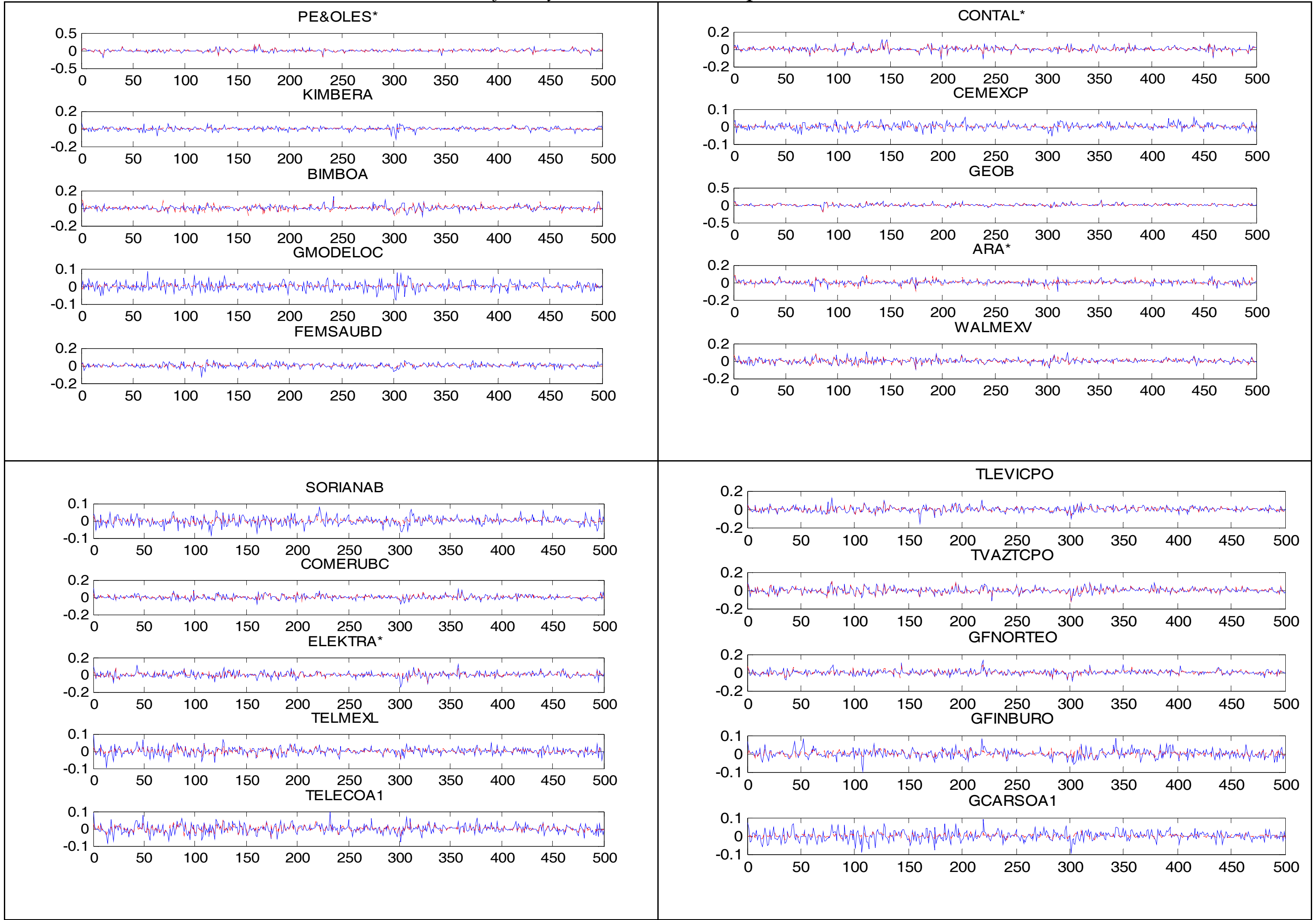
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 2. *Independent Component Analysis. Observed and reproduced variables. Line Plots. Database of weekly excesses. Nine components extracted.*



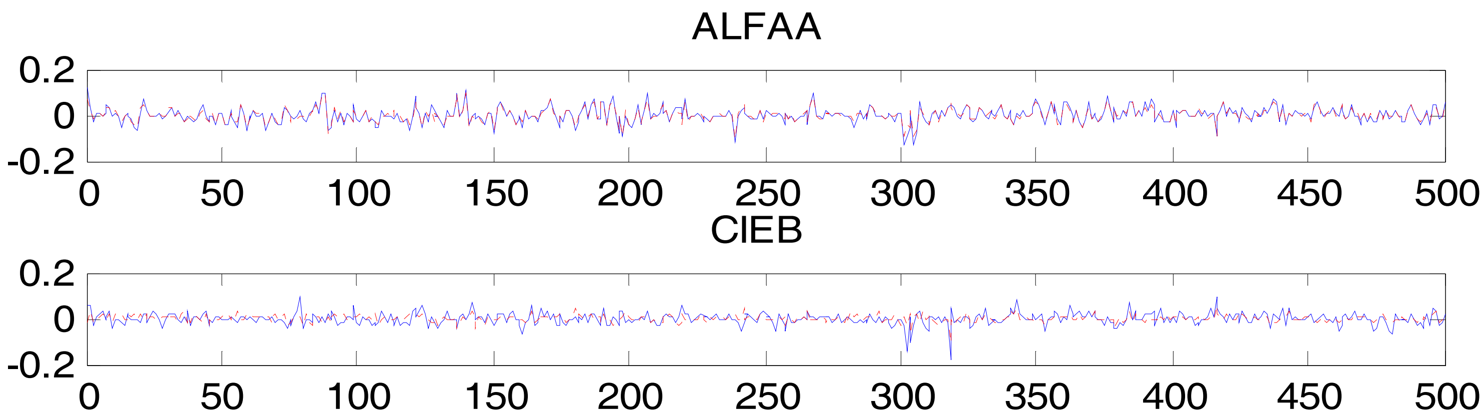
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 3. *Independent Component Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine components extracted.*



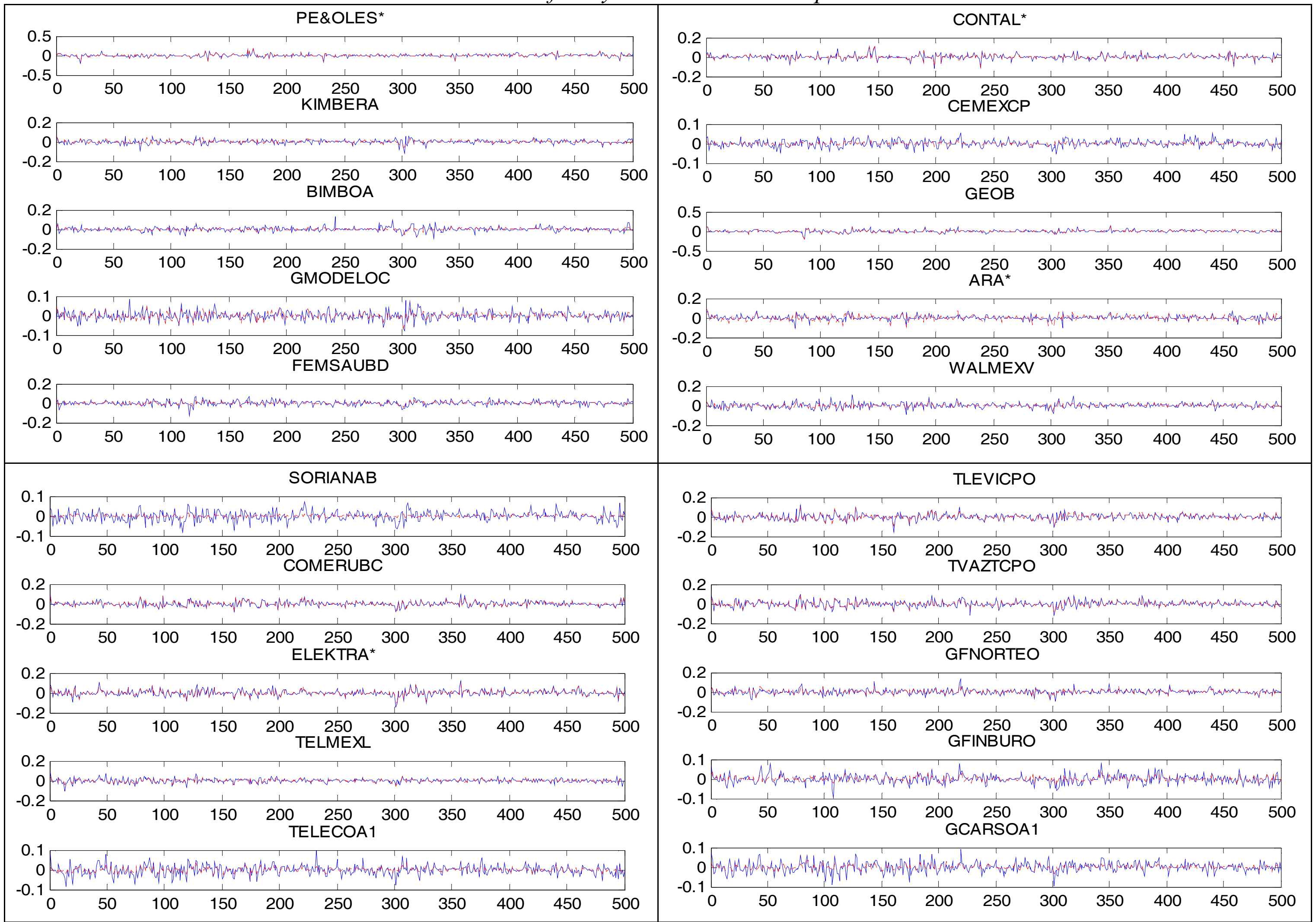
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 4. *Independent Component Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine components extracted. (Cont.)*



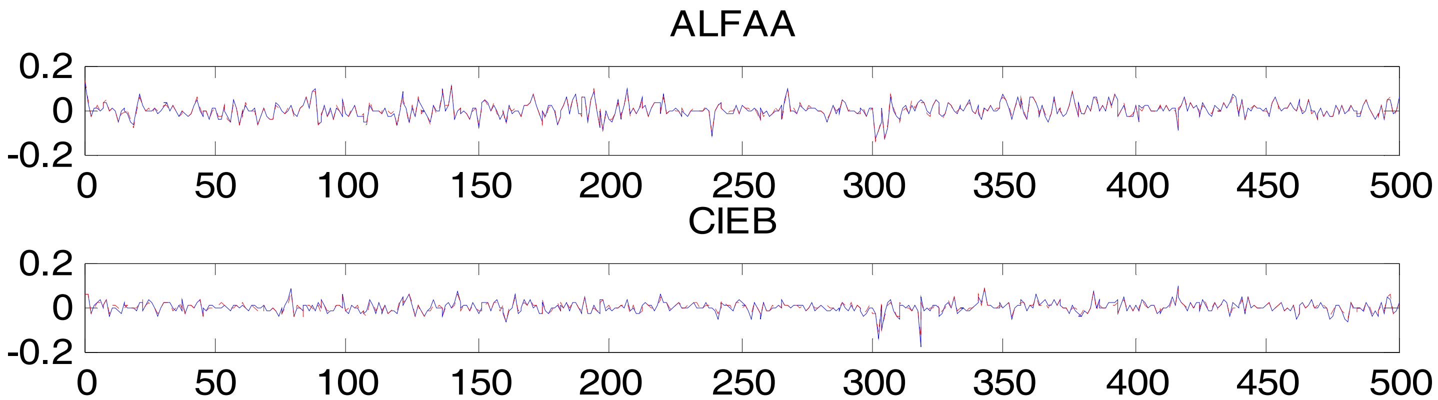
Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 5. *Independent Component Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine components extracted.*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 6. *Independent Component Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine components extracted. (Cont.)*

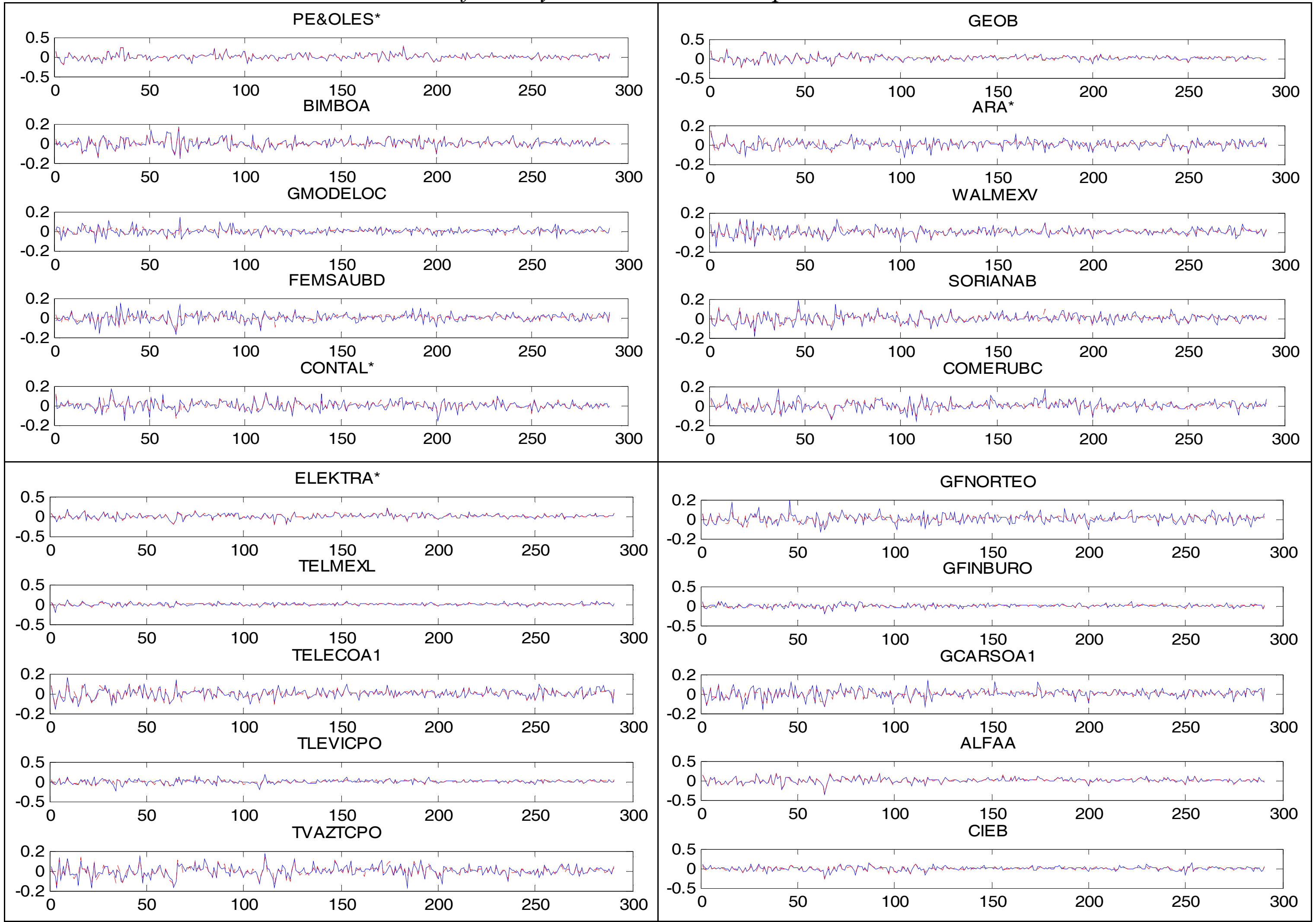


Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Appendix_2 (Chapter 6) **Figure 1.** *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of weekly returns. Nine components extracted.*

Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 2. *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of weekly excesses. Nine components extracted.*

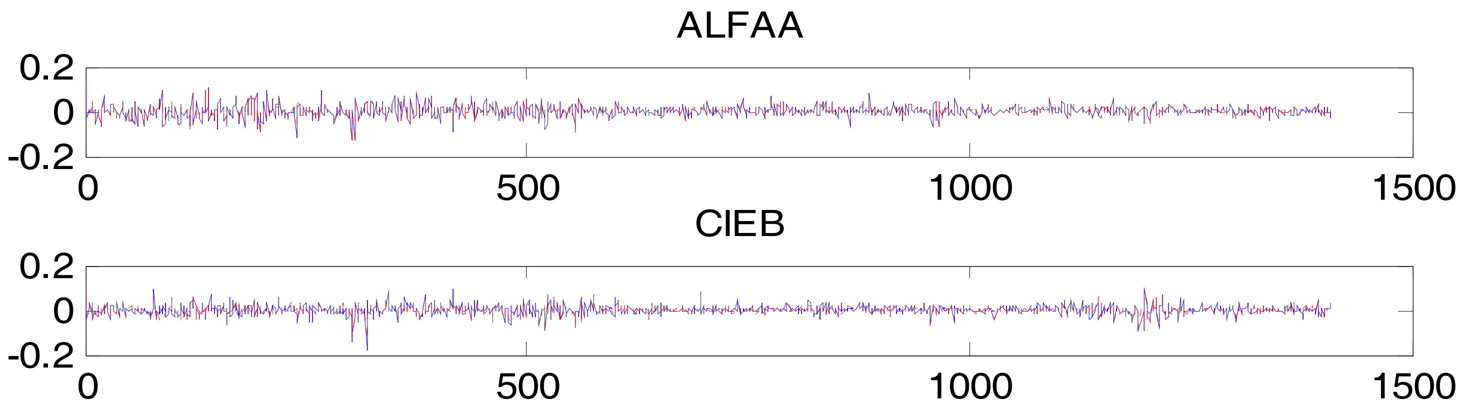


Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 3. *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine components extracted.*

Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 4. *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily returns. Nine components extracted. (Cont.)*

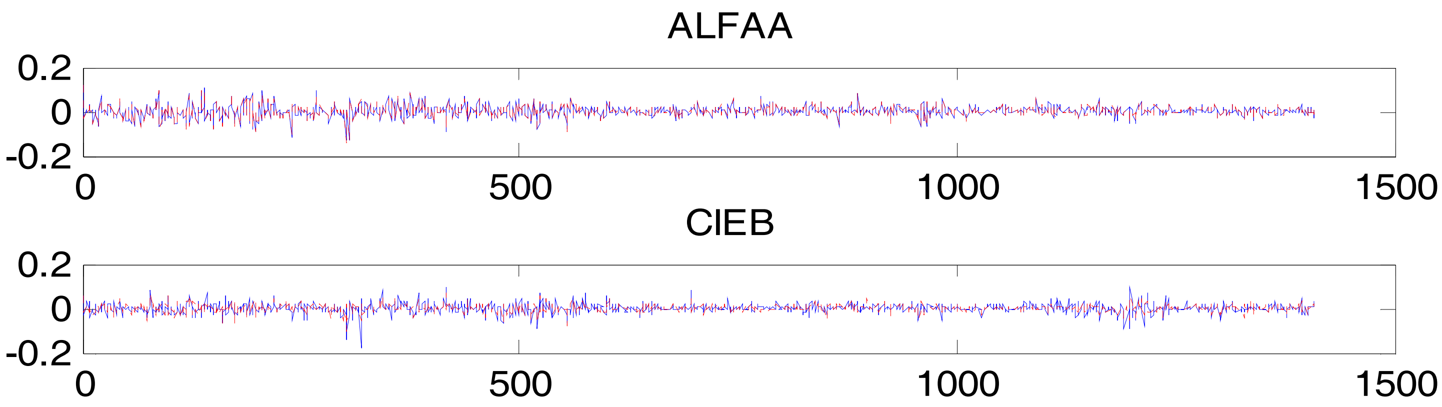


Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 5. *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine components extracted.*

Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Figure 6. *Neural Networks Principal Component Analysis. Observed and reproduced variables. Line Plots. Database of daily excesses. Nine components extracted. (Cont.)*



Note: Blue solid lines = Observed variables. Red dashed lines = Reproduced variables.

Appendix_2 (Chapter 7) **Figure 1.** *Observed vs. reconstructed returns. Database of weekly returns. Nine underlying factors extracted. Line plots.*

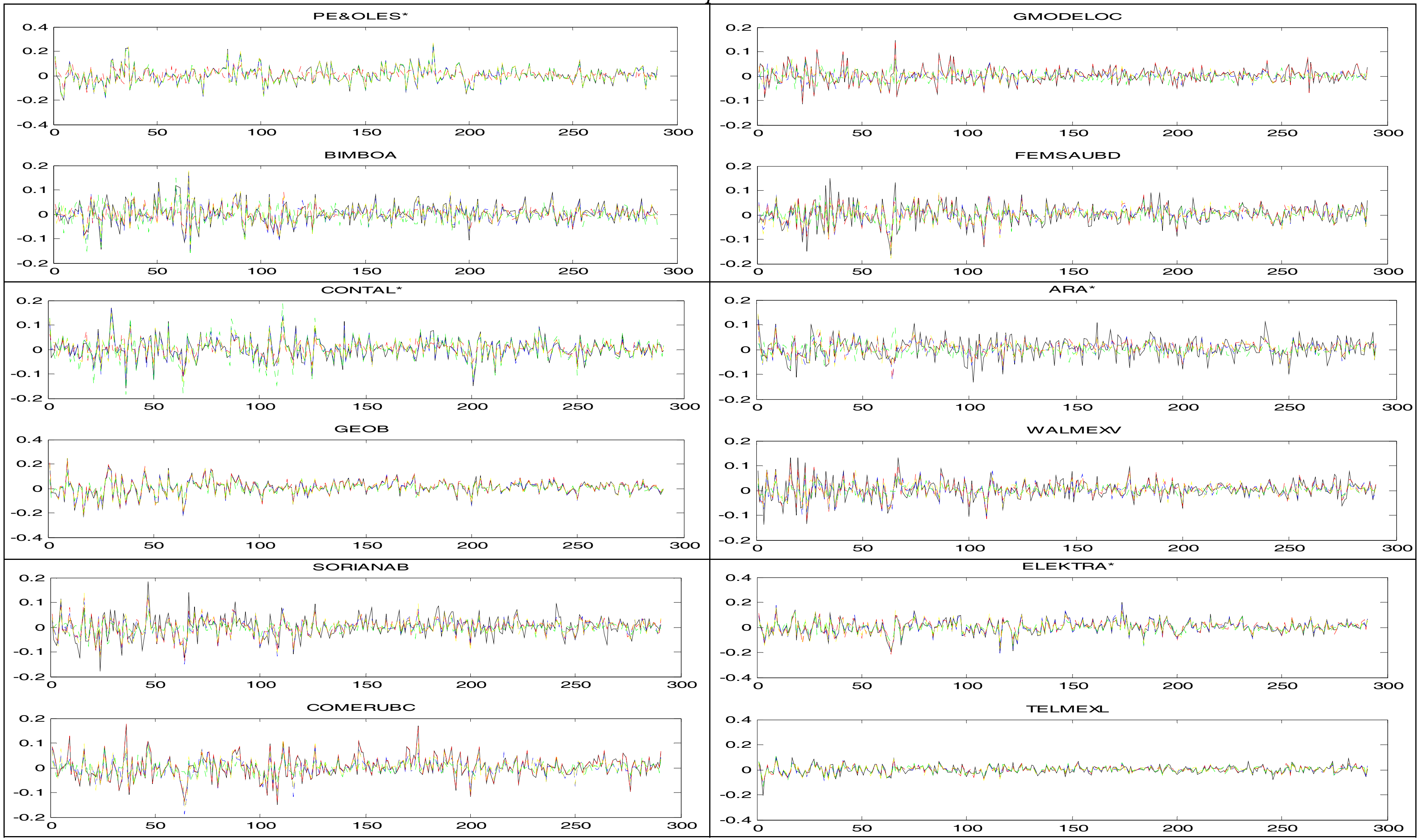
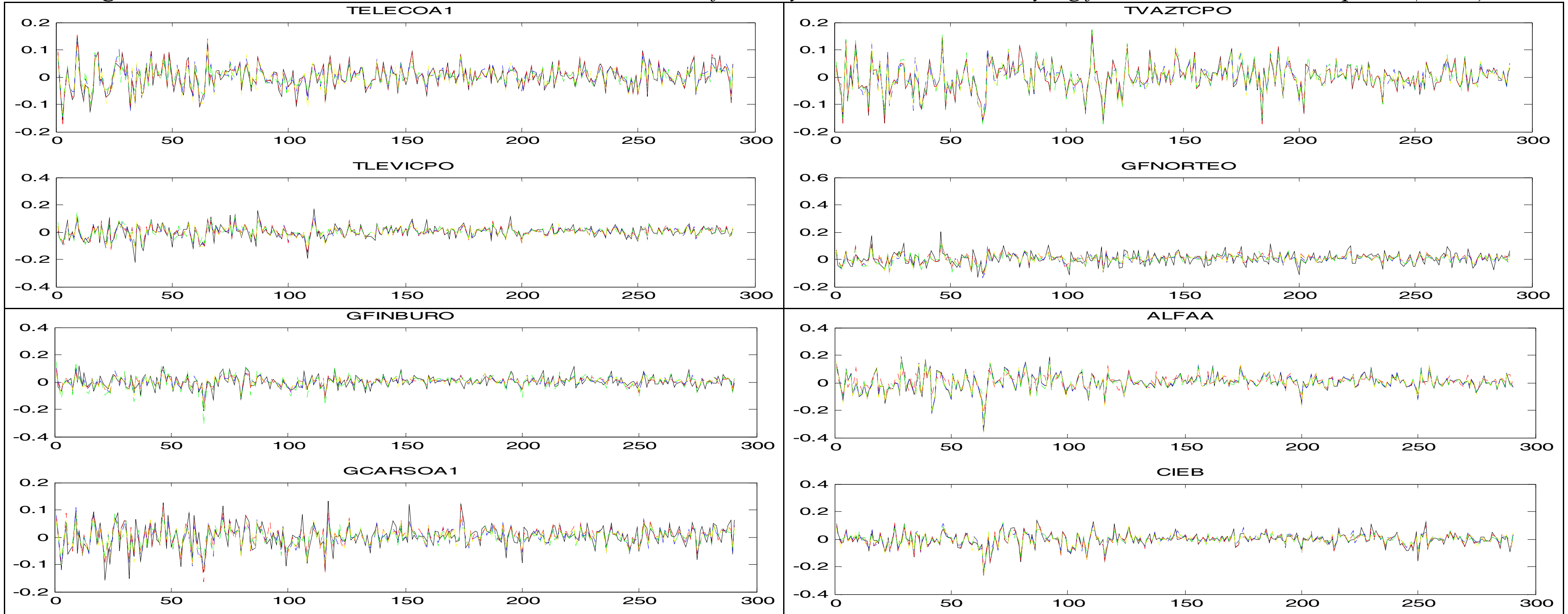


Figure 2. *Observed vs. reconstructed returns. Database of weekly returns. Nine underlying factors extracted. Line plots. (Cont.)*



Notes:

---------- Observed returns.

---------- PCA reconstruction.

---------- FA reconstruction.

---------- ICA reconstruction.

---------- NNPCA reconstruction.

Figure 3. *Observed vs. reconstructed returns. Database of weekly excesses. Nine underlying factors extracted. Line plots.*

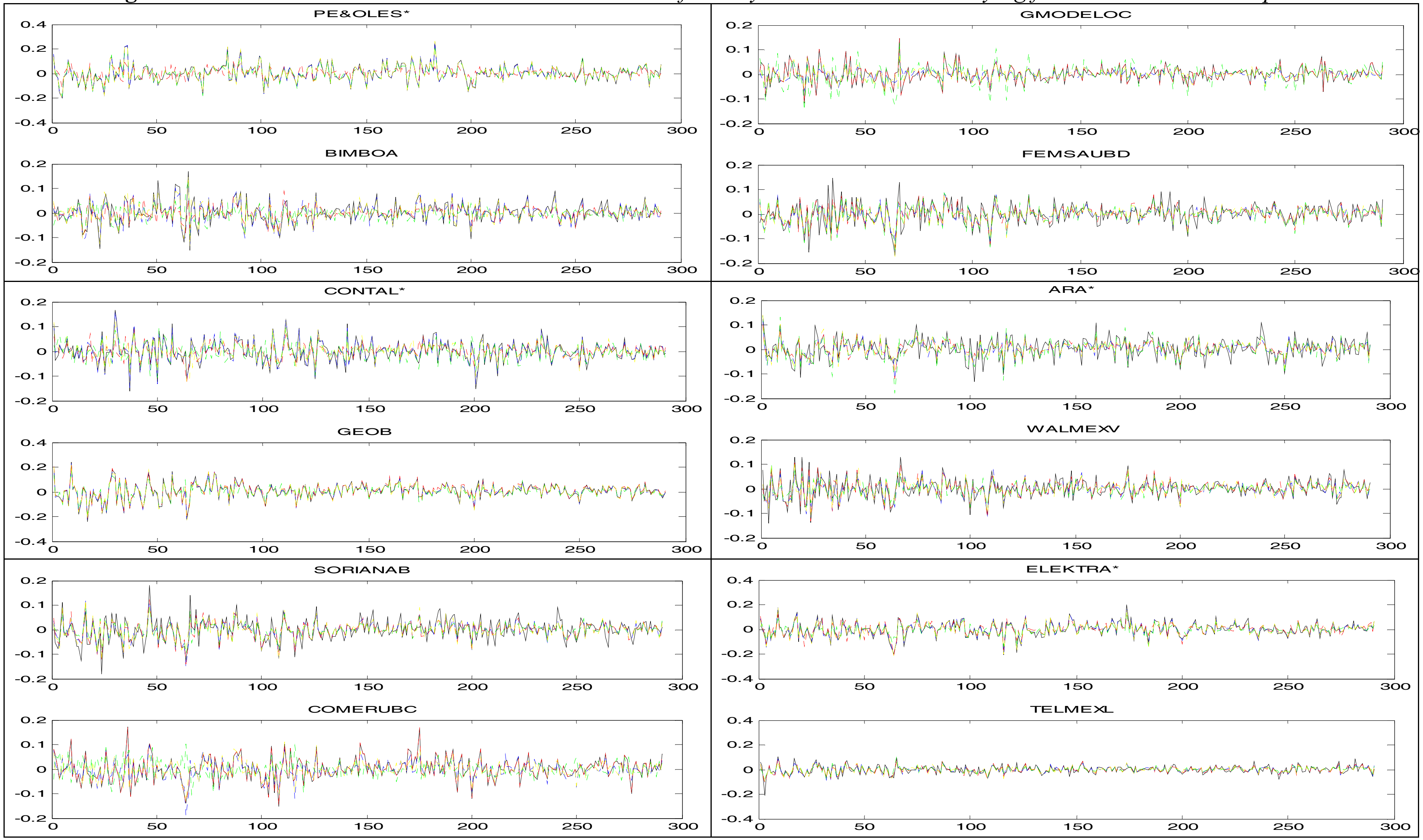
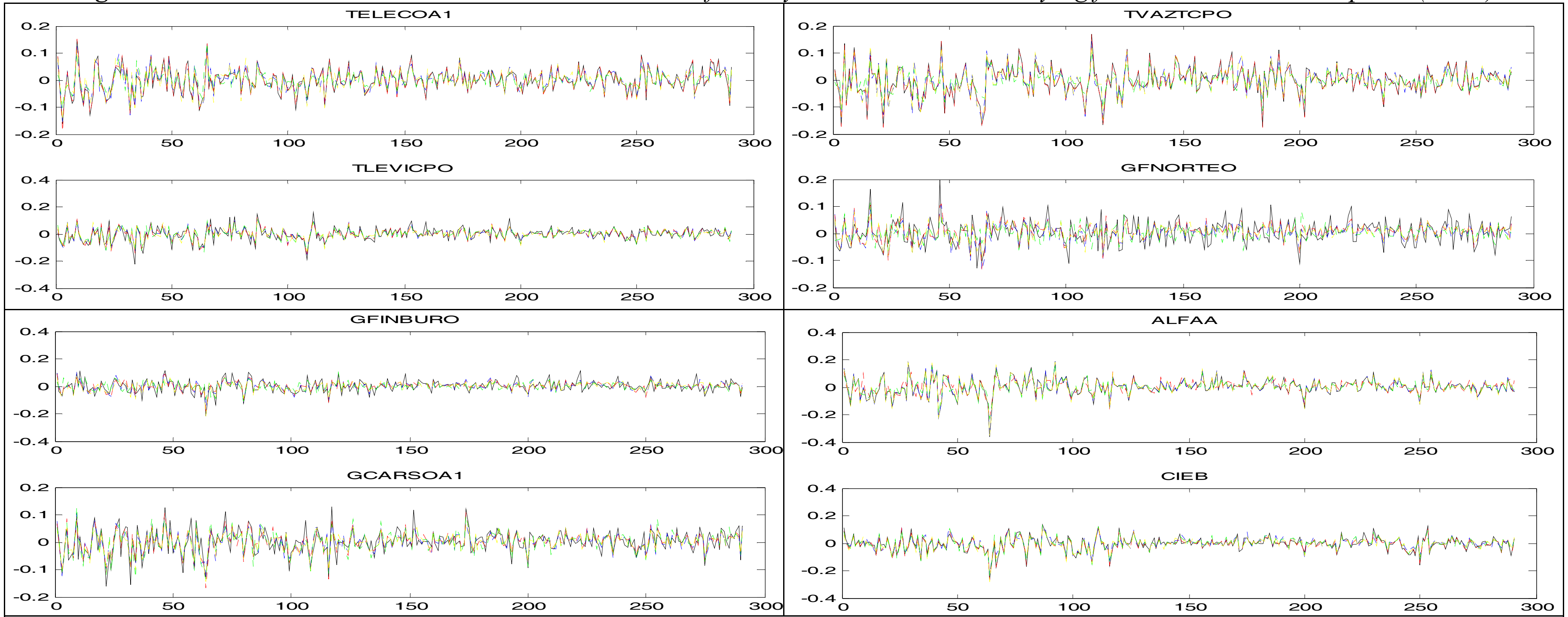


Figure 4. *Observed vs. reconstructed returns. Database of weekly excesses. Nine underlying factors extracted. Line plots. (Cont.)*



Notes:
---------- Observed returns.
---------- PCA reconstruction.
---------- FA reconstruction.
---------- ICA reconstruction.
---------- NNPCA reconstruction.

Figure 5. *Observed vs. reconstructed returns. Database of daily returns. Nine underlying factors extracted. Line plots.*

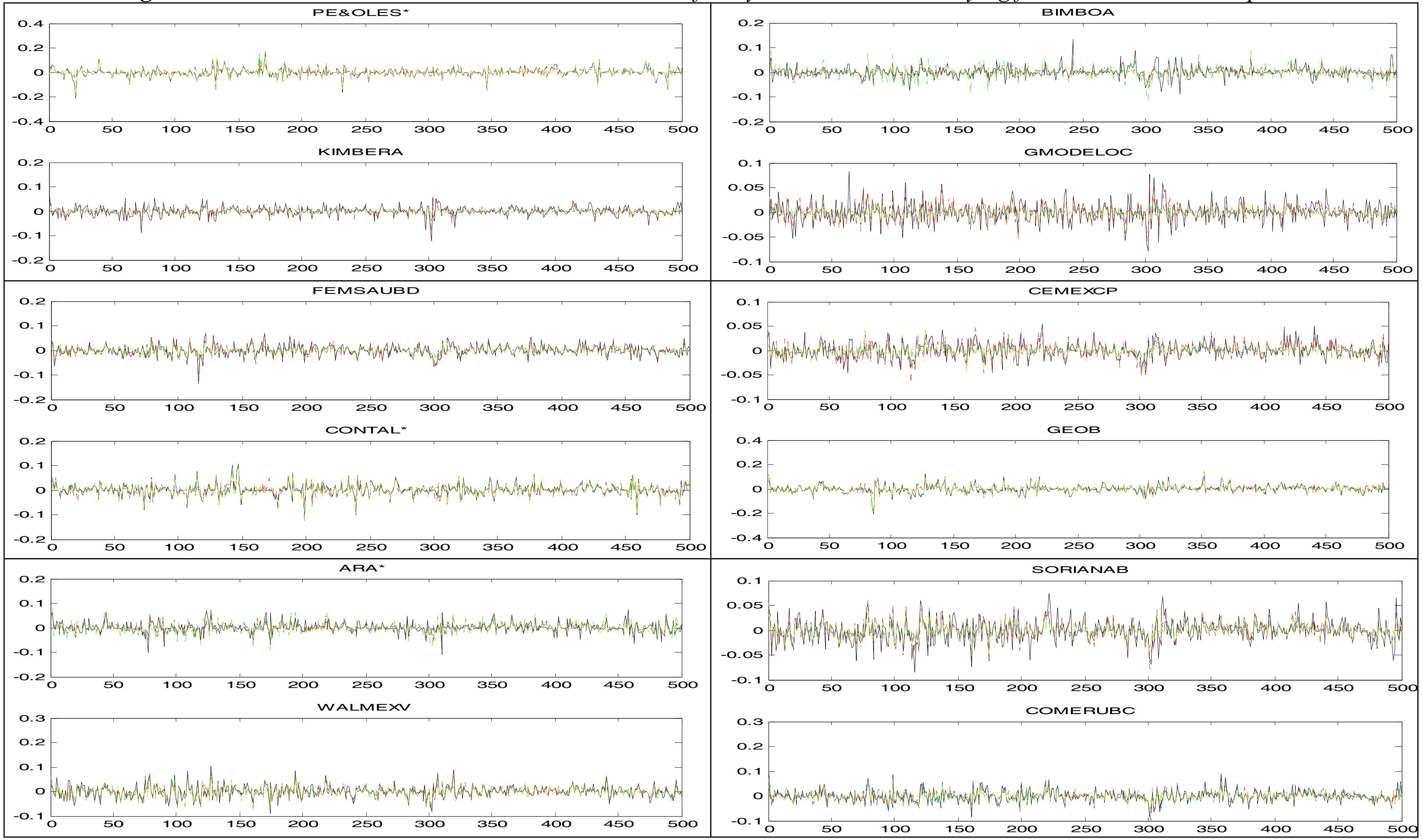


Figure 6. *Observed vs. reconstructed returns. Database of daily returns. Nine underlying factors extracted. Line plots. (Cont.)*

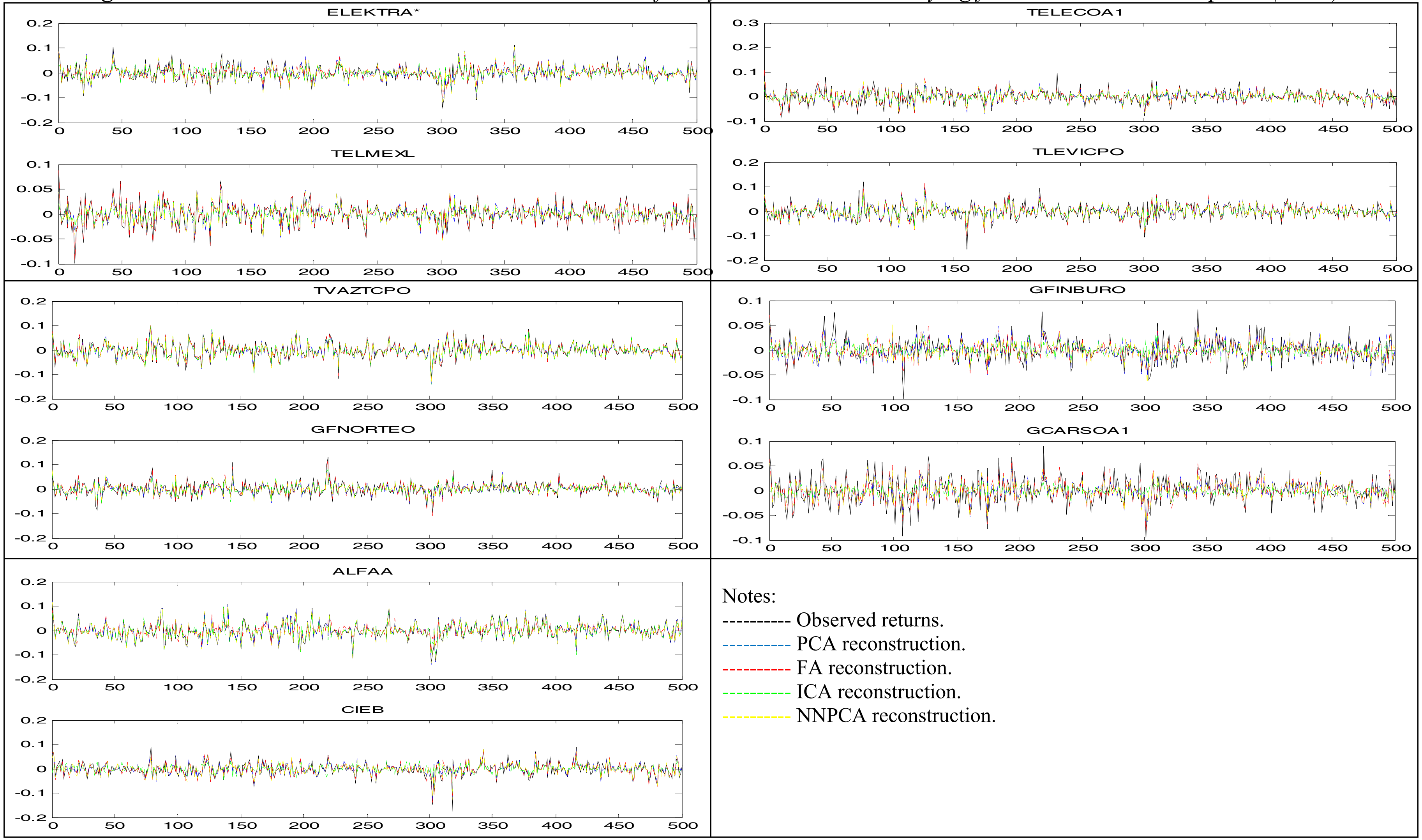


Figure 7. *Observed vs. reconstructed returns. Database of daily excesses. Nine underlying factors extracted. Line plots.*

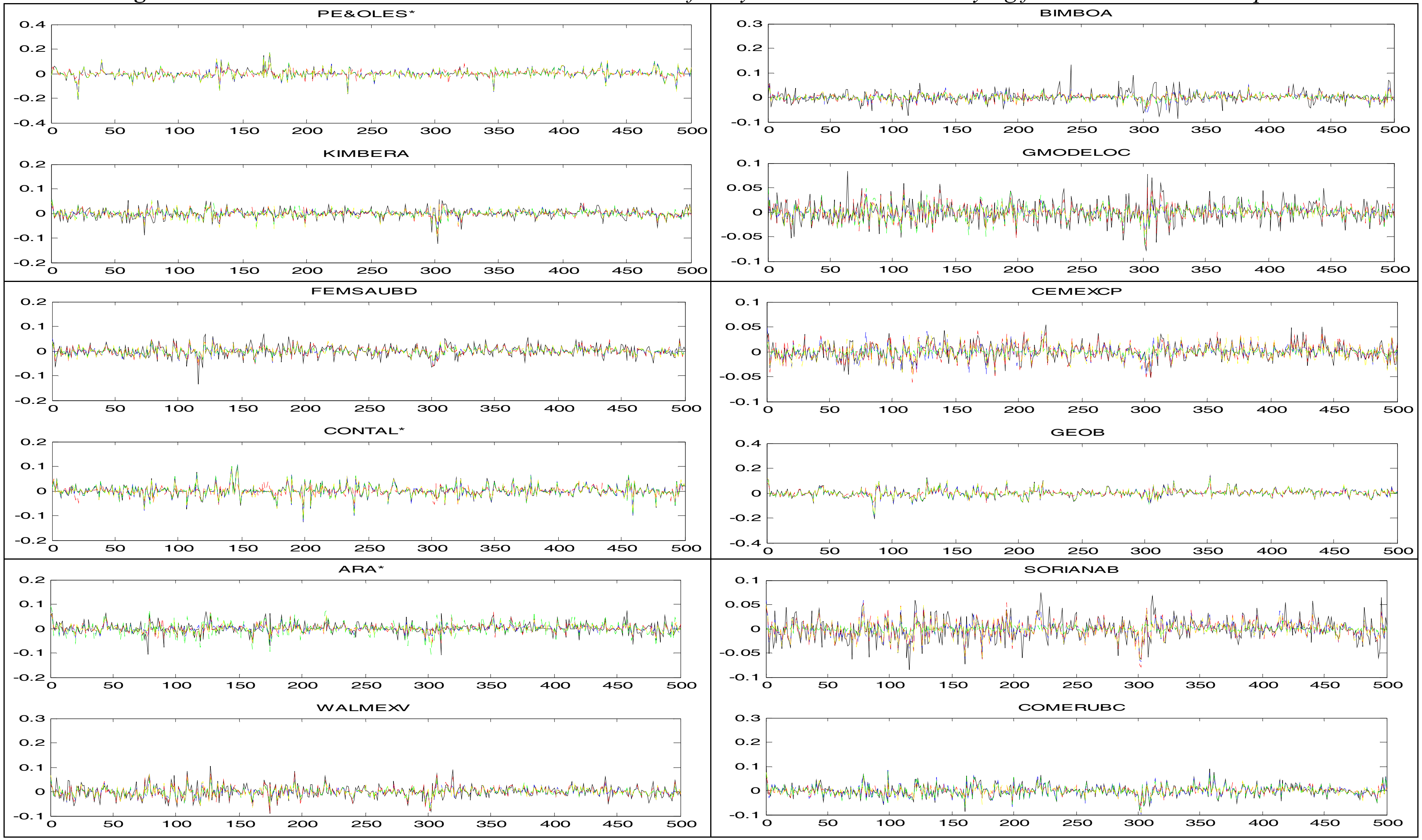
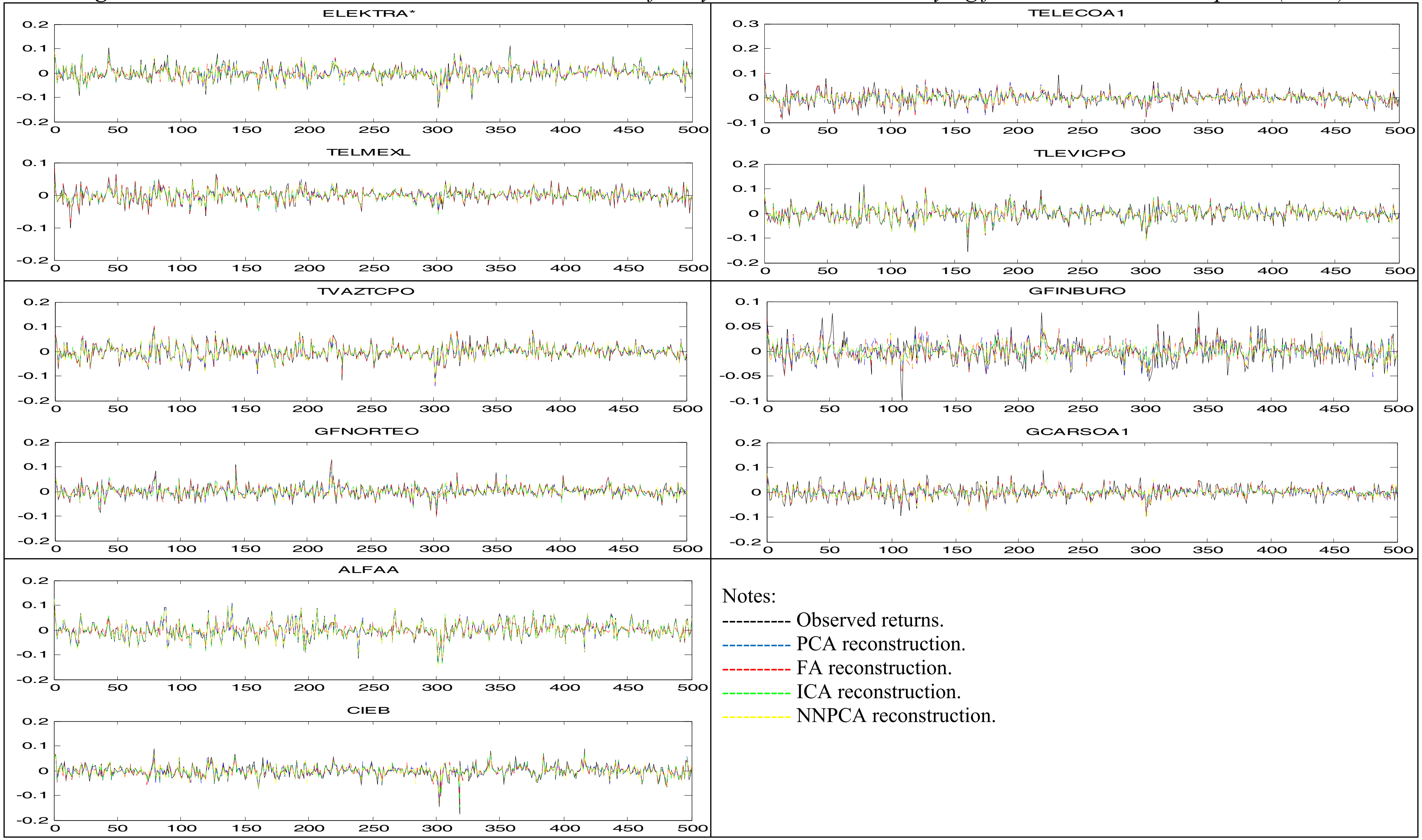


Figure 8. *Observed vs. reconstructed returns. Database of daily excesses. Nine underlying factors extracted. Line plots. (Cont.)*



Appendix_2 (Chapter 7)

Table 1. *Measures of reconstruction accuracy. Database of weekly returns. Nine underlying factors extracted by **Principal Component Analysis**.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00238	0.01233	0.01987	0.02200	0.00755	0.00683	0.02253	0.01934	0.02038	0.02194	0.01123	0.01411	0.01568	0.01807	0.01782	0.02383	0.02062	0.01942	0.00321	0.01865	0.01589	0.01836	0.00654
MAPE	24.38628	148.86221	148.64425	229.40075	83.01079	47.06025	117.84273	163.87517	131.15406	151.01142	82.64110	120.08024	130.25326	159.93665	89.10080	113.61154	172.80171	156.55299	31.39494	217.58479	125.96030	130.70366	54.93866
RMSE	0.00304	0.01564	0.02689	0.02984	0.00982	0.00865	0.02920	0.02557	0.02607	0.02951	0.01428	0.01853	0.01996	0.02402	0.02336	0.03042	0.02632	0.02553	0.00407	0.02411	0.02074	0.02407	0.00867
U-Theil	0.02256	0.19212	0.54068	0.41242	0.11358	0.06861	0.42159	0.36282	0.33032	0.36969	0.12762	0.30259	0.23711	0.27196	0.23387	0.40202	0.34554	0.31525	0.03288	0.25417	0.26787	0.28727	0.14074
CM	145 3	129 28	102 52	125 30	139 15	165 7	132 36	125 29	125 29	120 32	140 14	125 23	134 19	142 16	130 20	139 29	130 28	134 32	152 3	131 22			
	1 142	23 111	46 91	43 93	14 123	8 111	35 88	41 96	31 106	35 104	18 119	35 108	24 114	21 112	20 121	33 90	36 97	31 94	5 131	26 112			
CR	0.01375	0.17526	0.33677	0.25086	0.09966	0.05155	0.24399	0.24055	0.20619	0.23024	0.10997	0.19931	0.14777	0.12715	0.13746	0.21306	0.21993	0.21649	0.02749	0.16495	0.17062	0.18729	0.08203
χ^2	275.27103	122.42915	30.93801	71.35575	186.28856	232.18997	72.93307	77.69004	99.90738	84.31807	176.70721	105.72297	144.04897	160.86158	152.88207	91.83172	89.83217	90.83136	259.77247	130.24356			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-0.29260	-2.21428	-5.47305	-2.79415	-1.44879	1.56178	-2.77241	-2.77776	-2.64515	-3.36584	-0.83205	-2.52004	-1.42144	-0.66754	-2.16830	-1.37420	-2.43859	-1.86200	0.68663	-2.06638			
p-value	0.38491	0.01340	0.00000	0.00260	0.07370	0.94083	0.00278	0.00274	0.00408	0.00038	0.20269	0.00587	0.07759	0.25221	0.01507	0.08469	0.00737	0.03130	0.75384	0.01940			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 2. *Measures of reconstruction accuracy. Database of weekly returns.*
Nine underlying factors extracted by ***Factor Analysis.***

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.04365	0.02420	0.00186	0.01848	0.02577	0.01313	0.02513	0.01523	0.02101	0.00226	0.02511	0.01247	0.00385	0.01656	0.00035	0.02380	0.02227	0.01895	0.03045	0.01001	0.01773	0.01872	0.01081
MAPE	236.33019	211.10153	26.88912	183.94481	194.30879	111.29968	138.09238	136.07734	146.49039	23.49442	146.72212	109.64181	30.34334	152.26727	2.18568	118.31492	167.65046	162.56171	234.03268	98.90365	131.53262	142.29139	68.61165
RMSE	0.05627	0.03271	0.00186	0.02481	0.03448	0.01606	0.03201	0.02033	0.02688	0.00226	0.03198	0.01701	0.00507	0.02181	0.00038	0.03031	0.02902	0.02389	0.04082	0.01309	0.02305	0.02435	0.01418
U-Theil	0.53516	0.47522	0.02888	0.32201	0.48550	0.12671	0.47565	0.27227	0.34288	0.02488	0.30570	0.27352	0.05729	0.24323	0.00357	0.39229	0.39206	0.28960	0.37273	0.13186	0.27755	0.29765	0.16621
CM	106 42	108 49	154 0	135 20	123 31	166 6	145 23	135 19	130 24	152 0	134 20	132 16	150 3	145 13	145 5	155 13	130 28	141 25	134 21	135 18			
	67 76	46 88	6 131	35 101	49 88	27 92	48 75	40 97	33 104	8 131	47 90	29 114	6 132	24 109	0 141	55 68	51 82	33 92	54 82	16 122			
CR	0.37457	0.32646	0.02062	0.18900	0.27491	0.11340	0.24399	0.20275	0.19588	0.02749	0.23024	0.15464	0.03093	0.12715	0.01718	0.23368	0.27148	0.19931	0.25773	0.11684	0.18041	0.19759	0.10329
χ^2	18.50807	34.46063	267.82089	112.28480	58.34573	171.61811	71.08423	103.37939	107.09630	260.53921	85.66236	139.72667	256.09701	161.21623	271.66644	79.91704	59.27951	101.64309	69.22332	170.71901			
p-value	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-5.02647	-4.81617	0.58448	-1.73887	-3.20851	1.46967	-1.56318	-1.53731	-2.41809	0.15940	-1.70586	-1.81193	0.47465	-0.36111	-0.17677	-0.49977	-2.58314	-1.16554	-1.83988	-1.58885			
p-value	0.00000	0.00000	0.72055	0.04103	0.00067	0.92917	0.05901	0.06211	0.00780	0.56332	0.04402	0.03500	0.68248	0.35901	0.42984	0.30862	0.00490	0.12190	0.03289	0.05605			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 3. *Measures of reconstruction accuracy. Database of weekly returns.*
Nine underlying factors extracted by ***Independent Component Analysis****.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00837	0.02926	0.02636	0.02197	0.01946	0.02418	0.02963	0.02481	0.02822	0.02695	0.02143	0.01419	0.01784	0.02053	0.01209	0.02534	0.02327	0.02115	0.01221	0.01776	0.02125	0.02170	0.00604
MAPE	64.75006	295.93277	244.94080	160.38970	203.12454	136.97762	151.38348	139.91001	155.47398	167.36545	108.31655	128.14276	113.14190	150.83357	66.18740	122.04305	214.71830	134.36152	90.50956	165.42599	150.69645	145.37179	56.51906
RMSE	0.01075	0.03781	0.03396	0.02886	0.02598	0.03192	0.03816	0.03253	0.03685	0.03591	0.02737	0.01833	0.02243	0.02847	0.01553	0.03167	0.03064	0.02831	0.01605	0.02341	0.02775	0.02866	0.00787
U-Theil	0.08199	0.48858	0.65436	0.42004	0.27455	0.30371	0.61847	0.55591	0.56802	0.51805	0.28269	0.28687	0.29170	0.33545	0.14752	0.42003	0.32217	0.38563	0.14042	0.25837	0.36773	0.32881	0.16104
CM	139 9	95 62	68 86	114 41	126 28	149 23	109 59	112 42	97 57	107 45	124 30	125 23	127 26	140 18	134 16	137 31	133 25	128 38	138 17	132 21			
	10 133	43 91	50 87	39 97	27 110	27 92	39 84	55 82	46 91	38 101	19 118	35 108	29 109	30 103	10 131	37 86	41 92	29 96	8 128	30 108			
CR	0.06529	0.36082	0.46735	0.27491	0.18900	0.17182	0.33677	0.33333	0.35395	0.28522	0.16838	0.19931	0.18900	0.16495	0.08935	0.23368	0.22680	0.23024	0.08591	0.17526	0.23007	0.21306	0.10320
χ^2	219.94528	23.41937	1.76444	58.49817	112.17316	120.30600	31.26769	31.47260	25.09213	53.84063	128.86890	105.72297	112.11844	129.69669	196.65352	78.23813	85.49444	83.41037	200.33935	122.44880			
p-value	0.00000	0.00000	0.18407	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-0.87402	-6.12856	-9.26425	-3.86141	-3.09519	-0.41152	-5.13480	-4.32960	-6.40265	-4.63846	-2.51230	-2.63807	-2.23363	-1.20333	-1.82230	-2.00389	-2.15205	-2.33318	-1.00171	-2.07532			
p-value	0.19105	0.00000	0.00000	0.00006	0.00098	0.34035	0.00000	0.00001	0.00000	0.00000	0.00600	0.00417	0.01275	0.11443	0.03421	0.02254	0.01570	0.00982	0.15824	0.01898			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 4. *Measures of reconstruction accuracy. Database of weekly returns.*
Nine underlying factors extracted by ***Neural Networks Principal Component Analysis****.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00327	0.01343	0.02014	0.02139	0.01618	0.00783	0.02357	0.02156	0.01954	0.02173	0.01569	0.01514	0.01802	0.02060	0.01902	0.02370	0.02250	0.02161	0.00849	0.02066	0.01770	0.01984	0.00564
MAPE	28.95097	183.22391	155.90545	230.05069	153.20323	54.17013	120.55274	165.44554	133.42692	160.11589	104.44035	125.59720	133.82330	177.62795	94.98864	120.40022	167.20908	182.31004	91.70267	190.85457	138.69997	143.51326	48.30197
RMSE	0.00420	0.01725	0.02712	0.02838	0.02143	0.00988	0.03011	0.02803	0.02542	0.02835	0.02060	0.02016	0.02292	0.02783	0.02449	0.03011	0.02872	0.02836	0.01088	0.02704	0.02306	0.02623	0.00737
U-Theil	0.03117	0.21349	0.54500	0.38296	0.26005	0.07858	0.43390	0.40830	0.31761	0.34792	0.18767	0.33321	0.27623	0.32358	0.24626	0.39449	0.38706	0.35919	0.08836	0.28824	0.29516	0.32060	0.12809
CM	145 3	131 26	112 42	126 29	124 30	164 8	134 34	122 32	128 26	117 35	139 15	128 20	133 20	136 22	124 26	140 28	125 33	136 30	148 7	125 28			
	4 139	23 111	56 81	45 91	25 112	7 112	36 87	42 95	26 111	38 101	20 117	41 102	32 106	27 106	17 124	45 78	45 88	39 86	14 122	30 108			
CR	0.02405	0.16838	0.33677	0.25430	0.18900	0.05155	0.24055	0.25430	0.17869	0.25086	0.12027	0.20962	0.17869	0.16838	0.14777	0.25086	0.26804	0.23711	0.07216	0.19931	0.19003	0.19416	0.07847
χ^2	263.67498	127.45583	30.14226	69.45731	112.52152	232.33347	74.53255	69.52049	119.71109	71.85658	167.45945	99.84530	120.06848	126.80269	145.08568	67.01241	60.94914	76.54302	213.02648	104.78986			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-0.52159	-1.99269	-4.32113	-2.81993	-2.98580	1.47699	-2.45497	-2.99878	-2.40829	-3.60123	-0.95578	-2.29180	-1.58466	-1.25905	-2.88421	-1.70586	-3.06953	-1.78048	0.18158	-2.76968			
p-value	0.30098	0.02315	0.00001	0.00240	0.00141	0.93016	0.00704	0.00136	0.00801	0.00016	0.16959	0.01096	0.05652	0.10401	0.00196	0.04402	0.00107	0.03750	0.57204	0.00281			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 5. *Measures of reconstruction accuracy. Database of weekly excesses.*
Nine underlying factors extracted by ***Principal Component Analysis****.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00239	0.01221	0.01987	0.02200	0.00754	0.00683	0.02255	0.01932	0.02038	0.02193	0.01122	0.01412	0.01566	0.01806	0.01783	0.02375	0.02061	0.01939	0.00324	0.01861	0.01588	0.01833	0.00653
MAPE	63.51663	1141.86372	183.08889	200.28641	106.64852	68.98367	172.34345	197.41781	253.62837	885.96090	97.73153	143.56062	210.69336	406.78044	741.33417	177.97465	504.39862	314.23490	25.05059	316.22644	310.58618	198.85211	295.70373
RMSE	0.00305	0.01550	0.02683	0.02985	0.00982	0.00865	0.02920	0.02553	0.02608	0.02951	0.01427	0.01853	0.01991	0.02400	0.02337	0.03035	0.02632	0.02550	0.00411	0.02408	0.02072	0.02404	0.00866
U-Theil	0.02266	0.19027	0.53916	0.41255	0.11370	0.06871	0.42319	0.36272	0.32943	0.36900	0.12750	0.30270	0.23653	0.27117	0.23340	0.40231	0.34600	0.31479	0.03321	0.25330	0.26761	0.28693	0.14068
CM	141 0	119 28	95 51	117 29	126 9	159 6	122 36	120 31	117 25	108 32	135 15	118 24	125 22	133 17	123 18	136 26	119 30	123 31	149 1	124 18			
	3 147	27 117	49 96	47 98	18 138	8 118	41 92	39 101	32 117	40 111	18 123	36 113	26 118	26 115	22 128	33 96	39 103	35 102	4 137	31 118			
CR	0.01031	0.18900	0.34364	0.26117	0.09278	0.04811	0.26460	0.24055	0.19588	0.24742	0.11340	0.20619	0.16495	0.14777	0.13746	0.20275	0.23711	0.22680	0.01718	0.16838	0.17577	0.19244	0.08685
χ^2	279.23875	112.58123	28.46685	67.36360	193.69735	236.71926	63.06926	78.08112	107.98967	74.57736	173.88030	101.37013	130.71882	144.62385	153.09653	100.48911	80.45217	86.21603	271.42857	129.23581			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-0.53398	-3.11289	-5.93063	-3.38207	-2.30299	1.26093	-2.95798	-3.06799	-3.33823	-4.39370	-1.26208	-3.21118	-2.41599	-1.52366	-2.64432	-1.44771	-3.15926	-2.73838	0.38432	-2.50355			
p-value	0.29668	0.00093	0.00000	0.00036	0.01064	0.89633	0.00155	0.00108	0.00042	0.00001	0.10346	0.00066	0.00785	0.06380	0.00409	0.07385	0.00079	0.00309	0.64963	0.00615			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 6. *Measures of reconstruction accuracy. Database of weekly excesses.*
Nine underlying factors extracted by ***Factor Analysis****.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*
MAE	0.04359	0.02417	0.00017	0.01833	0.02580	0.01232	0.02500	0.01506	0.02096	0.00057	0.02482
MAPE	521.00959	766.60313	9.43772	188.19276	201.85124	123.47529	210.22801	165.01503	298.24406	28.21334	189.57948
RMSE	0.05623	0.03273	0.00018	0.02470	0.03442	0.01520	0.03190	0.02013	0.02686	0.00057	0.03172
U-Theil	0.53646	0.47594	0.00277	0.32182	0.48632	0.12068	0.47969	0.27116	0.34187	0.00633	0.30418
CM	100 41	96 51	146 0	126 20	104 31	159 6	132 26	129 22	118 24	140 0	128 22
	66 84	51 93	1 144	36 109	54 102	25 101	52 81	33 107	33 116	5 146	43 98
CR	0.36770	0.35052	0.00344	0.19244	0.29210	0.10653	0.26804	0.18900	0.19588	0.01718	0.22337
χ^2	21.49807	25.99735	287.02716	111.40098	52.48290	179.93791	61.35874	112.64179	108.19905	271.66202	90.19272
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
DA	-5.32233	-5.81561	0.05812	-2.31173	-4.78568	1.01571	-2.04691	-2.02414	-3.21647	-0.64817	-2.18166
p-value	0.00000	0.00000	0.52317	0.01040	0.00000	0.84512	0.02033	0.02148	0.00065	0.25844	0.01457

	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.01239	0.00365	0.01650	0.00203	0.02366	0.02216	0.01890	0.03011	0.01038	0.01753	0.01862	0.01092
MAPE	122.85918	43.43839	322.35893	111.38840	191.21319	493.97614	3183.55703	181.61566	130.03368	374.11451	188.88612	686.22969
RMSE	0.01693	0.00495	0.02166	0.00204	0.03012	0.02889	0.02383	0.04047	0.01367	0.02286	0.02426	0.01429
U-Theil	0.27202	0.05586	0.24134	0.01927	0.39448	0.39123	0.28992	0.37074	0.13702	0.27595	0.29705	0.16916
CM	120 22	143 4	132 18	137 4	141 21	119 30	128 26	125 25	123 19			
	28 121	6 138	25 116	0 150	52 77	48 94	35 102	50 91	17 132			
CR	0.17182	0.03436	0.14777	0.01375	0.25086	0.26804	0.20962	0.25773	0.12371	0.18419	0.19416	0.10822
χ^2	125.63196	252.41305	144.45503	275.40066	70.20198	63.08601	97.52606	69.48269	164.74700			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-2.98820	-0.29793	-1.63237	-1.03091	-1.22843	-3.20823	-2.19125	-2.56809	-2.65993			
p-value	0.00140	0.38288	0.05130	0.15129	0.10964	0.00067	0.01422	0.00511	0.00391			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 7. *Measures of reconstruction accuracy. Database of weekly excesses. Nine underlying factors extracted by* ***Independent Component Analysis****.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.01240	0.02783	0.02337	0.02185	0.02165	0.02116	0.02020	0.02085	0.02142	0.03639	0.02373	0.01523	0.01993	0.01928	0.02257	0.02942	0.02443	0.02199	0.01757	0.01407	0.02177	0.02153	0.00535
MAPE	98.63311	500.11353	1059.06266	232.88104	303.85734	145.08437	190.41471	180.51948	216.51927	775.77828	122.30686	125.88343	215.19561	285.53647	754.63538	170.67432	327.80976	3346.74473	95.49296	201.11109	467.41272	215.85744	725.91528
RMSE	0.01552	0.03687	0.03165	0.02925	0.02747	0.02871	0.02615	0.02799	0.02816	0.05046	0.03076	0.02059	0.02611	0.02616	0.02940	0.03692	0.03204	0.02831	0.02354	0.01846	0.02873	0.02823	0.00735
U-Theil	0.12216	0.53899	0.44259	0.36863	0.35058	0.25573	0.32981	0.42151	0.39282	0.64757	0.32513	0.36799	0.35637	0.29779	0.33464	0.53100	0.45294	0.33143	0.21330	0.18626	0.36336	0.35347	0.12374
CM	130 11	83 64	110 36	115 31	104 31	142 23	127 31	112 39	120 22	71 69	121 29	115 27	124 23	134 16	117 24	103 59	107 42	124 30	126 24	123 19			
	15 135	46 98	44 101	46 99	37 119	24 102	35 98	34 106	31 118	59 92	28 113	32 117	23 121	26 115	31 119	38 91	39 103	36 101	19 122	27 122			
CR	0.08935	0.37801	0.27491	0.26460	0.23368	0.16151	0.22680	0.25086	0.18213	0.43986	0.19588	0.20275	0.15808	0.14433	0.18900	0.33333	0.27835	0.22680	0.14777	0.15808	0.22680	0.21478	0.08499
χ^2	196.43151	17.71916	59.12239	65.13799	82.37708	130.93246	85.52885	72.31738	118.18553	3.98329	107.56166	103.00516	136.07254	147.57961	112.91452	33.47948	57.19801	86.18191	144.59941	136.59179			
p-value	0.00000	0.00003	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.04595	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-1.82221	-7.36780	-4.17983	-3.60883	-4.91442	-0.74112	-2.35438	-3.93662	-2.98142	-8.86886	-2.89093	-3.57800	-2.52700	-1.41030	-3.33857	-4.93380	-4.52303	-2.63766	-2.28836	-2.63104			
p-value	0.03421	0.00000	0.00001	0.00015	0.00000	0.22931	0.00928	0.00004	0.00143	0.00000	0.00192	0.00017	0.00575	0.07923	0.00042	0.00000	0.00000	0.00417	0.01106	0.00426			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 8. *Measures of reconstruction accuracy. Database of weekly excesses.*
Nine underlying factors extracted by ***Neural Networks Principal Component Analysis****.*

	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00333	0.01205	0.01897	0.02322	0.01863	0.00895	0.02313	0.02016	0.02039	0.02423	0.01219	0.01509	0.01732	0.02122	0.01938	0.02552	0.02146	0.02151	0.00811	0.01981	0.01773	0.01959	0.00595
MAPE	30.90712	1098.95294	163.27860	217.30132	182.79141	118.11590	188.70843	209.16978	283.36557	562.47343	119.18551	148.52232	189.99328	341.52203	481.45156	213.15501	486.20913	3386.24525	62.06549	308.41213	439.59131	211.16240	733.03182
RMSE	0.00450	0.01574	0.02522	0.03017	0.02469	0.01158	0.02947	0.02629	0.02700	0.03136	0.01604	0.01994	0.02220	0.02859	0.02518	0.03270	0.02737	0.02871	0.01029	0.02589	0.02315	0.02556	0.00772
U-Theil	0.03345	0.19596	0.48144	0.42023	0.31110	0.09189	0.42144	0.37377	0.34349	0.40032	0.14238	0.33231	0.26624	0.33442	0.25419	0.44898	0.36296	0.36558	0.08325	0.27565	0.29695	0.33337	0.12835
CM	138 3	120 27	99 47	115 31	116 19	157 8	129 29	117 34	116 26	101 39	135 15	126 16	132 15	129 21	119 22	131 31	117 32	127 27	138 12	117 25			
	3 147	26 118	48 97	55 90	31 125	10 116	46 87	39 101	28 121	42 109	14 127	42 107	35 109	28 113	20 130	49 80	44 98	44 93	11 130	34 115			
CR	0.02062	0.18213	0.32646	0.29553	0.17182	0.06186	0.25773	0.25086	0.18557	0.27835	0.09966	0.19931	0.17182	0.16838	0.14433	0.27491	0.26117	0.24399	0.07904	0.20275	0.19381	0.19244	0.08268
χ^2	267.47281	117.61246	35.05197	49.94222	126.31982	222.22441	66.71031	71.93884	115.07054	57.11657	186.49982	109.22002	127.58201	127.98277	147.11000	55.96361	66.47715	75.85229	206.22357	103.37109			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-0.89761	-2.99545	-5.46204	-3.64396	-3.45207	1.02343	-2.28289	-3.40264	-3.46902	-5.23813	-1.24624	-2.25370	-1.62941	-1.98581	-3.13901	-2.22590	-3.41035	-2.38458	-0.89380	-3.33400			
p-value	0.18470	0.00137	0.00000	0.00013	0.00028	0.84695	0.01122	0.00033	0.00026	0.00000	0.10634	0.01211	0.05161	0.02353	0.00085	0.01301	0.00032	0.00855	0.18571	0.00043			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 9. *Summary of measures of reconstruction accuracy.*
Database of weekly excesses. Nine underlying factors.

	PCA			FA			ICA			NNPCA		
	MEAN	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**
MAE	0.01588	0.01833	0.00653	0.01753	0.01862	0.01092	0.02177	0.02153	0.00535	0.01773	0.01959	0.00595
MAPE	310.58618	198.85211	295.70373	374.11451	188.88612	686.22969	467.41272	215.85744	725.91528	439.59131	211.16240	733.03182
RMSE	0.02072	0.02404	0.00866	0.02286	0.02426	0.01429	0.02873	0.02823	0.00735	0.02315	0.02556	0.00772
U-Theil	0.26761	0.28693	0.14068	0.27595	0.29705	0.16916	0.36336	0.35347	0.12374	0.29695	0.33337	0.12835
CR	0.17577	0.19244	0.08685	0.18419	0.19416	0.10822	0.22680	0.21478	0.08499	0.19381	0.19244	0.08268

Notes:
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
RMSE: Root mean square error.
U-*Theil*: Theil's U statistic.
CR: Confusion rate
Marked cells represents the best results for each statistic across the four techniques.

Table 10. *Measures of reconstruction accuracy. Database of daily returns. Nine underlying factors extracted by Principal Component Analysis.*

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC	ELEKTRA*	TELMEXL	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00066	0.00915	0.01015	0.00973	0.00959	0.00284	0.00945	0.00291	0.01051	0.00973	0.00986	0.00672	0.00546	0.00745	0.00896	0.00852	0.00800	0.00909	0.00959	0.01021	0.00271	0.00674	0.00764	0.00903	0.00291
MAPE	14.04408	175.10998	172.59098	150.21170	190.31924	52.82353	135.01519	40.65644	107.02219	149.50125	123.03559	92.86413	115.39920	107.67843	135.56941	149.99749	78.03250	123.70468	118.25280	145.00308	50.17161	124.84694	115.99320	123.37014	45.75802
RMSE	0.00086	0.01288	0.01412	0.01335	0.01303	0.00371	0.01239	0.00380	0.01399	0.01304	0.01311	0.00897	0.00715	0.00993	0.01186	0.01156	0.01068	0.01206	0.01248	0.01380	0.00358	0.00904	0.01025	0.01196	0.00396
U-Theil	0.01466	0.55906	0.45758	0.55138	0.44751	0.08855	0.46680	0.07773	0.44047	0.40523	0.41299	0.23111	0.14943	0.35856	0.33820	0.28460	0.23046	0.32473	0.36516	0.42340	0.07331	0.22258	0.31470	0.34838	0.15945
CM	701 98	520 244	550 206	523 215	538 188	686 124	558 173	739 85	571 233	575 178	577 194	606 144	652 110	591 165	596 155	619 126	625 121	614 181	580 190	560 211	685 44	597 144			
	14 597	250 396	192 462	225 447	210 474	45 555	204 475	30 556	182 424	185 472	178 461	109 551	73 575	156 498	141 518	109 556	81 583	130 485	147 493	191 448	41 640	115 554			
CR	0.07943	0.35035	0.28227	0.31206	0.28227	0.11986	0.26738	0.08156	0.29433	0.25745	0.26383	0.17943	0.12979	0.22766	0.20993	0.16667	0.14326	0.22057	0.23901	0.28511	0.06028	0.18369	0.21074	0.22411	0.08208
χ^2	1011.28302	121.75286	264.84278	197.37014	266.37307	822.63199	303.69893	987.73627	233.28001	328.09478	310.06039	580.43115	773.90020	415.36157	472.70540	625.87036	720.02673	437.77872	383.58920	256.42989	1090.21275	564.92515			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-4.10572	-11.97050	-10.32298	-11.00096	-9.75563	-5.36586	-8.74954	-1.79479	-11.40962	-8.21448	-9.65765	-8.31687	-4.11641	-8.05274	-6.59667	-5.35879	-6.92241	-7.53917	-10.11015	-9.70048	-1.86250	-8.12492			
p-value	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.03634	0.00000	0.00000	0.00000	0.00000	0.00002	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.03127	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 11. *Measures of reconstruction accuracy. Database of daily returns. Nine underlying factors extracted by Factor Analysis.*

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICP O	TVAZTCPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.01744	0.00775	0.01062	0.00783	0.00628	0.01119	0.00687	0.01288	0.00897	0.00697	0.00969	0.01150	0.01209	0.00134	0.00694	0.00715	0.00323	0.00453	0.01077	0.00836	0.01285	0.00664	0.00872	0.00809	0.00359
MAPE	221.96630	187.47029	180.76977	153.58010	166.57924	160.19465	119.85489	135.42971	97.66074	122.33090	126.01342	138.65036	201.70571	24.37325	110.80487	133.25973	35.27921	67.28081	118.78265	132.43440	169.97758	144.09367	134.02237	134.34472	48.61311
RMSE	0.02454	0.01043	0.01456	0.01038	0.00823	0.01531	0.00913	0.01833	0.01194	0.00908	0.01291	0.01531	0.01611	0.00177	0.00915	0.00955	0.00419	0.00589	0.01433	0.01100	0.01777	0.00864	0.01175	0.01071	0.00510
U-Theil	0.53492	0.39973	0.47926	0.37472	0.25021	0.42938	0.30863	0.44520	0.35293	0.25823	0.40372	0.44907	0.37517	0.05673	0.24865	0.22874	0.08649	0.14588	0.44183	0.31450	0.42668	0.21174	0.32829	0.36382	0.12895
	553 246	572 192	563 193	573 165	619 107	608 202	623 108	651 173	648 156	634 119	583 188	572 178	580 182	707 49	630 121	640 105	665 81	712 83	577 193	617 154	569 160	599 142			
CM	243 368	186 460	236 418	180 492	130 554	153 447	152 527	204 382	164 442	146 511	181 458	218 442	174 474	24 630	120 539	92 573	31 633	74 541	197 443	166 473	215 466	107 562			
CR	0.34681	0.26809	0.30426	0.24468	0.16809	0.25177	0.18440	0.26738	0.22695	0.18794	0.26170	0.28085	0.25248	0.05177	0.17092	0.13972	0.07943	0.11135	0.27660	0.22695	0.26596	0.17660	0.21567	0.23582	0.07446
χ^2	122.07321	298.94267	210.40687	365.57661	620.83637	340.81517	561.56652	280.20980	405.46649	545.21515	314.77313	266.38137	341.60702	1133.85105	608.11946	731.11016	1002.90244	844.81718	275.18718	413.33472	308.14317	591.30027			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-12.53817	-9.08071	-10.00677	-8.38348	-5.43198	-9.99071	-5.44041	-6.64916	-7.88568	-5.14191	-9.05792	-10.20659	-7.82762	-1.77544	-4.80284	-4.13834	-4.67326	-2.97717	-9.83988	-6.77886	-8.13807	-7.98827			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.03791	0.00000	0.00002	0.00000	0.00145	0.00000	0.00000	0.00000	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 12. *Measures of reconstruction accuracy. Database of daily returns. Nine underlying factors extracted by Independent Component Analysis.*

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC
MAE	0.00162	0.00970	0.01157	0.01147	0.01009	0.00476	0.01104	0.00580	0.01238	0.00961	0.01097	0.00747
MAPE	33.46406	130.89520	259.84127	126.89733	150.38011	80.57067	100.51408	67.42225	143.54997	176.70651	104.29250	95.82328
RMSE	0.00215	0.01416	0.01576	0.01581	0.01402	0.00642	0.01457	0.00804	0.01635	0.01269	0.01487	0.00996
U-Theil	0.03678	0.74546	0.37735	0.79971	0.55387	0.15898	0.73918	0.17375	0.41724	0.34940	0.57012	0.27362
CM	674 125	476 288	584 172	399 339	506 220	634 176	501 230	683 141	575 229	578 175	557 214	584 166
	20 591	250 396	182 472	306 366	206 478	68 532	231 448	61 525	186 420	173 484	197 442	100 560
CR	0.10284	0.38156	0.25106	0.45745	0.30213	0.17305	0.32695	0.14326	0.29433	0.24681	0.29149	0.18865
χ^2	910.71989	78.07690	345.15033	10.23519	220.71316	617.78022	167.99532	721.80300	231.82318	358.42182	240.88086	552.81083
p-value	0.00000	0.00000	0.00000	0.00138	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
DA	-5.81078	-14.47671	-8.79727	-17.90250	-11.24078	-8.00677	-11.82896	-4.84127	-10.89936	-8.14740	-10.51360	-9.11174
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	**MEAN**	**MEDIAN**	**STD. DEV.**
MAE	0.00928	0.00796	0.01015	0.00921	0.00733	0.00876	0.01209	0.01229	0.00559	0.01304	0.00919	0.00966	0.00286
MAPE	159.28527	97.93972	120.89040	139.81878	73.62928	115.08435	120.24047	125.82404	82.42687	197.97536	122.88508	120.56544	48.48872
RMSE	0.01265	0.01082	0.01350	0.01239	0.00967	0.01145	0.01600	0.01746	0.00781	0.01774	0.01247	0.01309	0.00391
U-Theil	0.30152	0.44255	0.44545	0.33413	0.20756	0.31001	0.55024	0.68505	0.17267	0.51925	0.41654	0.39730	0.21090
CM	599 163	567 189	574 177	600 145	626 120	618 177	524 246	493 278	622 107	450 291			
	117 531	149 505	159 500	109 556	81 583	129 486	184 456	218 421	73 608	217 452			
CR	0.19858	0.23972	0.23830	0.18014	0.14255	0.21702	0.30496	0.35177	0.12766	0.36028	0.25093	0.24326	0.09163
χ^2	513.75163	382.53580	384.69890	578.32379	722.73036	448.45169	215.94721	124.35131	783.99538	112.89753			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-7.09392	-9.25627	-7.60368	-6.02572	-6.86500	-7.48469	-12.83115	-13.15868	-4.95717	-15.94377			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 13. *Measures of reconstruction accuracy. Database of daily returns. Nine underlying factors extracted by Neural Networks Principal Component Analysis.*

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC
MAE	0.00082	0.00919	0.01056	0.00974	0.00965	0.00358	0.00949	0.00323	0.01137	0.00973	0.01025	0.01051
MAPE	17.69108	177.45250	174.85017	149.95884	192.69450	65.50270	136.40245	44.12774	102.19402	151.15144	126.30740	126.99367
RMSE	0.00112	0.01297	0.01477	0.01337	0.01313	0.00468	0.01242	0.00432	0.01568	0.01302	0.01367	0.01412
U-Theil	0.01892	0.56549	0.49030	0.55381	0.45235	0.11239	0.46791	0.08864	0.52798	0.40411	0.43822	0.40243
CM	704 95	523 241	568 188	527 211	547 179	672 138	566 165	733 91	584 220	577 176	553 218	552 198
	16 595	255 391	220 434	234 438	213 471	53 547	213 466	28 558	226 380	185 472	185 454	178 482
CR	0.07872	0.35177	0.28936	0.31560	0.27801	0.13546	0.26809	0.08440	0.31631	0.25603	0.28582	0.26667
χ^2	1012.67755	118.87743	244.88065	189.53422	276.95427	758.24659	302.03647	976.81738	176.57144	331.87091	256.27086	305.72363
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
DA	-3.97432	-11.92185	-9.85019	-10.84015	-9.17572	-5.81982	-8.38913	-2.06333	-10.47837	-8.11079	-10.69723	-10.64670
p-value	0.00004	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.01954	0.00000	0.00000	0.00000	0.00000

	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	**MEAN**	**MEDIAN**	**STD. DEV.**
MAE	0.00552	0.00747	0.00899	0.00865	0.00799	0.00983	0.01110	0.01020	0.00202	0.00672	0.00803	0.00934	0.00307
MAPE	120.44250	106.91376	137.27803	151.77436	78.45733	128.64360	119.01178	147.08345	39.36300	142.60267	119.85895	127.81864	45.95939
RMSE	0.00722	0.00999	0.01197	0.01179	0.01066	0.01315	0.01477	0.01379	0.00268	0.00887	0.01083	0.01269	0.00421
U-Theil	0.15094	0.36103	0.34179	0.29183	0.23012	0.36224	0.46347	0.42247	0.05460	0.21676	0.33717	0.38234	0.16745
CM	660 102	594 162	592 159	611 134	617 129	604 191	554 216	569 202	689 40	596 145			
	69 579	150 504	140 519	110 555	87 577	149 466	189 451	193 446	40 641	102 567			
CR	0.12128	0.22128	0.21206	0.17305	0.15319	0.24113	0.28723	0.28014	0.05674	0.17518	0.22034	0.24858	0.08544
χ^2	809.30692	435.48962	466.23635	602.77424	680.82280	373.14251	252.26152	267.39540	1107.82691	597.62147			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-3.58643	-8.00172	-6.80232	-5.72192	-7.41026	-8.33735	-11.08168	-9.27978	-1.54242	-8.33980			
p-value	0.00017	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.06149	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 14. *Measures of reconstruction accuracy. Database of daily excesses.*
Nine underlying factors extracted by Principal Component Analysis.

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC	ELEKTRA*	TELMEXL	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00068	0.00914	0.01015	0.00973	0.00958	0.00281	0.00944	0.00293	0.01049	0.00972	0.00986	0.00662	0.00547	0.00745	0.00897	0.00852	0.00800	0.00903	0.00965	0.01021	0.00269	0.00682	0.00763	0.00900	0.00291
MAPE	64.01302	898.54840	361.29302	248.42817	271.60307	201.54638	207.29064	162.22866	434.28193	276.59018	331.51445	311.24061	232.55076	215.72164	203.71372	353.45525	299.05284	406.97458	377.79056	309.04129	73.33729	331.97519	298.73598	287.82151	165.01988
RMSE	0.00089	0.01287	0.01412	0.01335	0.01303	0.00366	0.01238	0.00382	0.01395	0.01303	0.01312	0.00884	0.00717	0.00992	0.01187	0.01157	0.01070	0.01198	0.01257	0.01380	0.00357	0.00915	0.01024	0.01192	0.00396
U-Theil	0.01504	0.55811	0.45733	0.55152	0.44771	0.08739	0.46716	0.07818	0.43873	0.40520	0.41347	0.22730	0.14981	0.35888	0.33847	0.28467	0.23066	0.32208	0.36899	0.42335	0.07304	0.22548	0.31466	0.34867	0.15944
CM	619 13	465 225	501 174	489 200	512 184	596 45	533 169	671 30	489 153	548 167	520 154	545 95	622 81	549 138	578 143	603 118	566 84	562 130	509 153	519 180	667 34	547 103			
	62 716	284 436	225 510	242 479	224 490	118 651	216 492	90 619	262 506	202 493	230 506	158 612	96 611	191 532	149 540	118 571	123 637	180 538	209 539	220 491	54 655	158 602			
CR	0.05319	0.36099	0.28298	0.31348	0.28936	0.11560	0.27305	0.08511	0.29433	0.26170	0.27234	0.17943	0.12553	0.23333	0.20709	0.16738	0.14681	0.21986	0.25674	0.28369	0.06241	0.18511	0.21225	0.22660	0.08627
χ^2	1130.50922	110.50539	267.91018	197.47576	251.43266	842.97062	291.97907	978.10865	248.42610	320.42636	297.71606	584.08272	791.26249	404.23448	483.43395	623.67925	704.68457	445.53274	336.66739	265.03727	1080.87811	562.67563			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-4.71733	-12.76250	-10.82657	-11.48513	-10.27213	-5.76460	-9.17228	-1.80032	-11.31384	-8.41633	-9.77153	-8.53486	-4.42113	-8.27447	-6.79663	-5.45544	-7.47453	-7.59333	-10.40265	-9.90642	-2.02037	-8.41844			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.03590	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.02167	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 15. *Measures of reconstruction accuracy. Database of daily excesses. Nine underlying factors extracted by Factor Analysis.*

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC	ELEKTRA*	TELMEXL	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.01688	0.00768	0.01059	0.00781	0.00781	0.01172	0.00551	0.01136	0.00948	0.00714	0.00973	0.01178	0.01211	0.00159	0.00680	0.00748	0.00327	0.00407	0.01044	0.00825	0.01285	0.00694	0.00869	0.00803	0.00348
MAPE	879.76492	1035.67658	356.87661	295.33775	280.34243	561.45932	162.41181	554.67716	441.41868	227.31411	305.91633	382.33148	364.35525	57.08020	175.25285	374.86629	125.62686	206.98741	355.31411	290.04579	240.54848	387.51019	366.41430	330.61522	229.48457
RMSE	0.02334	0.01032	0.01458	0.01033	0.01042	0.01603	0.00723	0.01581	0.01270	0.00934	0.01306	0.01585	0.01611	0.00210	0.00897	0.01001	0.00423	0.00529	0.01384	0.01087	0.01778	0.00903	0.01169	0.01065	0.00487
U-Theil	0.49049	0.39433	0.48089	0.37282	0.33090	0.46009	0.23628	0.36279	0.38358	0.26723	0.41080	0.47454	0.37554	0.06762	0.24309	0.24130	0.08721	0.13077	0.42106	0.31016	0.42767	0.22211	0.32688	0.36781	0.12538
CM	466 166	517 173	498 177	531 158	558 138	494 147	615 87	581 120	537 105	607 108	516 158	497 143	545 158	660 27	608 113	615 106	610 40	649 43	518 144	568 131	538 163	544 106			
	312 466	203 517	263 472	199 522	175 539	251 518	127 581	229 480	251 517	159 536	222 514	290 480	186 521	49 674	115 574	102 587	73 687	119 599	230 518	184 527	222 487	147 613			
CR	0.33901	0.26667	0.31206	0.25319	0.22199	0.28227	0.15177	0.24752	0.25248	0.18936	0.26950	0.30709	0.24397	0.05390	0.16170	0.14752	0.08014	0.11489	0.26525	0.22340	0.27305	0.17943	0.21983	0.24574	0.07596
χ^2	159.48054	307.94144	204.47697	345.29045	437.48287	276.90145	686.25904	368.93439	368.38452	546.28909	303.57792	226.68084	370.36276	1123.51886	645.11983	700.53068	995.48987	847.08405	318.11881	434.33663	292.85505	580.54910			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-12.39812	-10.00214	-10.93681	-9.24652	-7.81947	-11.06670	-4.79353	-6.64930	-8.61598	-5.28749	-10.00381	-10.75266	-8.52687	-2.39225	-5.19174	-4.81052	-5.15568	-2.93359	-9.84218	-7.29445	-8.90849	-8.63818			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00837	0.00000	0.00000	0.00000	0.00168	0.00000	0.00000	0.00000	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 16. *Measures of reconstruction accuracy. Database of daily excesses. Nine underlying factors extracted by Independent Component Analysis.*

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC
MAE	0.00160	0.01002	0.01098	0.01004	0.00969	0.00240	0.01060	0.00346	0.01326	0.00991	0.01281	0.00483
MAPE	138.51127	1190.93107	293.69166	348.06470	222.44258	160.77993	133.26909	188.11519	757.46743	256.54305	209.16412	243.99977
RMSE	0.00213	0.01365	0.01575	0.01363	0.01344	0.00319	0.01401	0.00473	0.01764	0.01322	0.01742	0.00635
U-Theil	0.03628	0.51209	0.57456	0.49401	0.50631	0.07669	0.68027	0.09941	0.43632	0.42817	0.76254	0.16216
CM	598 34	476 214	475 200	491 198	504 192	593 48	528 174	649 52	496 146	545 170	421 253	570 70
	89 689	283 437	259 476	244 477	215 499	112 657	217 491	101 608	267 501	204 491	290 446	129 641
CR	0.08723	0.35248	0.32553	0.31348	0.28865	0.11348	0.27730	0.10851	0.29291	0.26525	0.38511	0.14113
χ^2	965.75180	124.88329	174.01233	197.70103	252.36915	849.62591	280.91768	868.77579	254.28465	310.91373	74.84388	731.02257
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
DA	-5.80229	-12.17596	-12.19926	-11.37622	-10.70212	-5.96750	-9.43692	-2.97622	-10.89657	-8.57497	-15.11837	-7.22271
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00146	0.00000	0.00000	0.00000	0.00000

	ELEKTRA*	TELMEXL	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00545	0.00750	0.01117	0.00836	0.00862	0.00823	0.01122	0.01138	0.00380	0.00564	0.00823	0.00915	0.00342
MAPE	259.91599	208.38972	164.56585	399.24138	287.38694	369.46196	345.72736	222.42241	100.63946	300.17020	309.13187	250.27141	239.01061
RMSE	0.00719	0.01002	0.01497	0.01127	0.01168	0.01085	0.01486	0.01601	0.00497	0.00730	0.01110	0.01245	0.00470
U-Theil	0.15440	0.36598	0.53723	0.26501	0.26720	0.28640	0.50083	0.60537	0.10172	0.18040	0.36515	0.39708	0.21279
CM	623 80	544 143	544 177	592 129	554 96	573 119	491 171	492 207	653 48	559 91			
	98 609	178 545	182 507	123 566	136 624	162 556	248 500	228 483	69 640	124 636			
CR	0.12624	0.22766	0.25461	0.17872	0.16454	0.19929	0.29716	0.30851	0.08298	0.15248	0.22469	0.24113	0.09247
χ^2	788.43185	419.77866	339.16035	581.98682	635.71070	512.43633	236.85262	207.11287	981.75829	681.17659			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-4.36777	-8.55765	-8.60750	-6.03348	-8.10966	-7.01000	-11.30485	-11.34467	-2.76629	-7.87435			
p-value	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00283	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 17. *Measures of reconstruction accuracy. Database of daily excesses.*
Nine underlying factors extracted by Neural Networks Principal Component Analysis.

	PE&OLES*	KIMBERA	BIMBOA	GMODELOC	FEMSA UBD	CONTAL*	CEMEXCP	GEOB	ARA*	WALMEXV	SORIANAB	COMER UBC	ELEKTRA*	TELMEXL	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTEO	GFINBURO	GCARSO A1	ALFAA	CIEB	MEAN	MEDIAN	STD. DEV.
MAE	0.00142	0.00918	0.01053	0.00976	0.00937	0.00527	0.00871	0.00331	0.01117	0.00986	0.01007	0.01200	0.00614	0.00743	0.00891	0.00904	0.00886	0.01046	0.01063	0.00951	0.00334	0.01025	0.00842	0.00928	0.00280
MAPE	141.56359	788.17718	351.20025	247.53902	282.61137	366.03502	242.98183	187.08432	424.15472	274.76746	322.12206	354.94969	245.47541	240.20368	206.94231	312.02176	331.11462	364.52242	355.96698	362.74210	87.25119	496.85516	317.55828	317.07191	140.37384
RMSE	0.00193	0.01226	0.01461	0.01342	0.01273	0.00696	0.01129	0.00444	0.01536	0.01307	0.01342	0.01628	0.00812	0.00990	0.01175	0.01230	0.01184	0.01419	0.01407	0.01273	0.00441	0.01371	0.01131	0.01251	0.00382
U-Theil	0.03284	0.44079	0.48897	0.56070	0.43300	0.17139	0.38139	0.09106	0.50315	0.40161	0.42787	0.49132	0.17204	0.35437	0.33606	0.30506	0.25834	0.39760	0.43323	0.36379	0.09065	0.36399	0.34087	0.37269	0.14619
CM	607 25	473 217	498 177	504 185	519 177	568 73	542 160	662 39	497 145	546 169	504 170	486 154	623 80	535 152	580 141	582 139	550 100	542 150	493 169	555 144	656 45	494 156			
	92 686	253 467	249 486	254 467	206 508	166 603	173 535	95 614	287 481	201 494	235 501	251 519	99 608	170 553	153 536	131 558	140 620	216 502	222 526	206 505	58 651	214 546			
CR	0.08298	0.33333	0.30213	0.31135	0.27163	0.16950	0.23617	0.09504	0.30638	0.26241	0.28723	0.28723	0.12695	0.22837	0.20851	0.19149	0.17021	0.25957	0.27730	0.24823	0.07305	0.26241	0.22689	0.25390	0.07754
χ^2	989.44194	157.47393	224.86757	203.80188	294.89099	629.26744	392.75467	930.98982	227.14938	318.43145	258.97212	263.14009	785.50345	416.41046	478.72914	536.70601	614.33616	329.87535	281.89785	360.78065	1028.47159	320.77186			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000			
DA	-5.25486	-12.34292	-10.95345	-10.67566	-9.90070	-7.16533	-8.68345	-2.28159	-10.77422	-8.51859	-10.64226	-11.52327	-4.36776	-9.05781	-6.69930	-6.56369	-8.32283	-8.65727	-11.26426	-7.99205	-2.60827	-11.22998			
p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.01126	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00455	0.00000			

Notes:

MAE: Mean absolute error.

MAPE: Mean absolute percentage error.

RMSE: Root mean square error.

U-*Theil*: Theil's U statistic.

CM: Confusion matrix.

CR: Confusion rate

χ^2: Chi-squared independence contrast statistic.

DA: Pesaran & Timmerman's directional accuracy statistic.

Marked cells represents the best results for each statistic across the four techniques.

Table 18. *Summary of measures of reconstruction accuracy. Database of daily excesses. Nine underlying factors.*

	PCA			FA			ICA			NNPCA		
	MEAN	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**	**MEAN**	**MEDIAN**	**STD. DEV.**
MAE	0.00763	0.00900	0.00291	0.00869	0.00803	0.00348	0.00823	0.00915	0.00342	0.00842	0.00928	0.00280
MAPE	298.73598	287.82151	165.01988	366.41430	330.61522	229.48457	309.13187	250.27141	239.01061	317.55828	317.07191	140.37384
RMSE	0.01024	0.01192	0.00396	0.01169	0.01065	0.00487	0.01110	0.01245	0.00470	0.01131	0.01251	0.00382
U-Theil	0.31466	0.34867	0.15944	0.32688	0.36781	0.12538	0.36515	0.39708	0.21279	0.34087	0.37269	0.14619
CR	0.21225	0.22660	0.08627	0.21983	0.24574	0.07596	0.22469	0.24113	0.09247	0.22689	0.25390	0.07754

Notes:
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
RMSE: Root mean square error.
U-*Theil*: Theil's U statistic.
CR: Confusion rate
Marked cells represents the best results for each statistic across the four techniques.

Table 19. *Factor Analysis (FA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in FA minus measures of reconstruction accuracy obtained in PCA. Database of weekly excesses. Nine underlying factors.*

																					FA > PCA		FA = PCA		FA < PCA	
	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	Num.	%	Num.	%	Num.	%
MAE	0.04120	0.01196	-0.01970	-0.00367	0.01826	0.00550	0.00245	-0.00426	0.00058	-0.02136	0.01360	-0.00173	-0.01201	-0.00156	-0.01580	-0.00009	0.00154	-0.00049	0.02687	-0.00822	9	45%	0	0%	11	55%
MAPE	457.49297	-375.26059	-173.65117	-12.09366	95.20272	54.49162	37.88456	-32.40278	44.61568	-857.74756	91.84795	-20.70144	-167.25497	-84.42151	-629.94577	13.23854	-10.42248	2869.32213	156.56507	-186.19276	9	45%	0	0%	11	55%
RMSE	0.05318	0.01724	-0.02666	-0.00515	0.02460	0.00655	0.00269	-0.00540	0.00078	-0.02893	0.01745	-0.00161	-0.01496	-0.00233	-0.02133	-0.00023	0.00257	-0.00167	0.03636	-0.01041	9	45%	0	0%	11	55%
U-Theil	0.51379	0.28567	-0.53638	-0.09073	0.37262	0.05197	0.05650	-0.09156	0.01245	-0.36267	0.17668	-0.03068	-0.18067	-0.02983	-0.21413	-0.00783	0.04523	-0.02488	0.33753	-0.11628	9	45%	0	0%	11	55%
CR	0.35739	0.16151	-0.34021	-0.06873	0.19931	0.05842	0.00344	-0.05155	0.00000	-0.23024	0.10997	-0.03436	-0.13058	0.00000	-0.12371	0.04811	0.03093	-0.01718	0.24055	-0.04467	9	45%	2	10%	9	45%

Notes:

FA > PCA: Cases where FA reproduce worse than PCA. i.e., FA's error in reproduction is greater than PCA's one.

FA = PCA: Cases where FA reproduce just the same as PCA. i.e., FA's error in reproduction is equal to PCA's one.

FA < PCA: Cases where FA reproduce better than PCA. i.e., FA's error in reproduction is less than PCA's one.

Table 20. *Independent Component Analysis (ICA) vs. Principal Component Analysis (PCA).Measures of reconstruction accuracy obtained in ICA minus measures of reconstruction accuracy obtained in PCA. Database of weekly excesses. Nine underlying factors.*

																					ICA > PCA		ICA = PCA		ICA< PCA	
	PE&OLES*	BIMBOA	GMODELOC	FEMSAUBD	CONTAL*	GEOB	ARA*	WALMEXV	SORIANAB	COMERUBC	ELEKTRA*	TELMEXL	TELECOA1	TLEVICPO	TVAZTCPO	GFNORTEO	GFINBURO	GCARSOA1	ALFAA	CIEB	Num.	%	Num.	%	Num.	%
MAE	0.01000	0.01562	0.00349	-0.00015	0.01411	0.01433	-0.00235	0.00153	0.00103	0.01446	0.01250	0.00111	0.00428	0.00122	0.00474	0.00567	0.00382	0.00260	0.01433	-0.00454	17	85%	0	0%	3	15%
MAPE	35.11648	-641.75018	875.97377	32.59463	197.20882	76.10070	18.07126	-16.89834	-37.10911	-110.18263	24.57533	-17.67718	4.50226	-121.24397	13.30122	-7.30033	-176.58886	#######	70.44237	-115.11535	11	55%	0	0%	9	45%
RMSE	0.01247	0.02137	0.00481	-0.00060	0.01765	0.02006	-0.00305	0.00246	0.00208	0.02096	0.01649	0.00206	0.00620	0.00217	0.00603	0.00657	0.00572	0.00280	0.01943	-0.00561	17	85%	0	0%	3	15%
U-Theil	0.09950	0.34872	-0.09657	-0.04392	0.23688	0.18702	-0.09338	0.05879	0.06339	0.27858	0.19763	0.06530	0.11984	0.02661	0.10123	0.12868	0.10694	0.01664	0.18009	-0.06704	16	80%	0	0%	4	20%
CR	0.07904	0.18900	-0.06873	0.00344	0.14089	0.11340	-0.03780	0.01031	-0.01375	0.19244	0.08247	-0.00344	-0.00687	-0.00344	0.05155	0.13058	0.04124	0.00000	0.13058	-0.01031	12	60%	1	5%	7	35%

Notes:

ICA > PCA: Cases where ICA reproduce worse than PCA. i.e., ICA's error in reproduction is greater than PCA's one.

ICA = PCA: Cases where ICA reproduce just the same as PCA. i.e., ICA's error in reproduction is equal to PCA's one.

ICA < PCA: Cases where ICA reproduce better than PCA. i.e., ICA's error in reproduction is less than PCA's one.

Table 21. *Neural Networks Principal Component Analysis (NNPCA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in NNPCA minus measures of reconstruction accuracy obtained in PCA. Database of weekly excesses. Nine underlying factors.*

																					NNPCA > PCA		NNPCA = PCA		NNPCA < PCA	
	PE&OLES*	**BIMBOA**	**GMODELOC**	**FEMSAUBD**	**CONTAL***	**GEOB**	**ARA***	**WALMEXV**	**SORIANAB**	**COMERUBC**	**ELEKTRA***	**TELMEXL**	**TELECOA1**	**TLEVICPO**	**TVAZTCPO**	**GFNORTEO**	**GFINBURO**	**GCARSOA1**	**ALFAA**	**CIEB**	**Num.**	**%**	**Num.**	**%**	**Num.**	**%**
MAE	0.00094	-0.00016	-0.00090	0.00122	0.01109	0.00212	0.00058	0.00084	0.00001	0.00229	0.00097	0.00097	0.00167	0.00317	0.00156	0.00177	0.00084	0.00212	0.00487	0.00120	18	90%	0	0%	2	10%
MAPE	-32.60951	-42.91078	-19.81029	17.01491	76.14289	49.13223	16.36498	11.75197	29.73720	-323.48748	21.45398	4.96170	-20.70007	-65.25841	-259.88261	35.18036	-18.18950	3072.01035	37.01490	-7.81431	11	55%	0	0%	9	45%
RMSE	0.00145	0.00025	-0.00161	0.00032	0.01487	0.00293	0.00027	0.00076	0.00092	0.00185	0.00177	0.00141	0.00228	0.00459	0.00181	0.00235	0.00105	0.00321	0.00618	0.00182	19	95%	0	0%	1	5%
U-Theil	0.01078	0.00569	-0.05772	0.00768	0.19740	0.02318	-0.00175	0.01105	0.01406	0.03133	0.01488	0.02962	0.02971	0.06325	0.02079	0.04667	0.01696	0.05079	0.05004	0.02235	18	90%	0	0%	2	10%
CR	0.01031	-0.00687	-0.01718	0.03436	0.07904	0.01375	-0.00687	0.01031	-0.01031	0.03093	-0.01375	-0.00687	0.00687	0.02062	0.00687	0.07216	0.02405	0.01718	-11.00000	-7.00000	12	60%	0	0%	8	40%

Notes:

NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one.

NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one.

NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

Table 22. *Factor Analysis (FA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in FA minus measures of reconstruction accuracy obtained in PCA. Database of daily returns. Nine underlying factors.*

	PE&OLES *	**KIMBER A**	**BIMBO A**	**GMODELO C**	**FEMSA UBD**	**CONTAL ***	**CEMEX CP**	**GEO B**	**ARA ***	**WALMEX V**	**SORIANA B**	**COMER UBC**
MAE	0.01678	-0.00140	0.00046	-0.00190	-0.00331	0.00835	-0.00257	0.00997	-0.00154	-0.00277	-0.00017	0.00478
MAPE	207.92222	12.36031	8.17879	3.36839	-23.74001	107.37112	-15.16030	94.77327	-9.36146	-27.17035	2.97783	45.78623
RMSE	0.02367	-0.00246	0.00044	-0.00297	-0.00480	0.01160	-0.00326	0.01454	-0.00206	-0.00396	-0.00021	0.00633
U-Theil	0.52026	-0.15933	0.02168	-0.17666	-0.19731	0.34083	-0.15817	0.36747	-0.08754	-0.14700	-0.00926	0.21796
CR	0.26738	-0.08227	0.02199	-0.06738	-0.11418	0.13191	-0.08298	0.18582	-0.06738	-0.06950	-0.00213	0.10142

											FA > PCA		FA = PCA		FA < PCA	
	ELEKTRA *	**TELMEX L**	**TELECO A1**	**TLEVI CPO**	**TVAZT CPO**	**GFNORTE O**	**GFINBUR O**	**GCARSO A1**	**ALFA A**	**CIE B**	**Num.**	**%**	**Num.**	**%**	**Num.**	**%**
MAE	0.00663	-0.00612	-0.00202	-0.00137	-0.00477	-0.00456	0.00118	-0.00185	0.01014	-0.00010	7	32%	0	0%	14	64%
MAPE	86.30651	-83.30519	-24.76454	-16.73775	-42.75329	-56.42387	0.52985	-12.56868	119.80597	19.24673	10	45%	0	0%	10	45%
RMSE	0.00896	-0.00816	-0.00271	-0.00201	-0.00649	-0.00617	0.00185	-0.00279	0.01418	-0.00040	8	36%	0	0%	14	64%
U-Theil	0.22574	-0.30183	-0.08955	-0.05586	-0.14396	-0.17885	0.07667	-0.10890	0.35337	-0.01084	8	36%	0	0%	14	64%
CR	0.12270	-0.17589	-0.03901	-0.02695	-0.06383	-0.10922	0.03759	-0.05816	0.20567	2.00000	9	41%	0	0%	13	59%

Notes:

FA > PCA: Cases where FA reproduce worse than PCA. i.e., FA's error in reproduction is greater than PCA's one.

FA = PCA: Cases where FA reproduce just the same as PCA. i.e., FA's error in reproduction is equal to PCA's one.

FA < PCA: Cases where FA reproduce better than PCA. i.e., FA's error in reproduction is less than PCA's one.

Table 23. *Independent Component Analysis (ICA) vs. Principal Component Analysis (PCA).Measures of reconstruction accuracy obtained in ICA minus measures of reconstruction accuracy obtained in PCA. Database of daily returns. Nine underlying factors.*

	PE&OLES *	KIMBER A	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	CEMEX CP	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B	ICA > PCA Num.	ICA > PCA %	ICA = PCA Num.	ICA = PCA %	ICA< PCA Num.	ICA< PCA %
MAE	0.00096	0.00055	0.00141	0.00174	0.00050	0.00191	0.00159	0.00289	0.00187	-0.00012	0.00111	0.00075	0.00382	0.00051	0.00118	0.00069	-0.00067	-0.00033	0.00251	0.00208	0.00289	0.00630	19	86%	0	0%	3	14%
MAPE	19.41998	-44.21478	87.25029	-23.31437	-39.93913	27.74714	-34.50111	26.76582	36.52778	27.20526	-18.74309	2.95915	43.88607	-9.73872	-14.67900	-10.17870	-4.40322	-8.62033	1.98767	-19.17904	32.25526	73.12842	11	50%	0	0%	11	50%
RMSE	0.00129	0.00128	0.00164	0.00246	0.00099	0.00271	0.00218	0.00424	0.00235	-0.00035	0.00176	0.00099	0.00550	0.00090	0.00164	0.00083	-0.00101	-0.00062	0.00352	0.00367	0.00422	0.00869	19	86%	0	0%	3	14%
U-Theil	0.02211	0.18640	-0.08023	0.24833	0.10636	0.07043	0.27237	0.09602	-0.02323	-0.05583	0.15713	0.04251	0.15209	0.08398	0.10725	0.04953	-0.02289	-0.01472	0.18508	0.26165	0.09937	0.29667	17	77%	0	0%	5	23%
CR	0.02340	0.03121	-0.03121	0.14539	0.01986	0.05319	0.05957	0.06170	0.00000	-0.01064	0.02766	0.00922	0.06879	0.01206	0.02837	0.01348	-0.00071	-0.00355	0.06596	0.06667	0.06738	0.17660	17	77%	1	5%	4	18%

Notes:

ICA > PCA: Cases where ICA reproduce worse than PCA. i.e., ICA's error in reproduction is greater than PCA's one.

ICA = PCA: Cases where ICA reproduce just the same as PCA. i.e., ICA's error in reproduction is equal to PCA's one.

ICA < PCA: Cases where ICA reproduce better than PCA. i.e., ICA's error in reproduction is less than PCA's one.

Table 24. *Neural Networks Principal Component Analysis (NNPCA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in NNPCA minus measures of reconstruction accuracy obtained in PCA. Database of daily returns. Nine underlying factors.*

	PE&OLES *	KIMBER A	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	CEMEX CP	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B	NNPCA > PCA Num.	NNPCA > PCA %	NNPCA = PCA Num.	NNPCA = PCA %	NNPCA < PCA Num.	NNPCA < PCA %
MAE	0.00015	0.00004	0.00041	0.00001	0.00006	0.00073	0.00004	0.00032	0.00085	0.00000	0.00038	0.00379	0.00006	0.00002	0.00003	0.00013	-0.00001	0.00074	0.00151	0.00000	-0.00068	-0.00002	17	77%	0	0%	5	23%
MAPE	3.64701	2.34251	2.25919	-0.25286	2.37525	12.67917	1.38726	3.47130	-4.82818	1.65019	3.27180	34.12954	5.04330	-0.76467	1.70862	1.77687	0.42484	4.93892	0.75897	2.08037	-10.80862	17.75573	18	82%	0	0%	4	18%
RMSE	0.00025	0.00008	0.00065	0.00003	0.00010	0.00097	0.00003	0.00052	0.00168	-0.00002	0.00055	0.00515	0.00007	0.00006	0.00011	0.00022	-0.00003	0.00109	0.00229	0.00000	-0.00090	-0.00017	17	77%	0	0%	5	23%
U-Theil	0.00426	0.00642	0.03272	0.00243	0.00484	0.02384	0.00111	0.01091	0.08752	-0.00112	0.02524	0.17132	0.00151	0.00246	0.00360	0.00723	-0.00033	0.03752	0.09831	-0.00092	-0.01870	-0.00582	17	77%	0	0%	5	23%
CR	-0.00071	0.00142	0.00709	0.00355	-0.00426	0.01560	0.00071	0.00284	0.02199	-0.00142	0.02199	0.08723	-0.00851	-0.00638	0.00213	0.00638	0.00993	0.02057	-26.00000	9.00000	-0.00355	-0.00851	14	64%	0	0%	8	36%

Notes:

NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one.

NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one.

NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

Table 25. *Factor Analysis (FA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in FA minus measures of reconstruction accuracy obtained in PCA. Database of daily excesses. Nine underlying factors.*

																							FA > PCA		FA = PCA		FA < PCA	
	PE&OLES *	KIMBER A	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	CEMEX CP	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B	Num.	%	Num.	%	Num.	%
MAE	0.01620	-0.00146	0.00043	-0.00192	-0.00177	0.00891	-0.00393	0.00844	-0.00101	-0.00259	-0.00013	0.00517	0.00664	-0.00585	-0.00217	-0.00103	-0.00474	-0.00496	0.00079	-0.00196	0.01016	0.00012	7	32%	0	0%	13	59%
MAPE	815.75190	137.12818	-4.41641	46.90958	8.73936	359.91294	-44.87883	392.44850	7.13674	-49.27607	-25.59812	71.09088	131.80449	-158.64144	-28.46086	21.41105	-173.42598	-199.98716	-22.47645	-18.99550	167.21119	55.53499	10	45%	0	0%	10	45%
RMSE	0.02245	-0.00255	0.00046	-0.00301	-0.00261	0.01237	-0.00515	0.01199	-0.00125	-0.00369	-0.00006	0.00701	0.00894	-0.00782	-0.00290	-0.00155	-0.00647	-0.00668	0.00127	-0.00292	0.01421	-0.00012	8	36%	0	0%	14	64%
U-Theil	0.47545	-0.16378	0.02356	-0.17869	-0.11682	0.37270	-0.23088	0.28461	-0.05515	-0.13797	-0.00267	0.24724	0.22573	-0.29126	-0.09538	-0.04336	-0.14345	-0.19131	0.05206	-0.11319	0.35463	-0.00338	8	36%	0	0%	14	64%
CR	0.28582	-0.09433	0.02908	-0.06028	-0.06738	0.16667	-0.12128	0.16241	-0.04184	-0.07234	-0.00284	0.12766	0.11844	-0.17943	-0.04539	-0.01986	-0.06667	-0.10496	0.00851	-0.06028	0.21064	-3.00000	8	36%	0	0%	14	64%

Notes:

FA > PCA: Cases where FA reproduce worse than PCA. i.e., FA's error in reproduction is greater than PCA's one

FA = PCA: Cases where FA reproduce just the same as PCA. i.e., FA's error in reproduction is equal to PCA's one

FA < PCA: Cases where FA reproduce better than PCA. i.e., FA's error in reproduction is less than PCA's one.

Table 26. *Independent Component Analysis (ICA) vs. Principal Component Analysis (PCA).Measures of reconstruction accuracy obtained in ICA minus measures of reconstruction accuracy obtained in PCA. Database of daily excesses. Nine underlying factors.*

																							ICA > PCA		ICA = PCA		ICA< PCA	
	PE&OLES *	KIMBER A	BIMBO A	GMODELO C	FEMSA UBD	CONTAL *	CEMEX CP	GEO B	ARA *	WALMEX V	SORIANA B	COMER UBC	ELEKTRA *	TELMEX L	TELECO A1	TLEVI CPO	TVAZT CPO	GFNORTE O	GFINBUR O	GCARSO A1	ALFA A	CIE B	Num.	%	Num.	%	Num.	%
MAE	0.00092	0.00088	0.00083	0.00031	0.00011	-0.00041	0.00116	0.00054	0.00277	0.00018	0.00295	-0.00179	-0.00002	0.00005	0.00220	-0.00016	0.00061	-0.00080	0.00157	0.00117	0.00111	-0.00118	16	73%	0	0%	6	27%
MAPE	74.49825	292.38266	-67.60136	99.63653	-49.16049	-40.76645	-74.02155	25.88653	323.18549	-20.04713	-122.35033	-67.24084	27.36523	-7.33192	-39.14787	45.78613	-11.66590	-37.51262	-32.06320	-86.61888	27.30216	-31.80499	8	36%	0	0%	14	64%
RMSE	0.00124	0.00079	0.00164	0.00028	0.00041	-0.00047	0.00163	0.00091	0.00369	0.00019	0.00430	-0.00249	0.00002	0.00010	0.00310	-0.00029	0.00098	-0.00112	0.00230	0.00221	0.00140	-0.00184	17	77%	0	0%	5	23%
U-Theil	0.02124	-0.04602	0.11723	-0.05750	0.05860	-0.01070	0.21312	0.02124	-0.00240	0.02297	0.34907	-0.06514	0.00459	0.00710	0.19876	-0.01966	0.03654	-0.03569	0.13184	0.18202	0.02867	-0.04508	14	64%	0	0%	8	36%
CR	0.03404	-0.00851	0.04255	0.00000	-0.00071	-0.00213	0.00426	0.02340	-0.00142	0.00355	0.11277	-0.03830	0.00071	-0.00567	0.04752	0.01135	0.01773	-0.02057	0.04043	0.02482	0.02057	-0.03262	13	59%	1	5%	8	36%

Notes:

ICA > PCA: Cases where ICA reproduce worse than PCA. i.e., ICA's error in reproduction is greater than PCA's one.

ICA = PCA: Cases where ICA reproduce just the same as PCA. i.e., ICA's error in reproduction is equal to PCA's one.

ICA < PCA: Cases where ICA reproduce better than PCA. i.e., ICA's error in reproduction is less than PCA's one.

Table 27. *Neural Networks Principal Component Analysis (NNPCA) vs. Principal Component Analysis (PCA). Measures of reconstruction accuracy obtained in NNPCA minus measures of reconstruction accuracy obtained in PCA. Database of daily excesses. Nine underlying factors.*

																							NNPCA > PCA		NNPCA = PCA		NNPCA < PCA	
	PE&OLES *	**KIMBER A**	**BIMBO A**	**GMODELO C**	**FEMSA UBD**	**CONTAL ***	**CEMEX CP**	**GEO B**	**ARA ***	**WALMEX V**	**SORIANA B**	**COMER UBC**	**ELEKTRA ***	**TELMEX L**	**TELECO A1**	**TLEVI CPO**	**TVAZT CPO**	**GFNORTE O**	**GFINBUR O**	**GCARSO A1**	**ALFA A**	**CIE B**	**Num.**	**%**	**Num.**	**%**	**Num.**	**%**
MAE	0.00074	0.00004	0.00037	0.00003	-0.00021	0.00247	-0.00072	0.00038	0.00068	0.00013	0.00021	0.00538	0.00067	-0.00002	-0.00006	0.00052	0.00086	0.00144	0.00098	-0.00070	0.00065	0.00343	17	77%	0	0%	5	23%
MAPE	77.55057	-110.37122	-10.09277	-0.88915	11.00830	164.48863	35.69119	24.85566	-10.12721	-1.82272	-9.39239	43.70908	12.92465	24.48204	3.22859	-41.43349	32.06177	-42.45216	-21.82358	53.70081	13.91390	164.87997	13	59%	0	0%	9	41%
RMSE	0.00105	-0.00061	0.00049	0.00008	-0.00030	0.00330	-0.00109	0.00062	0.00141	0.00004	0.00030	0.00745	0.00095	-0.00002	-0.00011	0.00073	0.00114	0.00222	0.00151	-0.00106	0.00084	0.00457	16	73%	0	0%	6	27%
U-Theil	0.01780	-0.11732	0.03164	0.00918	-0.01471	0.08400	-0.08577	0.01289	0.06442	-0.00359	0.01440	0.26402	0.02223	-0.00451	-0.00241	0.02040	0.02768	0.07551	0.06424	-0.05956	0.01761	0.13850	15	68%	0	0%	7	32%
CR	0.02979	-0.02766	0.01915	-0.00213	-0.01773	0.05390	-0.03688	0.00993	0.01206	0.00071	0.01489	0.10780	0.00142	-0.00496	0.00142	0.02411	0.02340	0.03972	-16.00000	36.00000	0.01064	0.07730	16	73%	0	0%	6	27%

Notes:

NNPCA > PCA: Cases where NNPCA reproduce worse than PCA. i.e., NNPCA's error in reproduction is greater than PCA's one.

NNPCA = PCA: Cases where NNPCA reproduce just the same as PCA. i.e., NNPCA's error in reproduction is equal to PCA's one.

NNPCA < PCA: Cases where NNPCA reproduce better than PCA. i.e., NNPCA's error in reproduction is less than PCA's one.

Table 28. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of weekly excesses.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Mean	-0.003944	0.004444	-0.005162	-0.000683	0.001970	0.002940	0.001034	-0.001306	0.001183
Median	-0.018028	0.004528	-0.003617	-0.001256	0.003050	0.005046	0.001186	-0.001126	0.000367
Maximum	0.629557	0.221396	0.195834	0.164721	0.194416	0.155592	0.210075	0.121766	0.132099
Minimum	-0.363198	-0.271023	-0.187150	-0.181187	-0.162916	-0.142107	-0.177662	-0.123575	-0.098442
Std. Dev.	0.129471	0.068324	0.053651	0.049613	0.046942	0.043625	0.041983	0.040538	0.038966
Skewness	0.938542	-0.048849	0.194382	0.202973	0.165787	0.030853	0.197779	-0.075662	0.213711
Kurtosis	5.532192	4.420852	4.205177	4.470771	4.872565	4.106448	6.228674	3.118512	3.746119
Jarque-Bera	120.4672	24.59392	19.44352	28.22650	43.84936	14.88993	128.2922	0.447944	8.965015
Probability	0.000000	0.000005	0.000060	0.000001	0.000000	0.000584	0.000000	0.799337	0.011305
Observations	291	291	291	291	291	291	291	291	291

Table 29. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of weekly excesses.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
Mean	-0.010375	0.020263	0.094906	-0.001050	-0.050618	0.172400	0.089901	-0.057687	0.115530
Median	0.019440	0.037504	0.139633	0.010611	0.007328	0.210599	0.065640	0.074827	0.055845
Maximum	3.219921	4.585031	3.361418	3.009800	3.332350	4.393575	7.180688	5.202817	6.542632
Minimum	-3.495538	-4.555539	-5.050026	-3.881935	-4.527498	-4.267591	-3.652854	-6.636535	-5.250893
Std. Dev.	1.001466	1.043466	1.167205	1.003160	1.004565	1.299144	1.414999	1.623506	1.717104
Skewness	-0.280476	-0.096280	-0.367291	-0.384665	-0.421962	0.065676	0.671595	-0.123232	0.266944
Kurtosis	4.407937	5.275117	4.295725	4.511692	5.254126	4.091403	5.621050	4.868059	4.810644
Jarque-Bera	27.85059	63.21049	26.89948	34.88460	70.24367	14.65202	105.1730	43.04846	43.20705
Probability	0.000001	0.000000	0.000001	0.000000	0.000000	0.000658	0.000000	0.000000	0.000000
Observations	291	291	291	291	291	291	291	291	291

Table 30. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of weekly excesses.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
Mean	-0.008638	-0.005140	0.000992	0.002767	0.006742	-0.007971	0.005398	-0.007975	0.007122
Median	-0.012539	-0.008304	-0.003487	0.005139	0.013511	-0.001292	0.004035	-0.006177	0.003603
Maximum	0.415626	0.501133	0.699571	0.801505	0.420690	0.381084	0.376822	0.385994	0.527122
Minimum	-0.496107	-0.489496	-0.500822	-0.430767	-0.546495	-0.498110	-0.403888	-0.412370	-0.486254
Std. Dev.	0.117125	0.117331	0.117440	0.117411	0.117250	0.117172	0.117319	0.117172	0.117227
Skewness	-0.026483	0.173564	0.725231	0.867447	-0.576825	-0.605917	0.184283	-0.003401	0.310700
Kurtosis	4.902311	5.239622	8.202715	11.05570	5.653329	5.375522	3.862407	4.365454	6.928474
Jarque-Bera	43.91181	62.27892	353.7115	823.3382	101.4991	86.22873	10.66499	22.60720	191.8060
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.004832	0.000012	0.000000
Observations	291	291	291	291	291	291	291	291	291

Table 31. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of weekly excesses.
Nine components estimated.

	NLPC1	NLPC2	NLPC3	NLPC4	NLPC5	NLPC6	NLPC7	NLPC8	NLPC9
Mean	-0.032427	0.001364	-0.007715	-0.000105	0.000289	2.83E-05	1.66E-05	-0.001149	0.000868
Median	-0.051926	-0.000716	-0.006380	0.002560	-0.001281	0.001611	-0.001294	-0.002289	0.000310
Maximum	0.912474	0.423712	0.552756	0.240414	0.088477	0.182419	0.112763	0.107839	0.030885
Minimum	-0.590841	-0.536643	-0.527206	-0.312991	-0.070386	-0.217993	-0.115541	-0.085313	-0.045956
Std. Dev.	0.197048	0.131792	0.155788	0.082926	0.022358	0.059835	0.027906	0.029189	0.009032
Skewness	0.849719	-0.040225	-0.059633	-0.259078	0.335065	-0.044494	-0.150707	0.483618	-0.245111
Kurtosis	5.315203	4.495666	4.068316	4.477247	4.272467	3.736754	5.790559	4.107664	5.752322
Jarque-Bera	100.0101	27.20232	14.01072	29.71526	25.07748	6.677540	95.52159	26.21990	94.76406
Probability	0.000000	0.000001	0.000907	0.000000	0.000004	0.035481	0.000000	0.000002	0.000000
Observations	291	291	291	291	291	291	291	291	291

Table 32. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of daily returns.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Mean	0.002356	-0.000888	-0.001444	3.56E-05	0.000459	0.000219	0.000173	-0.000464	-0.001062
Median	0.004679	-0.000175	-0.000674	0.000324	0.000285	-0.000131	0.000277	-0.000223	-0.001148
Maximum	0.281589	0.231344	0.201636	0.096705	0.076712	0.097097	0.094186	0.075873	0.071273
Minimum	-0.288696	-0.158477	-0.112046	-0.095009	-0.088460	-0.130121	-0.078700	-0.077866	-0.089422
Std. Dev.	0.055753	0.029222	0.022125	0.021004	0.020073	0.019779	0.018870	0.018061	0.017266
Skewness	-0.359818	0.458384	0.446221	0.102483	-0.053424	-0.206969	0.005597	-0.256610	-0.192315
Kurtosis	6.227632	10.75667	11.97917	4.624837	4.374398	6.236806	4.148166	4.633559	4.552262
Jarque-Bera	642.4597	3584.123	4783.543	157.5738	111.6477	625.5851	77.45655	172.2497	150.2506
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 33. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of daily returns.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
Mean	0.031484	0.026179	0.073571	-0.102281	-0.016817	-0.010096	0.054212	0.099900	0.011072
Median	0.056286	0.044787	0.075229	-0.060716	-0.060043	-0.044646	0.056825	0.123132	-0.004629
Maximum	5.437062	6.346658	8.526800	5.898412	7.925382	7.372848	8.861919	11.57495	8.929773
Minimum	-5.071681	-7.532544	-5.587499	-7.979299	-8.295717	-9.380654	-13.60707	-7.378506	-9.603469
Std. Dev.	1.026482	1.170193	1.311893	1.632713	1.722922	1.700520	1.957714	1.980070	2.212974
Skewness	-0.206572	-0.331211	0.353673	-0.304647	-0.078220	-0.092978	-0.174892	0.141992	0.080211
Kurtosis	5.619349	6.150133	6.519527	4.174457	4.710548	4.310302	5.689783	5.205288	4.417756
Jarque-Bera	413.1111	608.7757	757.1351	102.8470	173.3388	102.8989	432.2401	290.4566	119.6013
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 34. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of daily returns.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
Mean	-0.000716	-0.004623	-0.000710	0.000558	0.003100	0.000652	0.000872	0.000469	0.001338
Median	-0.000302	-0.002535	-0.000865	0.001314	0.001219	0.003475	-0.000983	-0.000647	-0.000403
Maximum	0.274543	0.217066	0.249965	0.310819	0.307332	0.257947	0.263235	0.284191	0.301550
Minimum	-0.212093	-0.257235	-0.354758	-0.221701	-0.487456	-0.266238	-0.282570	-0.293566	-0.410542
Std. Dev.	0.053276	0.053080	0.053277	0.053278	0.053191	0.053277	0.053274	0.053279	0.053264
Skewness	0.080145	0.000858	-0.342233	0.311607	-0.311076	-0.346124	0.011715	-0.125102	-0.434181
Kurtosis	5.246531	4.766196	7.193612	6.628106	12.39919	4.879718	6.729938	6.619434	10.88330
Jarque-Bera	298.0150	183.2678	1060.724	796.1534	5212.993	235.7371	817.3880	773.3206	3695.402
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 35. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of daily returns.
Nine components estimated.

	NLPC1	NLPC2	NLPC3	NLPC4	NLPC5	NLPC6	NLPC7	NLPC8	NLPC9
Mean	0.003576	6.58E-05	3.09E-05	-0.000143	-0.000230	9.18E-05	-0.000569	-0.000205	0.000123
Median	-0.000438	0.001537	0.001743	0.000376	-0.000252	-0.000453	-0.001856	-0.000549	0.000266
Maximum	0.510622	0.495791	0.514135	0.238636	0.094086	0.121683	0.382520	0.176716	0.014278
Minimum	-0.488768	-0.339496	-0.290268	-0.176419	-0.105797	-0.144047	-0.271144	-0.117490	-0.017372
Std. Dev.	0.098811	0.064724	0.059985	0.046905	0.020779	0.026247	0.070637	0.025368	0.003034
Skewness	0.347196	0.435479	0.328774	0.147100	-0.171743	-0.091483	0.137538	0.406506	-0.147188
Kurtosis	6.095872	10.13615	10.40109	4.606178	4.946722	5.797478	4.099136	6.078564	5.822009
Jarque-Bera	591.4130	3036.385	3243.496	156.6487	229.5779	461.7375	75.42137	595.6394	472.9604
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 36. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of daily excesses.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Mean	0.001299	-0.000775	-0.001450	-0.000186	0.000438	0.000231	0.000141	0.000445	0.001051
Median	0.003761	-8.33E-05	-0.000667	-2.56E-05	0.000281	3.52E-05	0.000277	0.000178	0.000922
Maximum	0.279606	0.231728	0.201739	0.096357	0.075342	0.096440	0.094476	0.078563	0.088257
Minimum	-0.289879	-0.158224	-0.111699	-0.095638	-0.088929	-0.128845	-0.078053	-0.076033	-0.072492
Std. Dev.	0.055779	0.029255	0.022144	0.020990	0.020079	0.019779	0.018865	0.018062	0.017227
Skewness	-0.370363	0.455393	0.448615	0.098302	-0.060974	-0.207582	0.011371	0.264926	0.189832
Kurtosis	6.220801	10.71636	11.93088	4.623772	4.366512	6.242142	4.137685	4.661385	4.542228
Jarque-Bera	641.6812	3546.842	4733.233	157.1732	110.5807	627.6759	76.07213	178.6553	148.2034
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 37. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of daily excesses.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
Mean	0.013640	0.021834	0.064796	-0.101075	-0.014891	-0.019101	0.109525	-0.036138	-0.017815
Median	0.040461	0.045539	0.052420	-0.064870	-0.011659	-0.018433	0.164255	-0.001650	0.039969
Maximum	5.342337	6.436236	8.390022	5.578374	6.637788	6.227631	11.64881	10.37396	7.136281
Minimum	-5.140210	-7.472201	-5.566796	-7.434362	-7.571372	-7.222651	-10.37229	-10.86416	-11.26957
Std. Dev.	1.027398	1.187039	1.310642	1.606169	1.735676	1.678947	1.987070	1.958003	2.198530
Skewness	-0.231324	-0.320561	0.332646	-0.329934	-0.123856	-0.038627	-0.032251	-0.075319	-0.232246
Kurtosis	5.633297	6.088529	6.412157	4.125209	4.535853	3.875016	5.576763	5.159592	4.573902
Jarque-Bera	419.9626	584.5655	710.0191	99.96426	142.1871	45.33276	390.3273	275.3336	158.2090
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 38. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of daily excesses.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
Mean	0.003770	-0.001501	0.002198	-0.000981	-0.000800	-0.000249	0.000224	0.002735	0.001359
Median	0.001574	-0.001192	0.001295	-0.001394	0.001749	-0.001340	0.000275	0.000582	-0.000744
Maximum	0.242804	0.242646	0.450886	0.221878	0.295940	0.302749	0.296157	0.297699	0.309549
Minimum	-0.222830	-0.224994	-0.236029	-0.308617	-0.272096	-0.274313	-0.275637	-0.480584	-0.407771
Std. Dev.	0.053148	0.053260	0.053236	0.053272	0.053275	0.053281	0.053281	0.053211	0.053264
Skewness	-0.030118	0.016222	0.672834	-0.315673	0.123218	0.302979	0.120556	-0.382851	-0.396603
Kurtosis	5.044371	4.595748	9.872250	6.485997	7.171820	5.214765	7.024793	11.93690	10.77099
Jarque-Bera	245.7559	149.6636	2881.021	737.3581	1026.058	309.7517	955.1041	4726.701	3584.776
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 39. *Descriptive Statistics.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of daily excesses.
Nine components estimated.

	NLPC1	NLPC2	NLPC3	NLPC4	NLPC5	NLPC6	NLPC7	NLPC8	NLPC9
Mean	0.003576	6.58E-05	3.09E-05	-0.000143	-0.000230	9.18E-05	-0.000569	-0.000205	0.000123
Median	-0.000438	0.001537	0.001743	0.000376	-0.000252	-0.000453	-0.001856	-0.000549	0.000266
Maximum	0.510622	0.495791	0.514135	0.238636	0.094086	0.121683	0.382520	0.176716	0.014278
Minimum	-0.488768	-0.339496	-0.290268	-0.176419	-0.105797	-0.144047	-0.271144	-0.117490	-0.017372
Std. Dev.	0.098811	0.064724	0.059985	0.046905	0.020779	0.026247	0.070637	0.025368	0.003034
Skewness	0.347196	0.435479	0.328774	0.147100	-0.171743	-0.091483	0.137538	0.406506	-0.147188
Kurtosis	6.095872	10.13615	10.40109	4.606178	4.946722	5.797478	4.099136	6.078564	5.822009
Jarque-Bera	591.4130	3036.385	3243.496	156.6487	229.5779	461.7375	75.42137	595.6394	472.9604
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1410	1410	1410	1410	1410	1410	1410	1410	1410

Table 40. *Correlation Matrix.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of weekly returns.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
PC1	1.000000								

PC2	1.46E-14	1.000000							
	2.49E-13	-----							
	1.0000	-----							
PC3	4.74E-16	-2.00E-17	1.000000						
	8.06E-15	-3.40E-16	-----						
	1.0000	1.0000	-----						
PC4	1.05E-17	-3.64E-18	2.31E-16	1.000000					
	1.79E-16	-6.19E-17	3.92E-15	-----					
	1.0000	1.0000	1.0000	-----					
PC5	1.03E-16	9.33E-17	-2.27E-16	-6.11E-16	1.000000				
	1.75E-15	1.59E-15	-3.85E-15	-1.04E-14	-----				
	1.0000	1.0000	1.0000	1.0000	-----				
PC6	5.73E-16	2.14E-16	-2.24E-16	-2.91E-17	-2.81E-16	1.000000			
	9.73E-15	3.63E-15	-3.80E-15	-4.95E-16	-4.78E-15	-----			
	1.0000	1.0000	1.0000	1.0000	1.0000	-----			
PC7	-1.04E-15	2.49E-16	-9.85E-17	-4.90E-17	9.71E-16	4.42E-16	1.000000		
	-1.77E-14	4.23E-15	-1.68E-15	-8.33E-16	1.65E-14	7.52E-15	-----		
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----		
PC8	1.66E-16	-8.97E-17	3.04E-16	-1.85E-16	-1.16E-16	-6.70E-17	-3.12E-15	1.000000	
	2.82E-15	-1.52E-15	5.18E-15	-3.14E-15	-1.98E-15	-1.14E-15	-5.30E-14	-----	
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----	
PC9	-6.52E-16	2.10E-16	6.32E-17	4.44E-16	5.34E-16	1.70E-16	9.89E-16	6.47E-16	1.000000
	-1.11E-14	3.58E-15	1.08E-15	7.54E-15	9.08E-15	2.90E-15	1.68E-14	1.10E-14	-----
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 41. *Correlation Matrix.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of weekly returns.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1.000000 ----- -----								
F2	-4.07E-16 -6.92E-15 1.0000	1.000000 ----- -----							
F3	7.87E-17 1.34E-15 1.0000	-1.76E-14 -2.99E-13 1.0000	1.000000 ----- -----						
F4	-2.27E-16 -3.85E-15 1.0000	2.94E-16 4.99E-15 1.0000	5.94E-16 1.01E-14 1.0000	1.000000 ----- -----					
F5	-5.78E-17 -9.83E-16 1.0000	1.51E-14 2.57E-13 1.0000	-1.17E-16 -1.99E-15 1.0000	-1.22E-16 -2.07E-15 1.0000	1.000000 ----- -----				
F6	-4.41E-16 -7.50E-15 1.0000	1.78E-16 3.03E-15 1.0000	-1.22E-15 -2.08E-14 1.0000	5.90E-16 1.00E-14 1.0000	3.63E-16 6.16E-15 1.0000	1.000000 ----- -----			
F7	1.72E-16 2.92E-15 1.0000	-1.50E-16 -2.54E-15 1.0000	4.67E-16 7.94E-15 1.0000	-2.62E-16 -4.46E-15 1.0000	-3.15E-17 -5.36E-16 1.0000	-1.48E-16 -2.52E-15 1.0000	1.000000 ----- -----		
F8	5.97E-16 1.02E-14 1.0000	-8.97E-16 -1.52E-14 1.0000	-2.21E-16 -3.76E-15 1.0000	3.58E-16 6.08E-15 1.0000	-1.16E-15 -1.98E-14 1.0000	6.46E-16 1.10E-14 1.0000	1.92E-16 3.26E-15 1.0000	1.000000 ----- -----	
F9	-4.28E-16 -7.27E-15 1.0000	-3.65E-16 -6.20E-15 1.0000	3.12E-16 5.31E-15 1.0000	-3.98E-16 -6.76E-15 1.0000	2.99E-16 5.08E-15 1.0000	3.88E-16 6.60E-15 1.0000	9.07E-17 1.54E-15 1.0000	1.79E-16 3.04E-15 1.0000	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 42. *Correlation Matrix.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of weekly returns.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
IC1	1.000000								

IC2	-0.001574	1.000000							
	-0.026757	-----							
	0.9787	-----							
IC3	-0.001544	-0.000235	1.000000						
	-0.026255	-0.003994	-----						
	0.9791	0.9968	-----						
IC4	-0.002650	-0.000403	-0.000396	1.000000					
	-0.045047	-0.006853	-0.006725	-----					
	0.9641	0.9945	0.9946	-----					
IC5	-0.006857	-0.001043	-0.001024	-0.001756	1.000000				
	-0.116571	-0.017734	-0.017401	-0.029856	-----				
	0.9073	0.9859	0.9861	0.9762	-----				
IC6	-0.002198	-0.000334	-0.000328	-0.000563	-0.001456	1.000000			
	-0.037358	-0.005683	-0.005577	-0.009568	-0.024760	-----			
	0.9702	0.9955	0.9956	0.9924	0.9803	-----			
IC7	-0.004272	-0.000650	-0.000638	-0.001094	-0.002831	-0.000907	1.000000		
	-0.072623	-0.011048	-0.010841	-0.018600	-0.048132	-0.015425	-----		
	0.9422	0.9912	0.9914	0.9852	0.9616	0.9877	-----		
IC8	0.006096	0.000927	0.000910	0.001561	0.004041	0.001295	0.002517	1.000000	
	0.103641	0.015767	0.015471	0.026544	0.068689	0.022013	0.042793	-----	
	0.9175	0.9874	0.9877	0.9788	0.9453	0.9825	0.9659	-----	
IC9	0.007061	0.001074	0.001054	0.001809	0.004680	0.001500	0.002916	-0.004161	1.000000
	0.120048	0.018263	0.017920	0.030746	0.079563	0.025498	0.049568	-0.070738	-----
	0.9045	0.9854	0.9857	0.9755	0.9366	0.9797	0.9605	0.9437	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 43. *Correlation Matrix.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of weekly returns.
Nine components estimated.

	NLPC1	NLPC2	NLPC3	NLPC4	NLPC5	NLPC6	NLPC7	NLPC8	NLPC9
NLPC1	1.000000								

NLPC2	-0.031396	1.000000							
	-0.533994	-----							
	0.5938	-----							
NLPC3	0.081554	0.013761	1.000000						
	1.391059	0.233967	-----						
	0.1653	0.8152	-----						
NLPC4	0.002295	-0.016403	0.008593	1.000000					
	0.039020	-0.278894	0.146084	-----					
	0.9689	0.7805	0.8840	-----					
NLPC5	-0.010637	0.012771	-0.015357	0.025418	1.000000				
	-0.180835	0.217130	-0.261103	0.432246	-----				
	0.8566	0.8283	0.7942	0.6659	-----				
NLPC6	0.011823	-0.001015	0.008820	0.007008	0.029393	1.000000			
	0.201007	-0.017249	0.149948	0.119139	0.499902	-----			
	0.8408	0.9862	0.8809	0.9052	0.6175	-----			
NLPC7	0.022828	-0.008263	-0.015000	0.003180	0.027881	-0.004091	1.000000		
	0.388179	-0.140481	-0.255025	0.054068	0.474165	-0.069548	-----		
	0.6982	0.8884	0.7989	0.9569	0.6357	0.9446	-----		
NLPC8	0.006632	-0.040477	0.014436	0.032910	-0.023997	0.012208	0.113703	1.000000	
	0.112738	-0.688670	0.245444	0.559766	-0.408064	0.207552	1.945569	-----	
	0.9103	0.4916	0.8063	0.5761	0.6835	0.8357	0.0527	-----	
NLPC9	0.834854	0.224315	-0.356144	0.139490	0.092716	0.034431	0.040925	0.151507	1.000000
	25.78245	3.913077	-6.479285	2.394742	1.582997	0.585677	0.696304	2.605696	-----
	0.0000	0.0001	0.0000	0.0173	0.1145	0.5585	0.4868	0.0096	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 44. *Correlation Matrix.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of weekly excesses.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
PC1	1.000000 ----- -----								
PC2	1.37E-14 2.32E-13 1.0000	1.000000 ----- -----							
PC3	6.45E-16 1.10E-14 1.0000	6.64E-16 1.13E-14 1.0000	1.000000 ----- -----						
PC4	-1.38E-16 -2.35E-15 1.0000	-7.62E-17 -1.30E-15 1.0000	-2.19E-16 -3.73E-15 1.0000	1.000000 ----- -----					
PC5	8.02E-16 1.36E-14 1.0000	-1.31E-17 -2.22E-16 1.0000	1.12E-16 1.90E-15 1.0000	-5.10E-16 -8.67E-15 1.0000	1.000000 ----- -----				
PC6	-4.74E-16 -8.06E-15 1.0000	-1.88E-19 -3.20E-18 1.0000	1.81E-16 3.07E-15 1.0000	3.06E-16 5.19E-15 1.0000	7.72E-16 1.31E-14 1.0000	1.000000 ----- -----			
PC7	-6.52E-17 -1.11E-15 1.0000	1.32E-16 2.24E-15 1.0000	-8.00E-17 -1.36E-15 1.0000	3.69E-16 6.27E-15 1.0000	-9.90E-17 -1.68E-15 1.0000	-1.81E-15 -3.07E-14 1.0000	1.000000 ----- -----		
PC8	5.89E-16 1.00E-14 1.0000	4.59E-18 7.80E-17 1.0000	1.68E-16 2.86E-15 1.0000	-1.17E-16 -1.99E-15 1.0000	1.74E-16 2.97E-15 1.0000	3.43E-16 5.82E-15 1.0000	-5.63E-15 -9.57E-14 1.0000	1.000000 ----- -----	
PC9	-6.07E-16 -1.03E-14 1.0000	-1.97E-17 -3.34E-16 1.0000	3.35E-16 5.69E-15 1.0000	3.83E-17 6.51E-16 1.0000	4.29E-17 7.30E-16 1.0000	-6.17E-16 -1.05E-14 1.0000	4.59E-16 7.81E-15 1.0000	-1.35E-16 -2.29E-15 1.0000	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 45. *Correlation Matrix.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of weekly excesses.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1.000000 ----- -----								
F2	1.62E-16 2.76E-15 1.0000	1.000000 ----- -----							
F3	4.36E-16 7.41E-15 1.0000	-1.95E-14 -3.31E-13 1.0000	1.000000 ----- -----						
F4	-1.60E-16 -2.72E-15 1.0000	9.07E-16 1.54E-14 1.0000	8.03E-16 1.36E-14 1.0000	1.000000 ----- -----					
F5	9.47E-16 1.61E-14 1.0000	1.30E-14 2.21E-13 1.0000	1.70E-16 2.89E-15 1.0000	1.89E-17 3.22E-16 1.0000	1.000000 ----- -----				
F6	2.80E-16 4.76E-15 1.0000	-2.79E-16 -4.74E-15 1.0000	-3.17E-16 -5.38E-15 1.0000	1.35E-16 2.29E-15 1.0000	-4.38E-17 -7.44E-16 1.0000	1.000000 ----- -----			
F7	-7.23E-16 -1.23E-14 1.0000	1.44E-16 2.44E-15 1.0000	1.03E-16 1.75E-15 1.0000	-2.46E-16 -4.18E-15 1.0000	-5.96E-17 -1.01E-15 1.0000	-8.02E-17 -1.36E-15 1.0000	1.000000 ----- -----		
F8	2.37E-16 4.03E-15 1.0000	-4.92E-16 -8.36E-15 1.0000	-4.42E-16 -7.51E-15 1.0000	1.62E-15 2.75E-14 1.0000	5.15E-16 8.75E-15 1.0000	-5.48E-16 -9.31E-15 1.0000	3.77E-16 6.41E-15 1.0000	1.000000 ----- -----	
F9	-5.34E-18 -9.08E-17 1.0000	4.28E-16 7.27E-15 1.0000	-5.94E-17 -1.01E-15 1.0000	-5.64E-16 -9.60E-15 1.0000	3.11E-17 5.28E-16 1.0000	1.68E-16 2.86E-15 1.0000	1.64E-17 2.80E-16 1.0000	-1.21E-15 -2.05E-14 1.0000	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 46. *Correlation Matrix.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of weekly excesses.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
IC1	1.000000 ----- -----								
IC2	-0.003242 -0.055111 0.9561	1.000000 ----- -----							
IC3	0.000625 0.010622 0.9915	0.000371 0.006309 0.9950	1.000000 ----- -----						
IC4	0.001744 0.029646 0.9764	0.001036 0.017608 0.9860	-0.000200 -0.003394 0.9973	1.000000 ----- -----					
IC5	0.004256 0.072346 0.9424	0.002528 0.042970 0.9658	-0.000487 -0.008282 0.9934	-0.001360 -0.023115 0.9816	1.000000 ----- -----				
IC6	-0.005034 -0.085584 0.9319	-0.002990 -0.050832 0.9595	0.000576 0.009798 0.9922	0.001609 0.027345 0.9782	0.003925 0.066729 0.9468	1.000000 ----- -----			
IC7	0.003405 0.057888 0.9539	0.002023 0.034383 0.9726	-0.000390 -0.006627 0.9947	-0.001088 -0.018496 0.9853	-0.002655 -0.045135 0.9640	0.003141 0.053394 0.9575	1.000000 ----- -----		
IC8	-0.005037 -0.085630 0.9318	-0.002992 -0.050860 0.9595	0.000577 0.009803 0.9922	0.001609 0.027360 0.9782	0.003927 0.066766 0.9468	-0.004646 -0.078983 0.9371	0.003143 0.053423 0.9574	1.000000 ----- -----	
IC9	0.004496 0.076439 0.9391	0.002671 0.045401 0.9638	-0.000515 -0.008751 0.9930	-0.001437 -0.024423 0.9805	-0.003506 -0.059599 0.9525	0.004147 0.070505 0.9438	-0.002805 -0.047689 0.9620	0.004150 0.070543 0.9438	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 47. *Correlation Matrix.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of weekly excesses.
Nine components estimated.

	NLPC1	NLPC2	NLPC3	NLPC4	NLPC5	NLPC6	NLPC7	NLPC8	NLPC9
NLPC1	1.000000 ----- -----								
NLPC2	-0.007002 -0.119045 0.9053	1.000000 ----- -----							
NLPC3	-0.064065 -1.091348 0.2760	-0.041441 -0.705109 0.4813	1.000000 ----- -----						
NLPC4	-0.033752 -0.574109 0.5663	-0.025272 -0.429759 0.6677	0.026521 0.451016 0.6523	1.000000 ----- -----					
NLPC5	0.037700 0.641353 0.5218	0.006554 0.111413 0.9114	0.001482 0.025186 0.9799	0.050342 0.856895 0.3922	1.000000 ----- -----				
NLPC6	-0.021561 -0.366624 0.7142	0.024785 0.421475 0.6737	-0.030980 -0.526910 0.5987	0.010405 0.176899 0.8597	-0.041740 -0.710206 0.4781	1.000000 ----- -----			
NLPC7	0.011832 0.201162 0.8407	-0.014836 -0.252242 0.8010	-0.002364 -0.040186 0.9680	0.019425 0.330291 0.7414	-0.047141 -0.802297 0.4230	-0.017784 -0.302374 0.7626	1.000000 ----- -----		
NLPC8	-0.012715 -0.216176 0.8290	-0.010108 -0.171841 0.8637	-0.028500 -0.484700 0.6283	0.029144 0.495651 0.6205	0.093808 1.601793 0.1103	-0.104539 -1.786954 0.0750	0.045230 0.769697 0.4421	1.000000 ----- -----	
NLPC9	-0.566061 -11.67330 0.0000	-0.066771 -1.137650 0.2562	-0.111176 -1.901779 0.0582	-0.032228 -0.548165 0.5840	0.608848 13.04750 0.0000	-0.154398 -2.656619 0.0083	-0.328179 -5.906146 0.0000	-0.276592 -4.892952 0.0000	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 48. *Correlation Matrix.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of daily returns.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
PC1	1.000000								

PC2	5.14E-15	1.000000							
	1.93E-13	-----							
	1.0000	-----							
PC3	-1.32E-16	8.67E-15	1.000000						
	-4.94E-15	3.25E-13	-----						
	1.0000	1.0000	-----						
PC4	-2.19E-16	-4.61E-17	5.30E-17	1.000000					
	-8.21E-15	-1.73E-15	1.99E-15	-----					
	1.0000	1.0000	1.0000	-----					
PC5	1.80E-16	4.55E-16	2.77E-16	-5.93E-16	1.000000				
	6.77E-15	1.71E-14	1.04E-14	-2.22E-14	-----				
	1.0000	1.0000	1.0000	1.0000	-----				
PC6	6.88E-16	1.32E-16	1.74E-16	-2.07E-16	-1.36E-16	1.000000			
	2.58E-14	4.96E-15	6.52E-15	-7.78E-15	-5.12E-15	-----			
	1.0000	1.0000	1.0000	1.0000	1.0000	-----			
PC7	-2.90E-16	-1.79E-17	-1.18E-17	-8.54E-17	2.44E-16	3.96E-17	1.000000		
	-1.09E-14	-6.70E-16	-4.43E-16	-3.21E-15	9.15E-15	1.49E-15	-----		
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----		
PC8	1.21E-16	2.24E-16	1.44E-17	-1.62E-16	2.95E-16	-1.03E-17	-5.64E-16	1.000000	
	4.54E-15	8.40E-15	5.42E-16	-6.09E-15	1.11E-14	-3.88E-16	-2.11E-14	-----	
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----	
PC9	-1.23E-15	-1.37E-16	1.35E-16	-2.72E-16	4.19E-16	-6.76E-16	-6.57E-16	-7.06E-16	1.000000
	-4.63E-14	-5.15E-15	5.08E-15	-1.02E-14	1.57E-14	-2.54E-14	-2.47E-14	-2.65E-14	-----
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 49. *Correlation Matrix.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of daily returns.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1.000000								

F2	-1.48E-14	1.000000							
	-5.55E-13	-----							
	1.0000	-----							
F3	4.49E-17	1.30E-16	1.000000						
	1.69E-15	4.88E-15	-----						
	1.0000	1.0000	-----						
F4	1.53E-16	3.48E-16	-6.10E-15	1.000000					
	5.76E-15	1.31E-14	-2.29E-13	-----					
	1.0000	1.0000	1.0000	-----					
F5	-1.48E-16	-2.75E-16	-8.59E-17	1.11E-15	1.000000				
	-5.56E-15	-1.03E-14	-3.22E-15	4.17E-14	-----				
	1.0000	1.0000	1.0000	1.0000	-----				
F6	5.20E-17	2.57E-16	-1.15E-16	5.67E-16	-1.11E-15	1.000000			
	1.95E-15	9.65E-15	-4.33E-15	2.13E-14	-4.17E-14	-----			
	1.0000	1.0000	1.0000	1.0000	1.0000	-----			
F7	-1.61E-16	-1.63E-16	2.36E-17	-1.58E-18	1.10E-15	-5.63E-16	1.000000		
	-6.03E-15	-6.11E-15	8.84E-16	-5.92E-17	4.13E-14	-2.11E-14	-----		
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----		
F8	-5.46E-17	6.96E-17	-1.55E-16	2.46E-16	5.20E-16	-2.19E-16	-1.40E-15	1.000000	
	-2.05E-15	2.61E-15	-5.83E-15	9.25E-15	1.95E-14	-8.20E-15	-5.24E-14	-----	
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----	
F9	2.22E-16	-8.37E-17	5.51E-16	1.90E-16	4.97E-16	-1.09E-15	-3.38E-16	6.86E-16	1.000000
	8.33E-15	-3.14E-15	2.07E-14	7.12E-15	1.87E-14	-4.09E-14	-1.27E-14	2.57E-14	-----
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 50. *Correlation Matrix.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of daily returns.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
IC1	1.000000 ----- -----								
IC2	-0.001171 -0.043957 0.9649	1.000000 ----- -----							
IC3	-0.000179 -0.006728 0.9946	-0.001162 -0.043609 0.9652	1.000000 ----- -----						
IC4	0.000141 0.005287 0.9958	0.000913 0.034266 0.9727	0.000140 0.005245 0.9958	1.000000 ----- -----					
IC5	0.000784 0.029413 0.9765	0.005080 0.190632 0.8488	0.000778 0.029180 0.9767	-0.000611 -0.022929 0.9817	1.000000 ----- -----				
IC6	0.000165 0.006180 0.9951	0.001067 0.040051 0.9681	0.000163 0.006131 0.9951	-0.000128 -0.004817 0.9962	-0.000714 -0.026799 0.9786	1.000000 ----- -----			
IC7	0.000220 0.008262 0.9934	0.001427 0.053549 0.9573	0.000218 0.008197 0.9935	-0.000172 -0.006441 0.9949	-0.000955 -0.035831 0.9714	-0.000201 -0.007528 0.9940	1.000000 ----- -----		
IC8	0.000118 0.004438 0.9965	0.000767 0.028763 0.9771	0.000117 0.004403 0.9965	-9.22E-05 -0.003460 0.9972	-0.000513 -0.019246 0.9846	-0.000108 -0.004044 0.9968	-0.000144 -0.005406 0.9957	1.000000 ----- -----	
IC9	0.000338 0.012679 0.9899	0.002190 0.082177 0.9345	0.000335 0.012579 0.9900	-0.000263 -0.009884 0.9921	-0.001465 -0.054987 0.9562	-0.000308 -0.011553 0.9908	-0.000412 -0.015446 0.9877	-0.000221 -0.008297 0.9934	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 51. *Correlation Matrix.*

Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.

Database of daily returns.

Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
NLPC1	1.000000 ----- -----								
NLPC2	0.006846 0.256904 0.7973	1.000000 ----- -----							
NLPC3	-0.011131 -0.417697 0.6762	0.009930 0.372634 0.7095	1.000000 ----- -----						
NLPC4	-0.004152 -0.155788 0.8762	0.001389 0.052125 0.9584	0.005626 0.211104 0.8328	1.000000 ----- -----					
NLPC5	0.001019 0.038241 0.9695	0.000724 0.027163 0.9783	0.002434 0.091345 0.9272	0.000349 0.013112 0.9895	1.000000 ----- -----				
NLPC6	-0.002984 -0.111962 0.9109	-0.000808 -0.030316 0.9758	-0.000312 -0.011706 0.9907	-0.001940 -0.072785 0.9420	0.007762 0.291250 0.7709	1.000000 ----- -----			
NLPC7	-0.008100 -0.303967 0.7612	-0.005810 -0.217998 0.8275	0.006042 0.226721 0.8207	-0.003105 -0.116499 0.9073	0.002493 0.093561 0.9255	-0.029730 -1.116077 0.2646	1.000000 ----- -----		
NLPC8	0.000494 0.018525 0.9852	-0.002052 -0.076986 0.9386	-0.004535 -0.170187 0.8649	-0.012528 -0.470125 0.6383	0.008983 0.337096 0.7361	0.001942 0.072852 0.9419	-0.022507 -0.844746 0.3984	1.000000 ----- -----	
NLPC9	-0.772205 -45.60420 0.0000	0.035355 1.327462 0.1846	0.106552 4.021086 0.0001	0.252924 9.809512 0.0000	0.006187 0.232178 0.8164	-0.332129 -13.21260 0.0000	0.456862 19.27182 0.0000	-0.128653 -4.867934 0.0000	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 52. *Correlation Matrix.*
Underlying systematic risk factors extracted by Principal Component Analysis.
Database of daily excesses.
Nine components estimated.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
PC1	1.000000								

PC2	1.30E-14	1.000000							
	4.89E-13	-----							
	1.0000	-----							
PC3	2.43E-16	1.27E-14	1.000000						
	9.13E-15	4.77E-13	-----						
	1.0000	1.0000	-----						
PC4	-5.05E-16	-2.24E-16	-2.91E-16	1.000000					
	-1.89E-14	-8.39E-15	-1.09E-14	-----					
	1.0000	1.0000	1.0000	-----					
PC5	-7.91E-17	8.17E-17	3.32E-17	-2.16E-16	1.000000				
	-2.97E-15	3.07E-15	1.25E-15	-8.11E-15	-----				
	1.0000	1.0000	1.0000	1.0000	-----				
PC6	1.07E-16	-3.28E-16	-2.88E-17	-3.26E-16	6.20E-16	1.000000			
	4.02E-15	-1.23E-14	-1.08E-15	-1.22E-14	2.33E-14	-----			
	1.0000	1.0000	1.0000	1.0000	1.0000	-----			
PC7	-5.34E-16	2.01E-16	-3.48E-16	1.23E-16	-3.38E-16	3.96E-17	1.000000		
	-2.00E-14	7.53E-15	-1.30E-14	4.61E-15	-1.27E-14	1.49E-15	-----		
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----		
PC8	6.72E-17	3.59E-16	-1.84E-16	1.30E-17	3.53E-16	7.82E-16	3.14E-16	1.000000	
	2.52E-15	1.35E-14	-6.92E-15	4.87E-16	1.32E-14	2.94E-14	1.18E-14	-----	
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----	
PC9	4.61E-17	-2.20E-17	-1.87E-16	-1.31E-16	-8.26E-16	-6.05E-16	-3.28E-16	-8.66E-17	1.000000
	1.73E-15	-8.25E-16	-7.02E-15	-4.92E-15	-3.10E-14	-2.27E-14	-1.23E-14	-3.25E-15	-----
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 53. *Correlation Matrix.*
Underlying systematic risk factors extracted by Factor Analysis.
Database of daily excesses.
Nine factors estimated.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1.000000								

F2	-3.58E-15	1.000000							
	-1.34E-13	-----							
	1.0000	-----							
F3	1.57E-16	3.56E-16	1.000000						
	5.90E-15	1.33E-14	-----						
	1.0000	1.0000	-----						
F4	-4.89E-16	6.41E-16	-1.22E-14	1.000000					
	-1.83E-14	2.41E-14	-4.57E-13	-----					
	1.0000	1.0000	1.0000	-----					
F5	-4.86E-16	2.74E-16	-5.32E-17	3.04E-16	1.000000				
	-1.83E-14	1.03E-14	-2.00E-15	1.14E-14	-----				
	1.0000	1.0000	1.0000	1.0000	-----				
F6	4.27E-16	3.98E-16	1.46E-16	-8.79E-16	7.06E-16	1.000000			
	1.60E-14	1.49E-14	5.46E-15	-3.30E-14	2.65E-14	-----			
	1.0000	1.0000	1.0000	1.0000	1.0000	-----			
F7	-5.83E-16	7.78E-16	4.03E-16	-3.92E-16	5.67E-16	-2.57E-16	1.000000		
	-2.19E-14	2.92E-14	1.51E-14	-1.47E-14	2.13E-14	-9.64E-15	-----		
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----		
F8	-1.00E-17	5.55E-16	-9.43E-17	3.51E-16	5.94E-16	1.49E-16	-1.56E-16	1.000000	
	-3.76E-16	2.08E-14	-3.54E-15	1.32E-14	2.23E-14	5.60E-15	-5.84E-15	-----	
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----	
F9	-7.14E-17	-5.80E-17	3.52E-16	-1.97E-16	8.03E-16	1.09E-17	1.11E-16	-1.04E-15	1.000000
	-2.68E-15	-2.18E-15	1.32E-14	-7.39E-15	3.01E-14	4.10E-16	4.16E-15	-3.90E-14	-----
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 54. *Correlation Matrix.*
Underlying systematic risk factors extracted by Independent Component Analysis.
Database of daily excesses.
Nine components estimated.

	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9
IC1	1.000000								

IC2	0.002000	1.000000							
	0.075057	-----							
	0.9402	-----							
IC3	-0.002931	0.001164	1.000000						
	-0.109975	0.043693	-----						
	0.9124	0.9652	-----						
IC4	0.001307	-0.000519	0.000761	1.000000					
	0.049029	-0.019479	0.028541	-----					
	0.9609	0.9845	0.9772	-----					
IC5	0.001067	-0.000424	0.000621	-0.000277	1.000000				
	0.040019	-0.015899	0.023296	-0.010386	-----				
	0.9681	0.9873	0.9814	0.9917	-----				
IC6	0.000332	-0.000132	0.000193	-8.61E-05	-7.03E-05	1.000000			
	0.012446	-0.004945	0.007245	-0.003230	-0.002636	-----			
	0.9901	0.9961	0.9942	0.9974	0.9979	-----			
IC7	-0.000299	0.000119	-0.000174	7.76E-05	6.33E-05	1.97E-05	1.000000		
	-0.011213	0.004455	-0.006527	0.002910	0.002375	0.000739	-----		
	0.9911	0.9964	0.9948	0.9977	0.9981	0.9994	-----		
IC8	-0.003648	0.001449	-0.002124	0.000947	0.000773	0.000240	-0.000217	1.000000	
	-0.136885	0.054384	-0.079684	0.035525	0.028996	0.009018	-0.008124	-----	
	0.8911	0.9566	0.9365	0.9717	0.9769	0.9928	0.9935	-----	
IC9	-0.001811	0.000720	-0.001054	0.000470	0.000384	0.000119	-0.000108	-0.001313	1.000000
	-0.067972	0.027005	-0.039568	0.017640	0.014398	0.004478	-0.004034	-0.049250	-----
	0.9458	0.9785	0.9684	0.9859	0.9885	0.9964	0.9968	0.9607	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 55. *Correlation Matrix.*
Underlying systematic risk factors extracted by Neural Networks Principal Component Analysis.
Database of daily excesses.
Nine components estimated.

	NLPC1	NLPC2	NLPC3	NLPC4	NLPC5	NLPC6	NLPC7	NLPC8	NLPC9
NLPC1	1.000000								

NLPC2	0.044574	1.000000							
	1.674222	-----							
	0.0943	-----							
NLPC3	-0.028272	-0.041707	1.000000						
	-1.061302	-1.566363	-----						
	0.2887	0.1175	-----						
NLPC4	0.041066	-0.021142	-0.012066	1.000000					
	1.542249	-0.793477	-0.452805	-----					
	0.1232	0.4276	0.6508	-----					
NLPC5	0.002983	-0.012726	0.008762	-0.034101	1.000000				
	0.111948	-0.477555	0.328778	-1.280309	-----				
	0.9109	0.6330	0.7424	0.2006	-----				
NLPC6	-0.016539	0.005358	0.051204	0.025883	-0.006191	1.000000			
	-0.620689	0.201069	1.923861	0.971548	-0.232309	-----			
	0.5349	0.8407	0.0546	0.3314	0.8163	-----			
NLPC7	-0.025707	-0.005844	0.010382	0.031880	0.038827	-0.059480	1.000000		
	-0.964945	-0.219295	0.389598	1.196861	1.458012	-2.235843	-----		
	0.3347	0.8265	0.6969	0.2316	0.1451	0.0255	-----		
NLPC8	-0.081394	0.016232	0.072651	-0.041117	-0.078575	0.155891	-0.094338	1.000000	
	-3.064326	0.609162	2.733342	-1.544167	-2.957556	5.921950	-3.555720	-----	
	0.0022	0.5425	0.0063	0.1228	0.0032	0.0000	0.0004	-----	
NLPC9	0.826611	0.153200	0.017111	-0.131789	-0.012831	-0.095547	0.307618	0.292922	1.000000
	55.11492	5.817254	0.642147	-4.988682	-0.481489	-3.601716	12.13109	11.49567	-----
	0.0000	0.0000	0.5209	0.0000	0.6302	0.0003	0.0000	0.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Appendix_2 (Chapter 7) **Figure 9.** *Plot of the underlying systematic risk factors extracted by Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

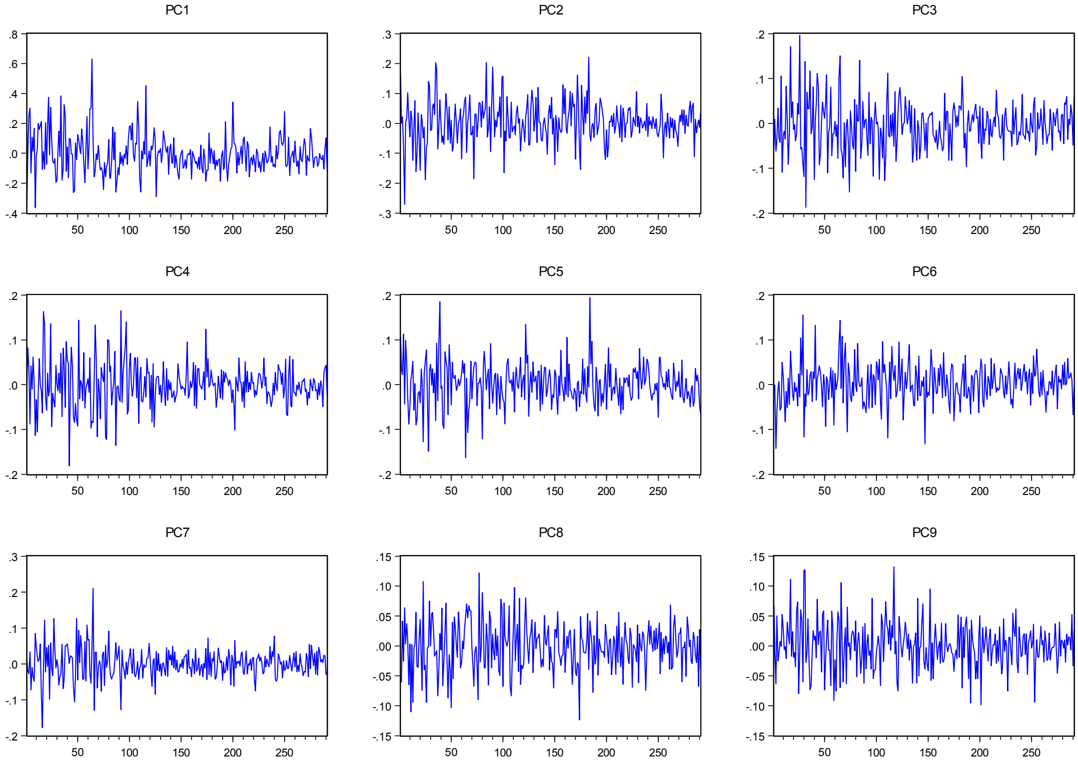


Figure 10. *Plot of the underlying systematic risk factors extracted by Factor Analysis. Database of weekly excesses. Nine factors estimated.*

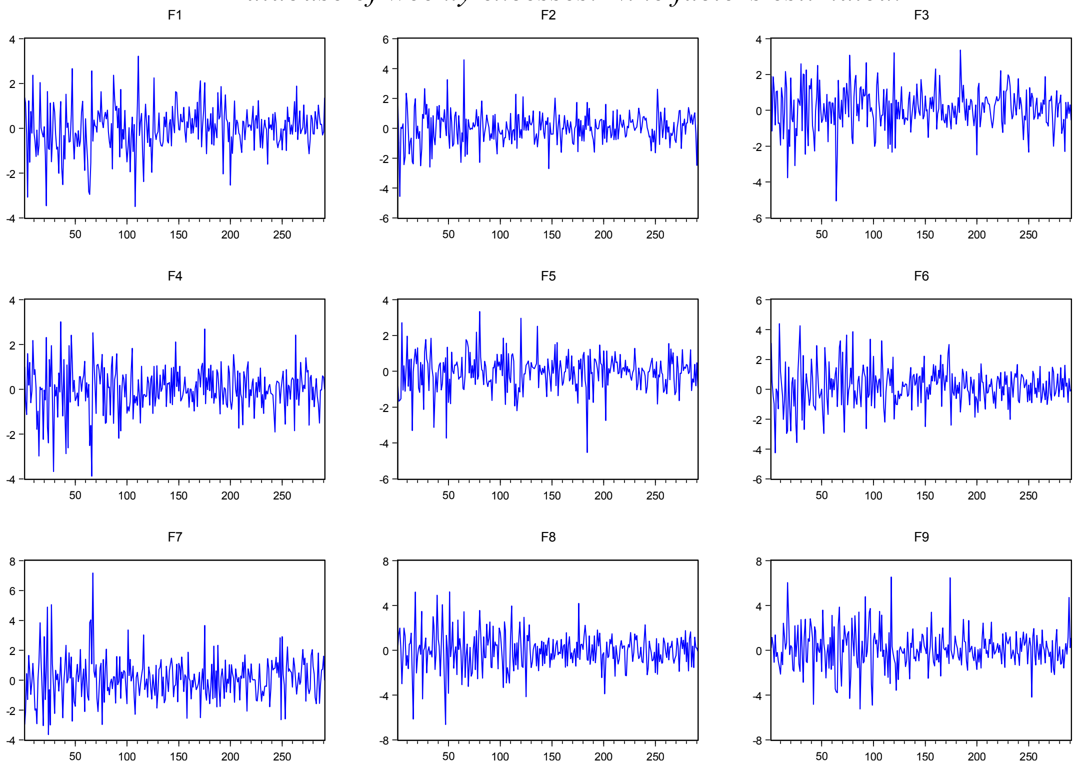


Figure 11. *Plot of the underlying systematic risk factors extracted by Independent Component Analysis. Database of weekly excesses. Nine components estimated.*

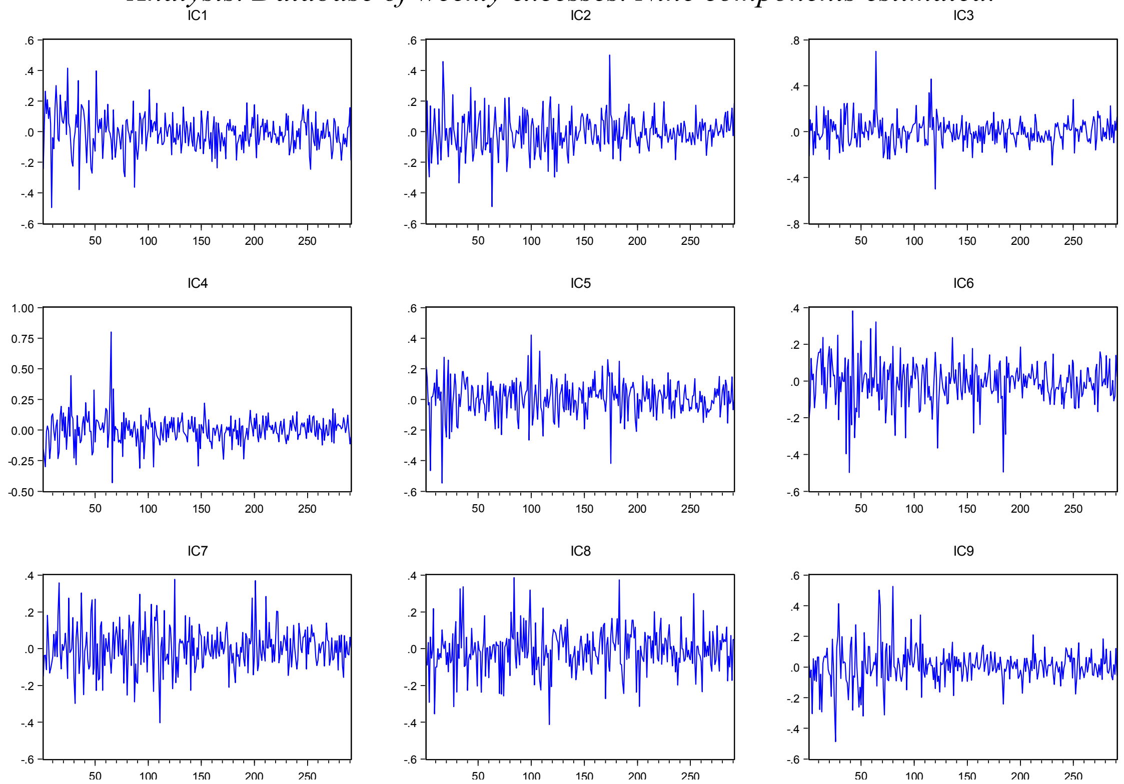


Figure 12. *Plot of the underlying systematic risk factors extracted by Neural Networks Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

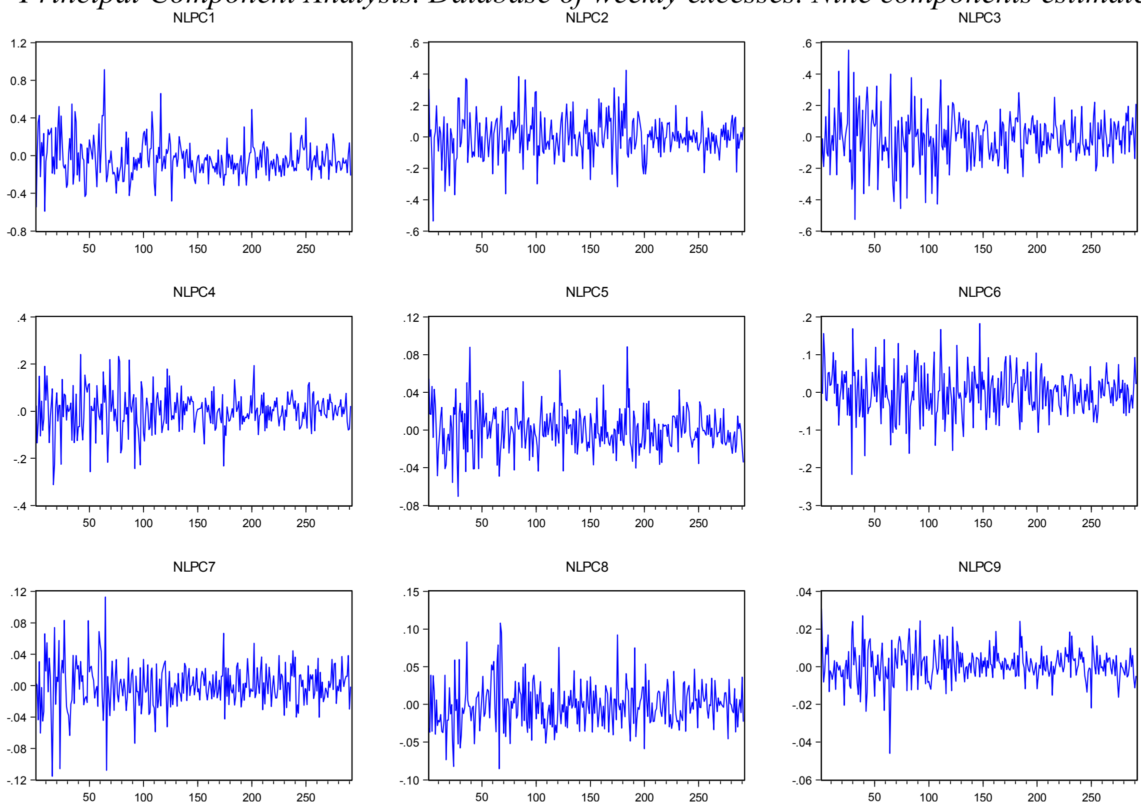


Figure 13. *Plot of the underlying systematic risk factors extracted by Principal Component Analysis. Database of daily returns. Nine components estimated.*

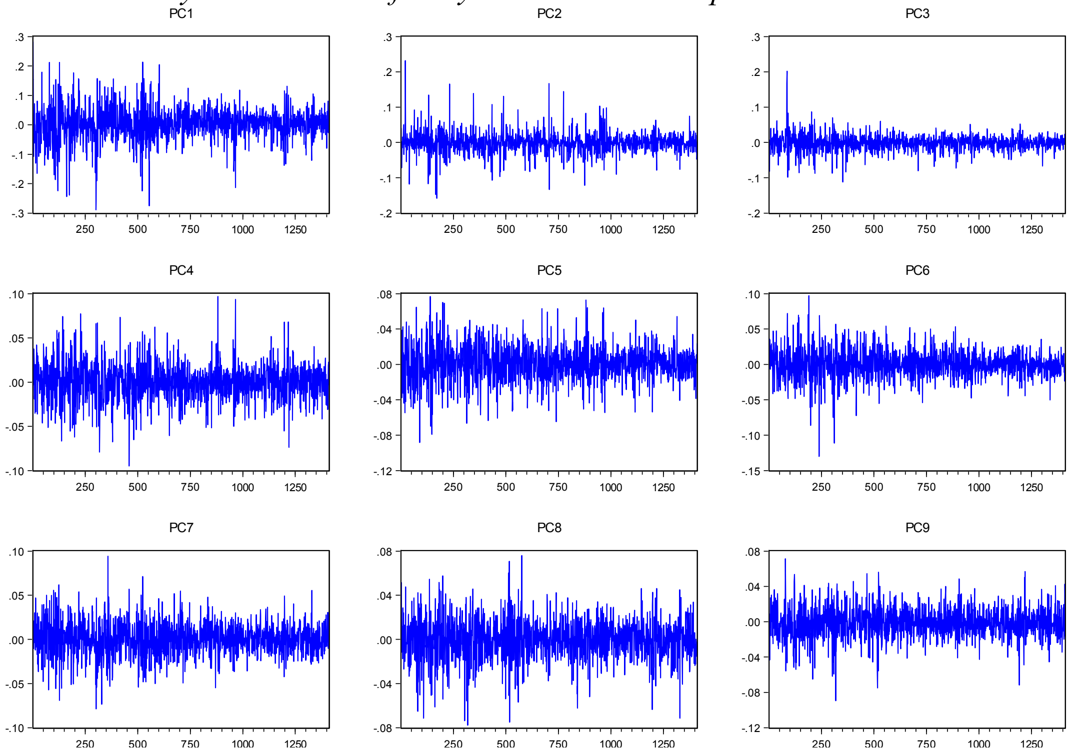


Figure 14. *Plot of the underlying systematic risk factors extracted by Factor Analysis. Database of daily returns. Nine factors estimated.*

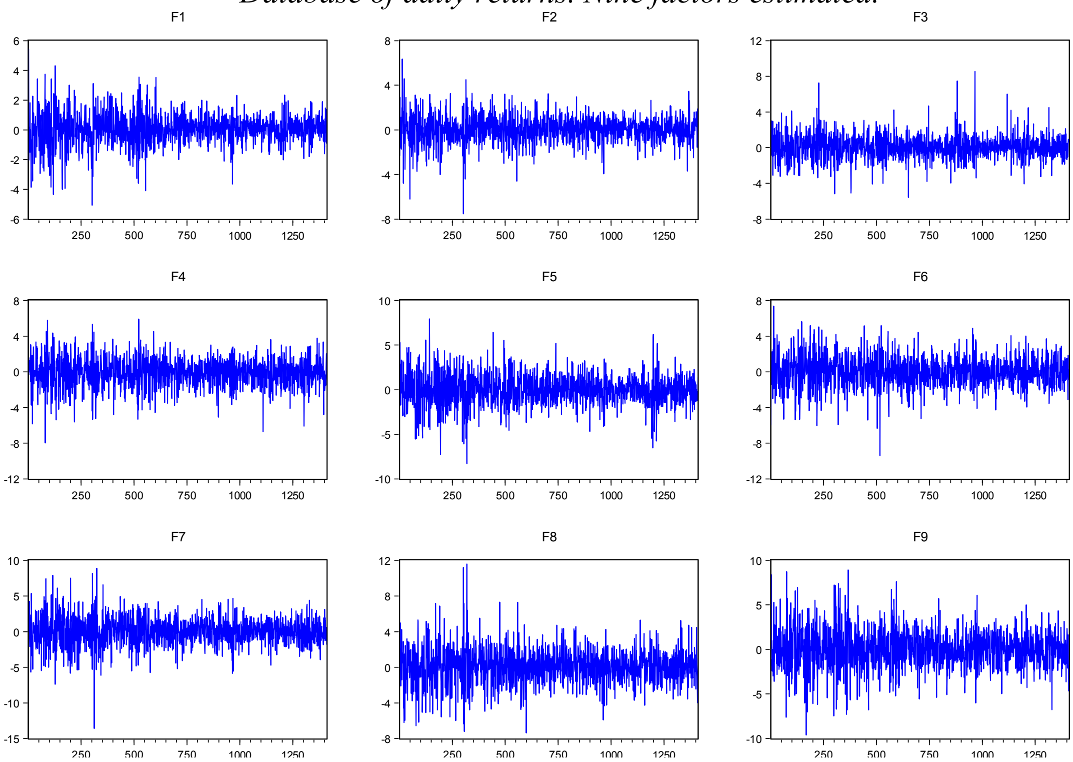


Figure 15. *Plot of the underlying systematic risk factors extracted by Independent Component Analysis. Database of daily returns. Nine components estimated.*

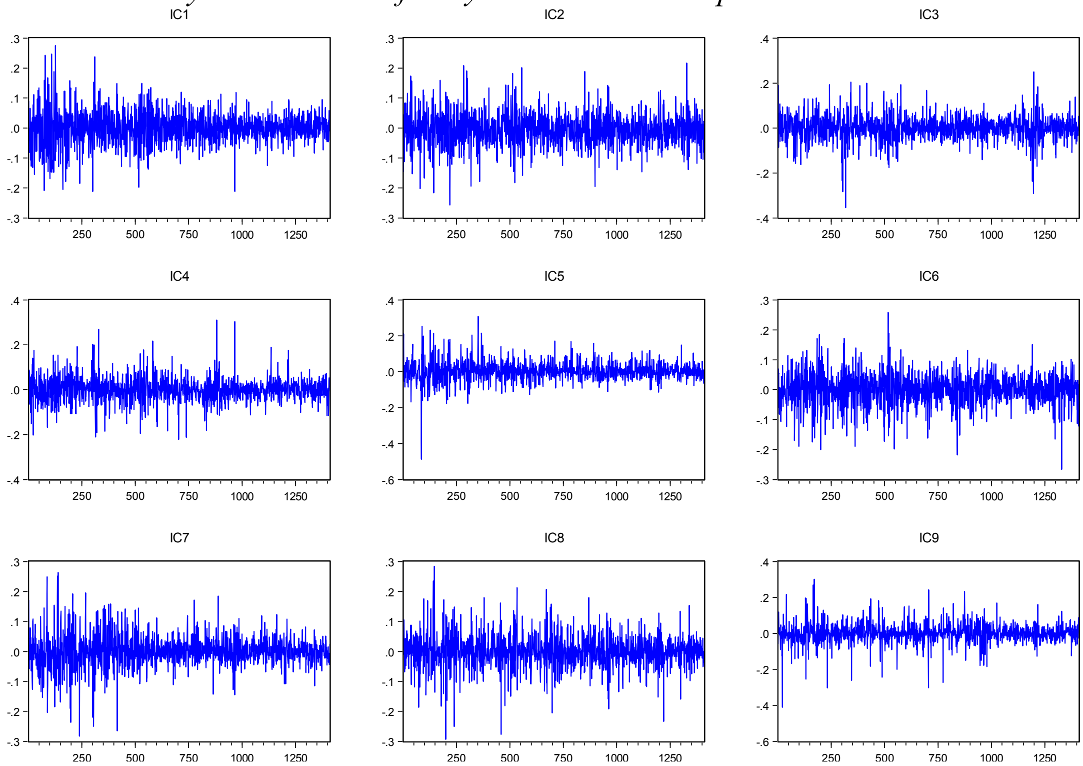


Figure 16. *Plot of the underlying systematic risk factors extracted by Neural Networks Principal Component Analysis. Database of daily returns. Nine components estimated.*

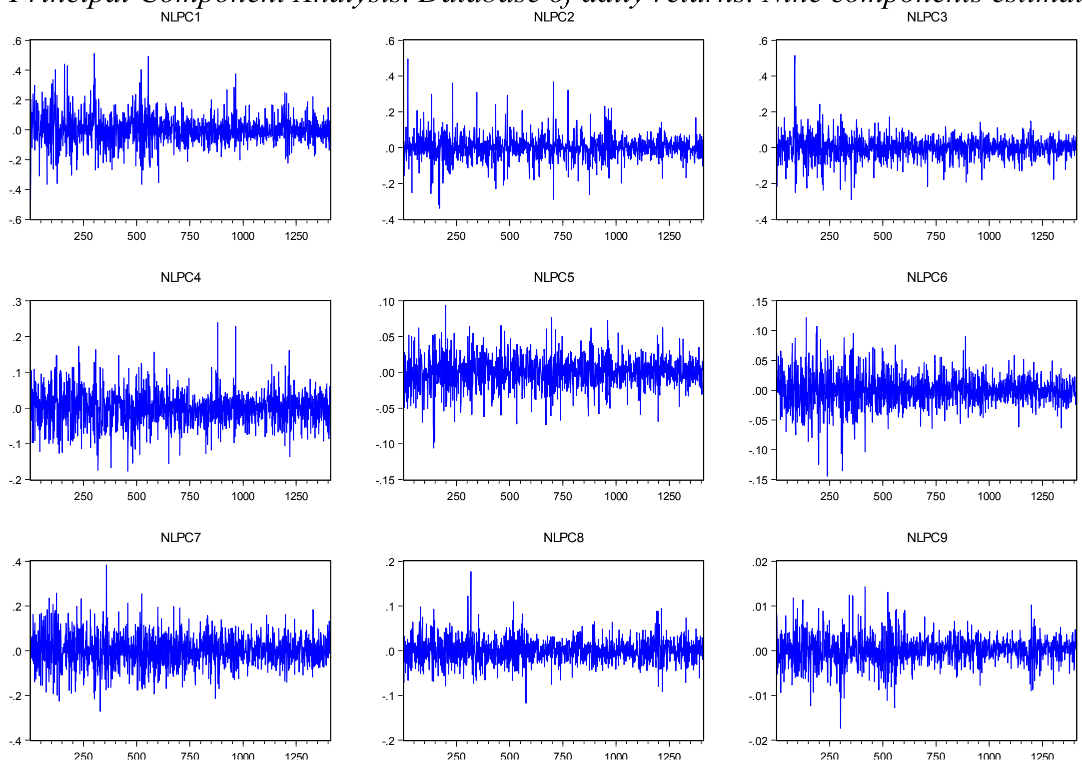


Figure 17. *Plot of the underlying systematic risk factors extracted by Principal Component Analysis. Database of daily excesses. Nine components estimated.*

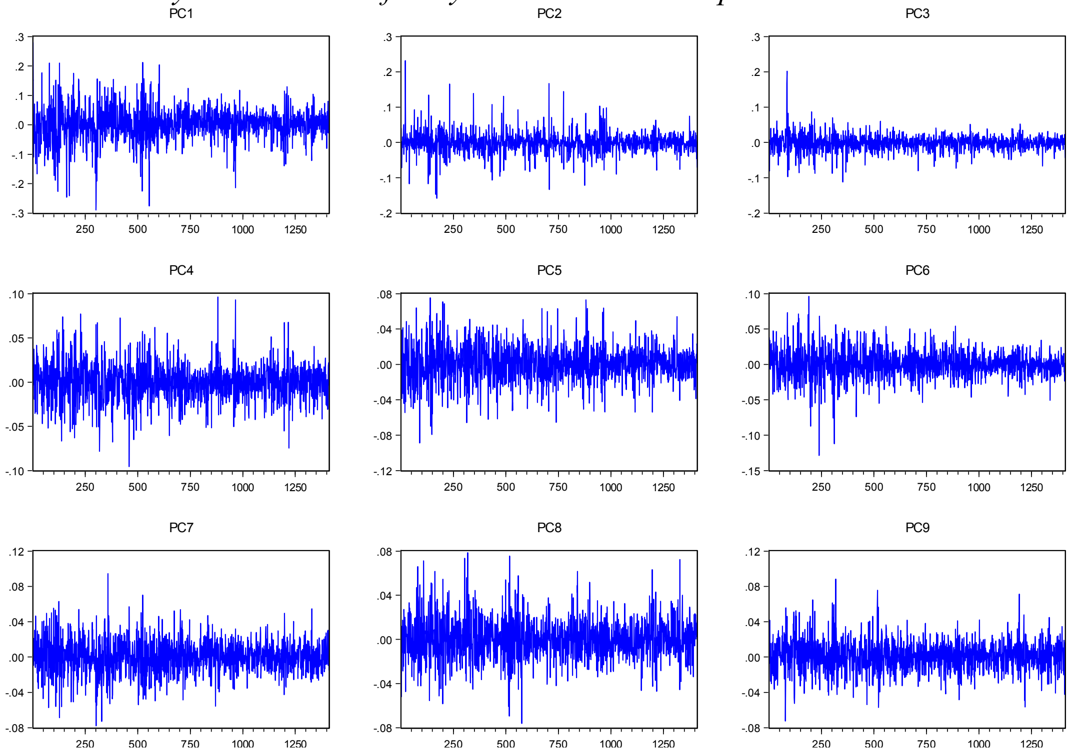


Figure 18. *Plot of the underlying systematic risk factors extracted by Factor Analysis. Database of daily excesses. Nine factors estimated.*

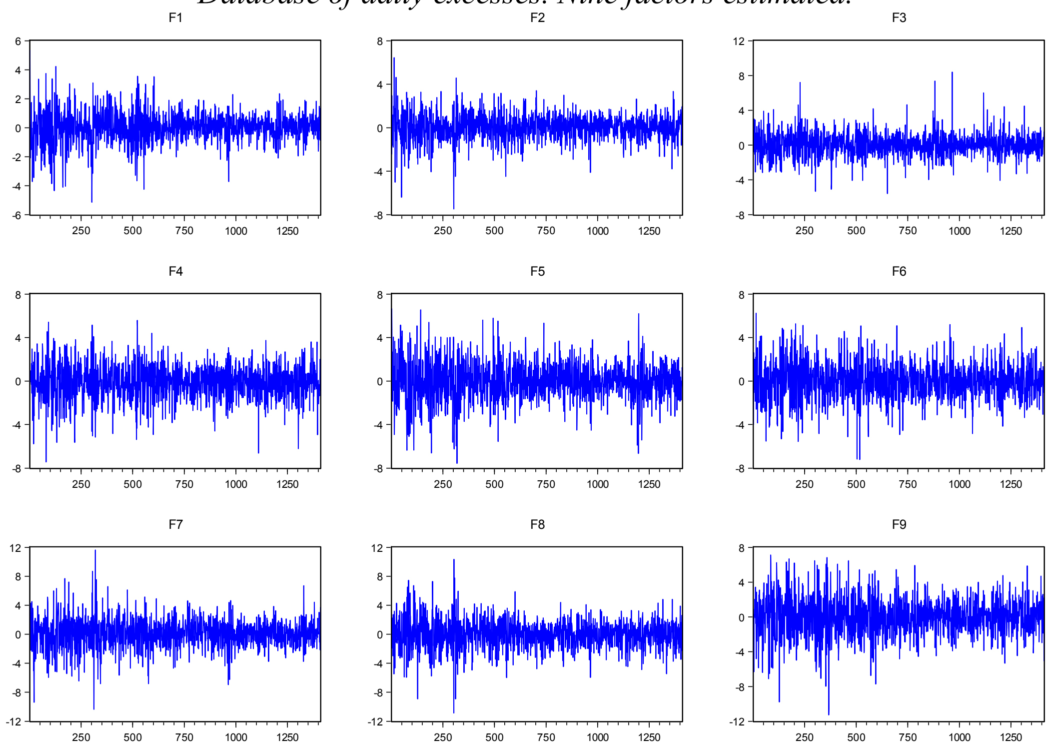


Figure 19. *Plot of the underlying systematic risk factors extracted by Independent Component Analysis. Database of daily excesses. Nine components estimated.*

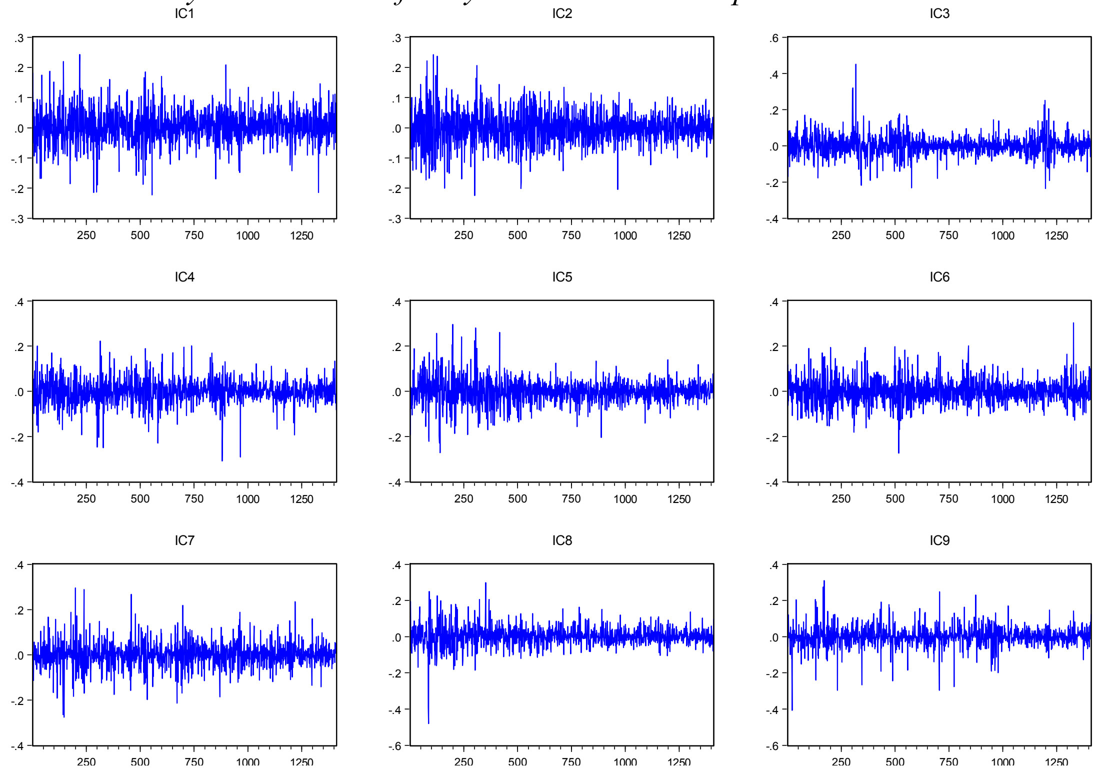


Figure 20. *Plot of the underlying systematic risk factors extracted by Neural Networks Principal Component Analysis. Database of daily excesses. Nine components estimated.*

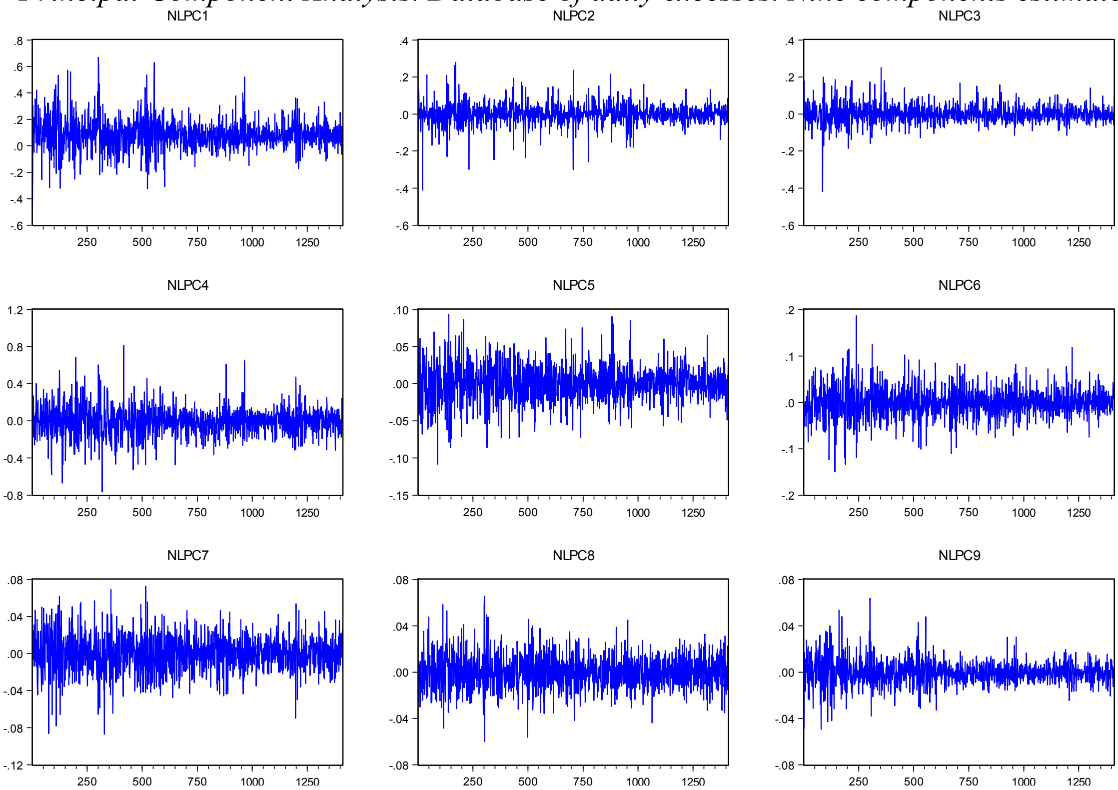


Figure 21. *First underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

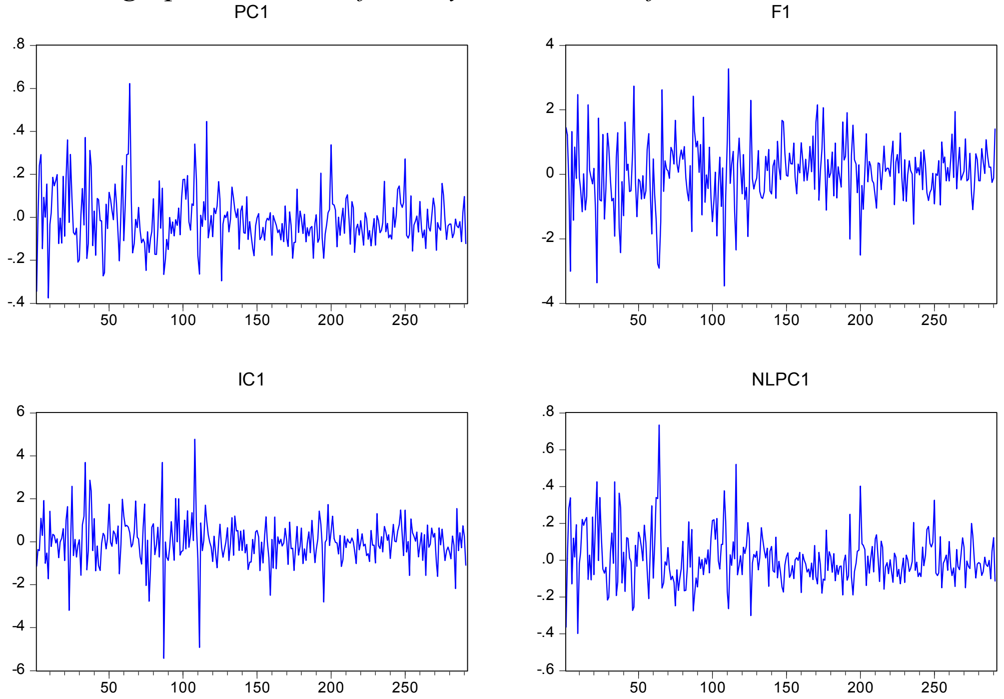


Figure 22. *Second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

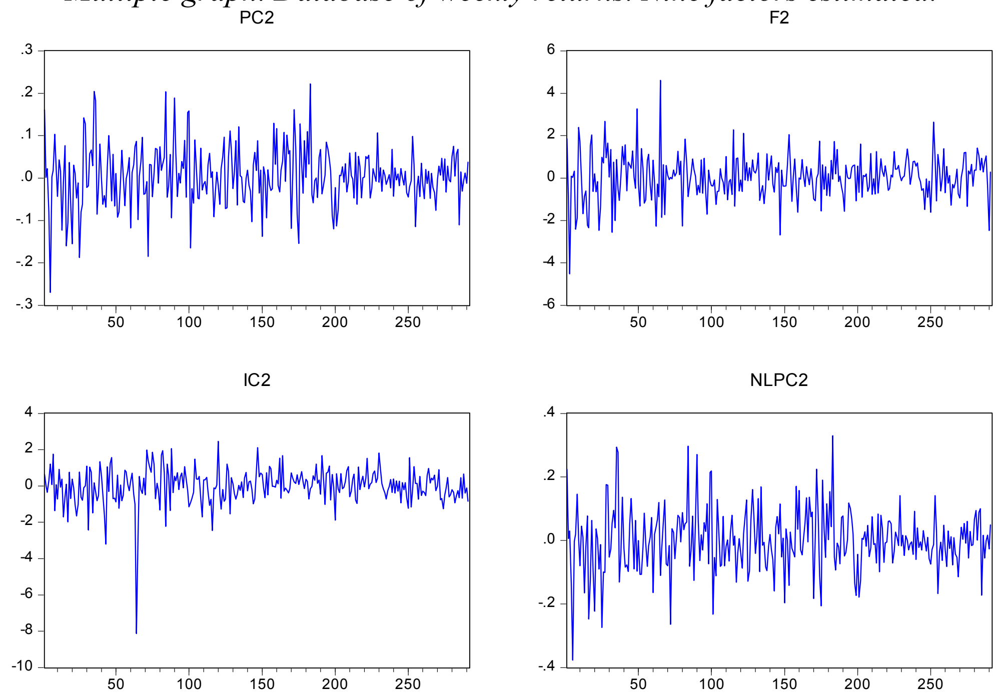


Figure 23. *Third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

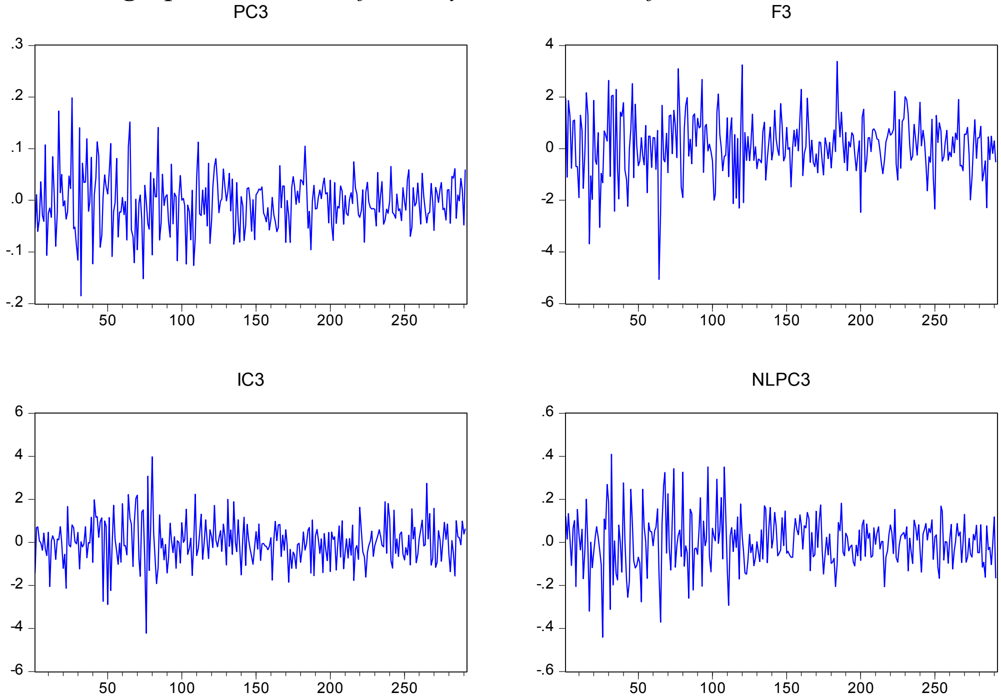


Figure 24. *Fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

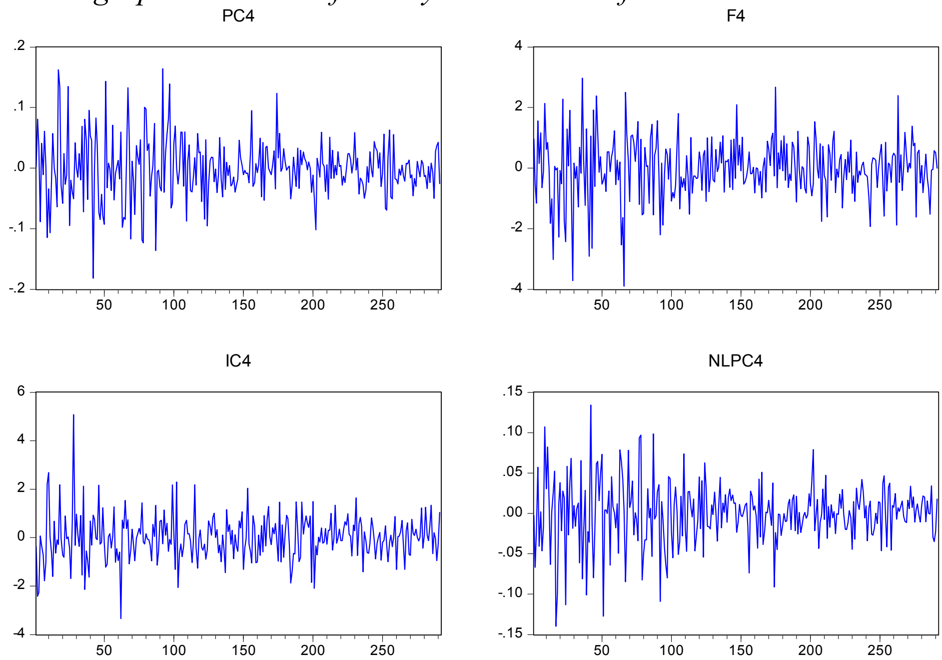


Figure 25. *Fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

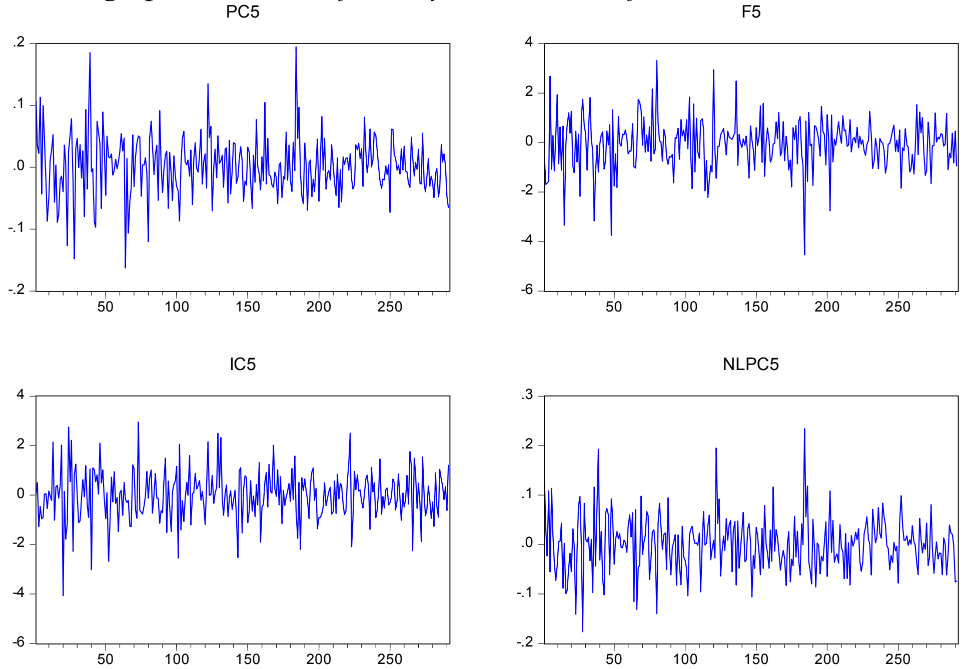


Figure 26. *Sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

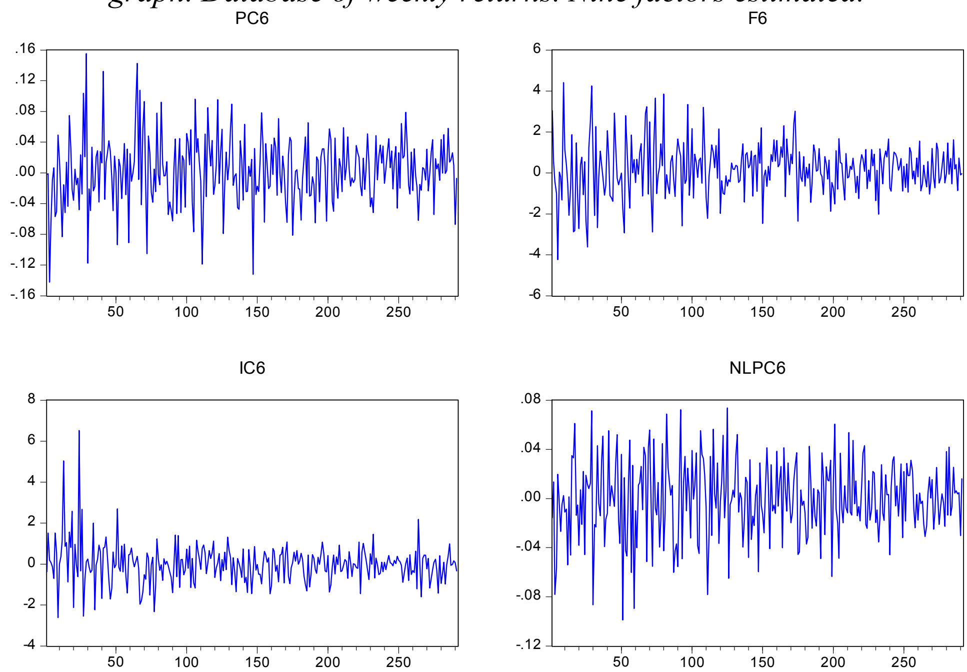


Figure 27. *Seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

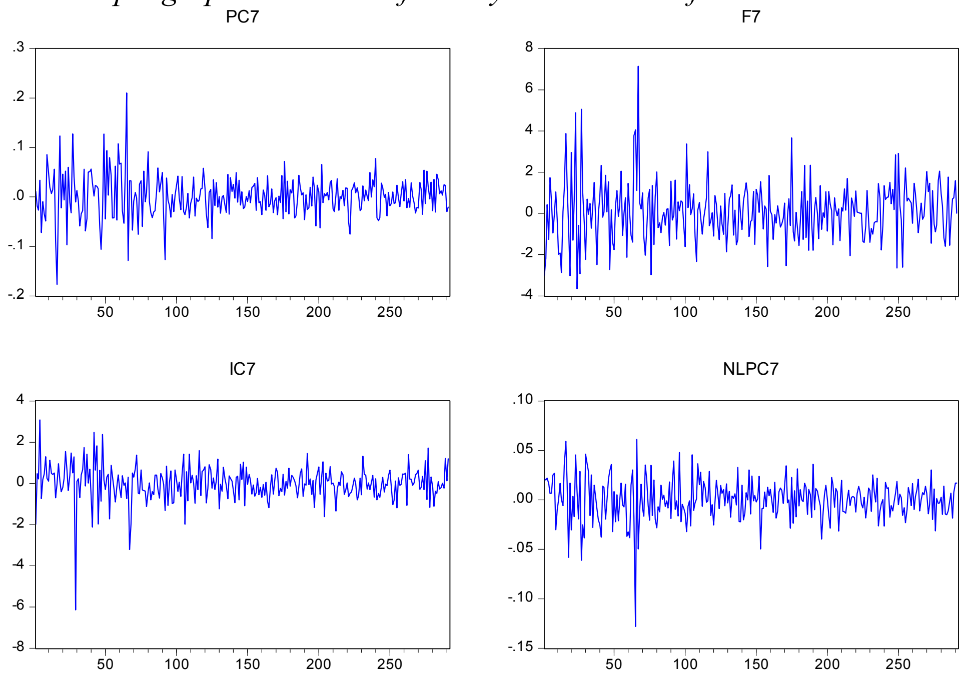


Figure 28. *Eight underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

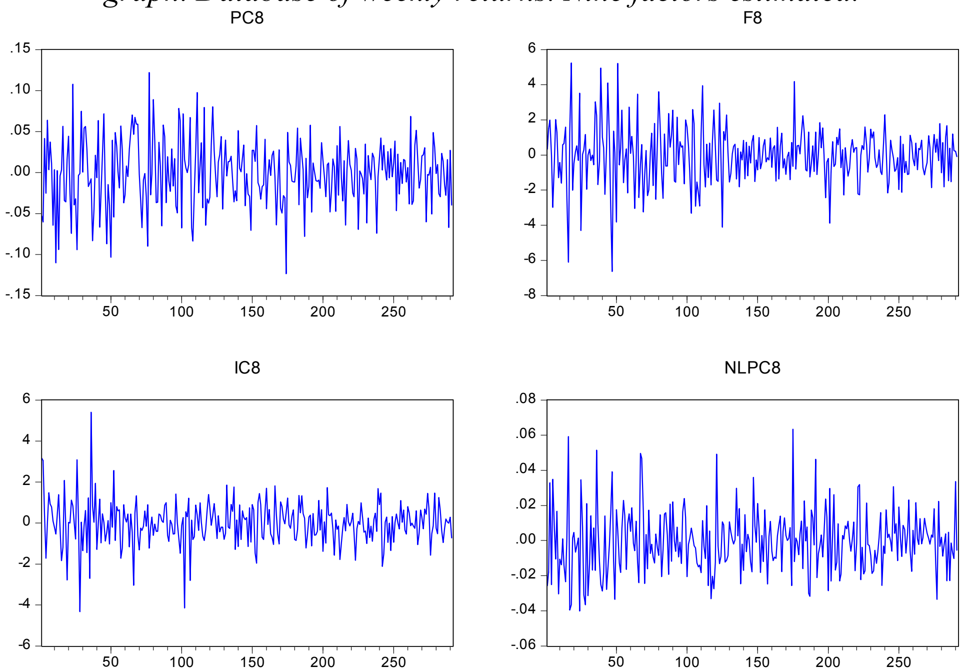


Figure 29. *Ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine factors estimated.*

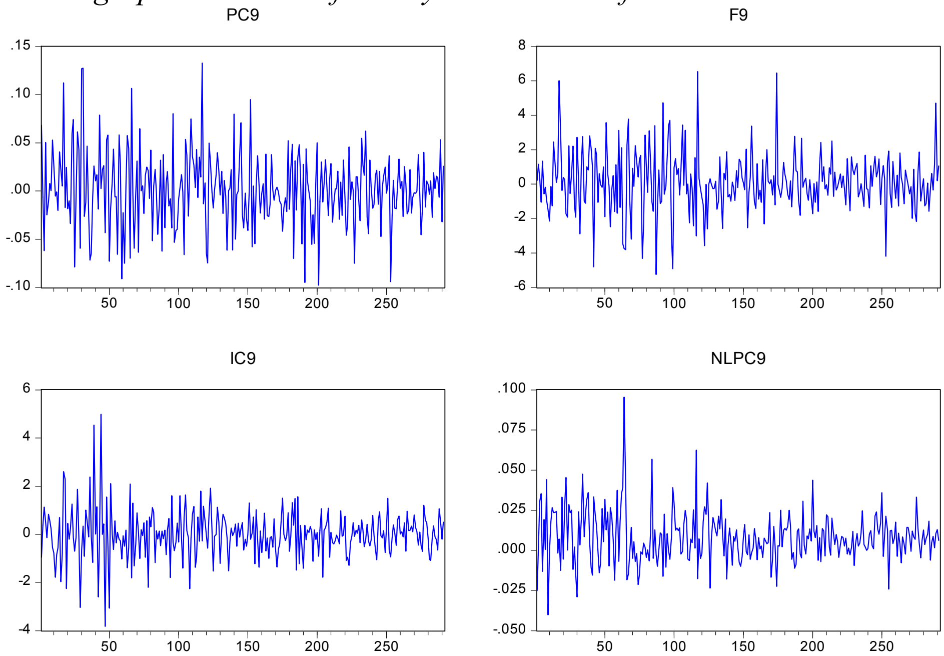


Figure 30. *First underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

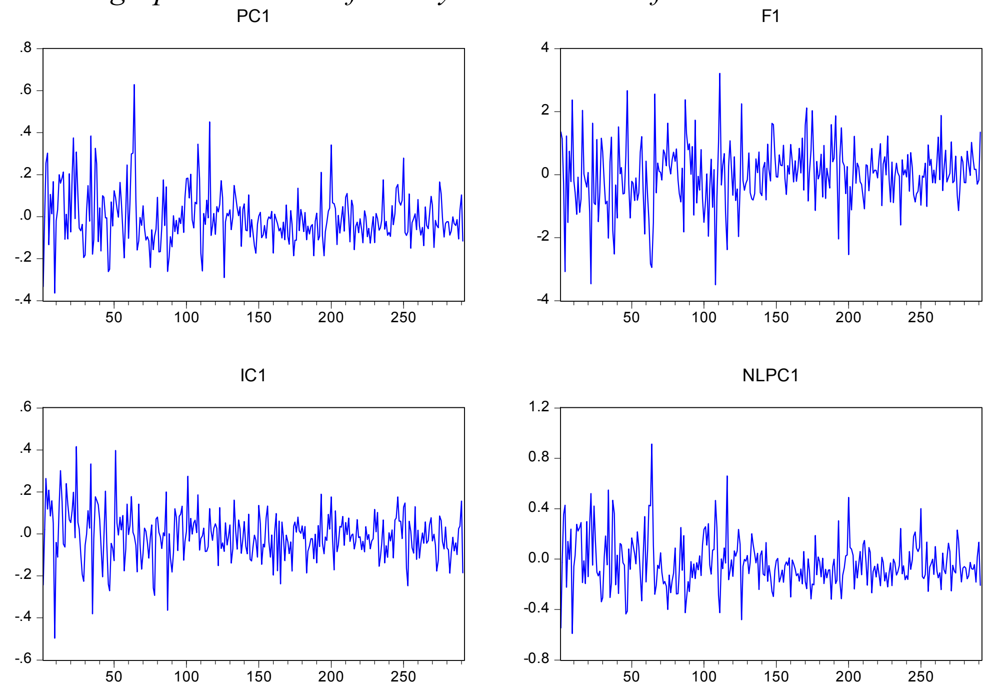


Figure 31. *Second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

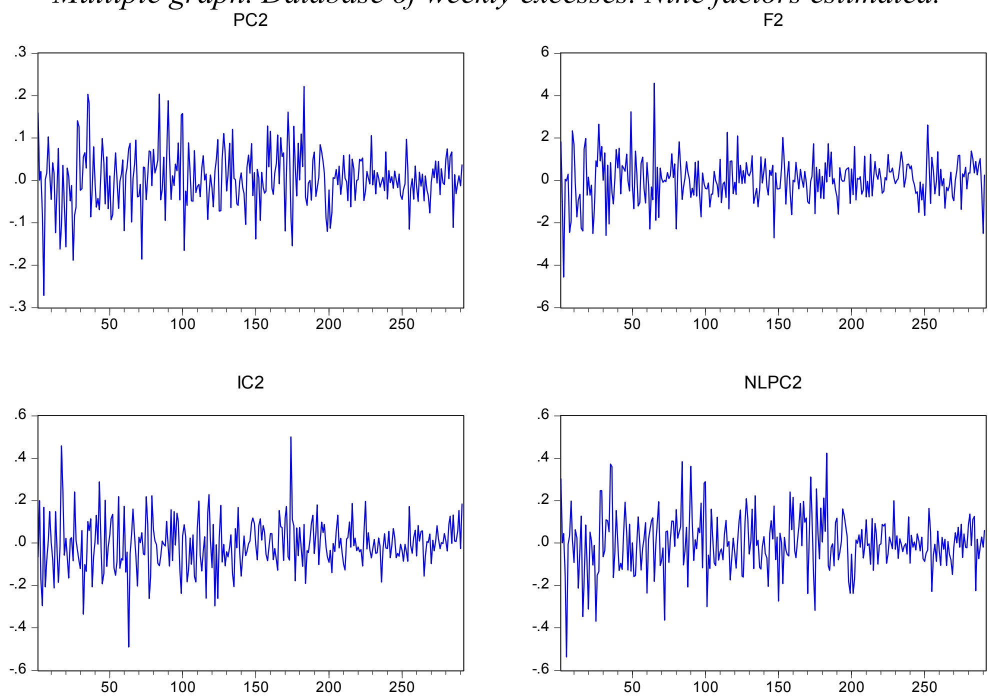


Figure 32. *Third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

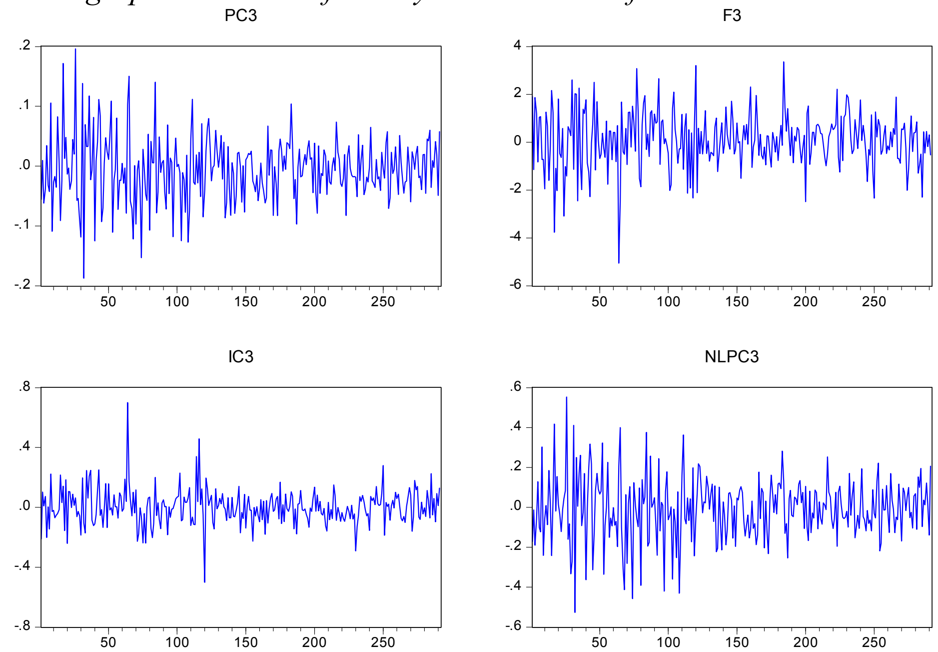


Figure 33. *Fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

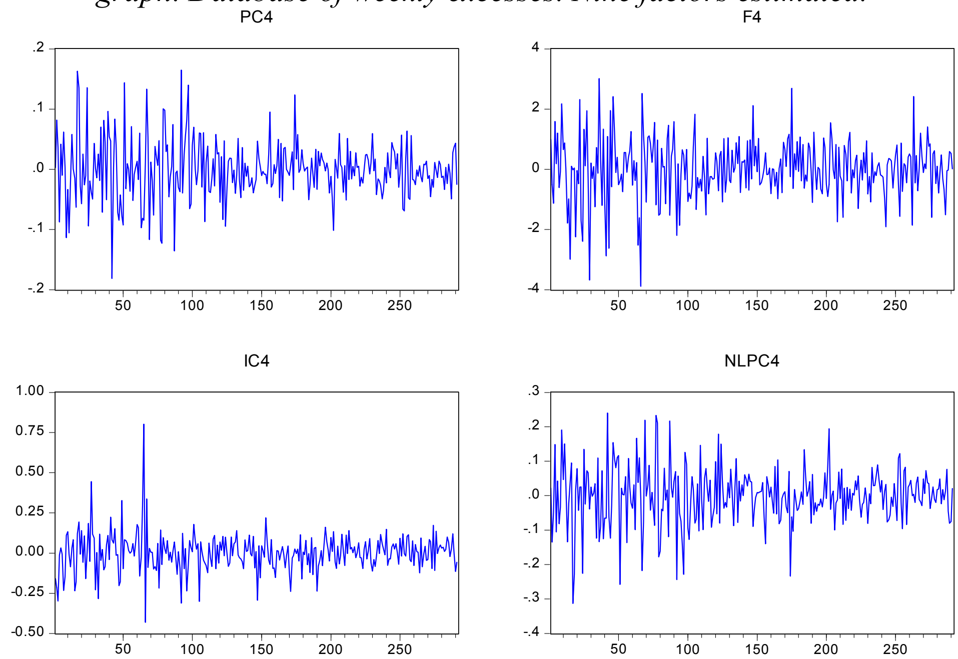


Figure 34. *Fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

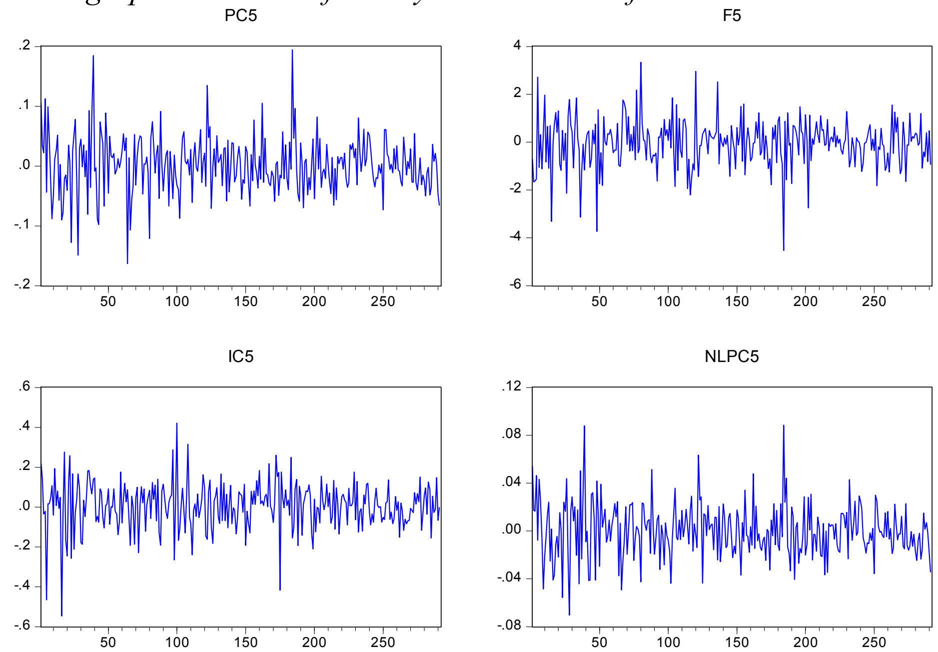


Figure 35. *Sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

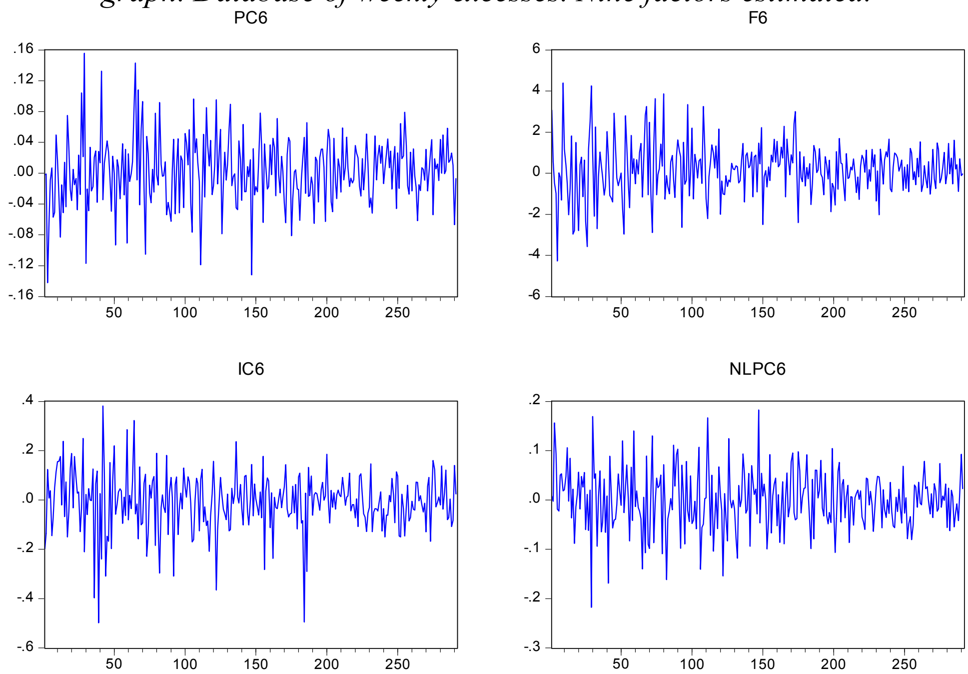


Figure 36. *Seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

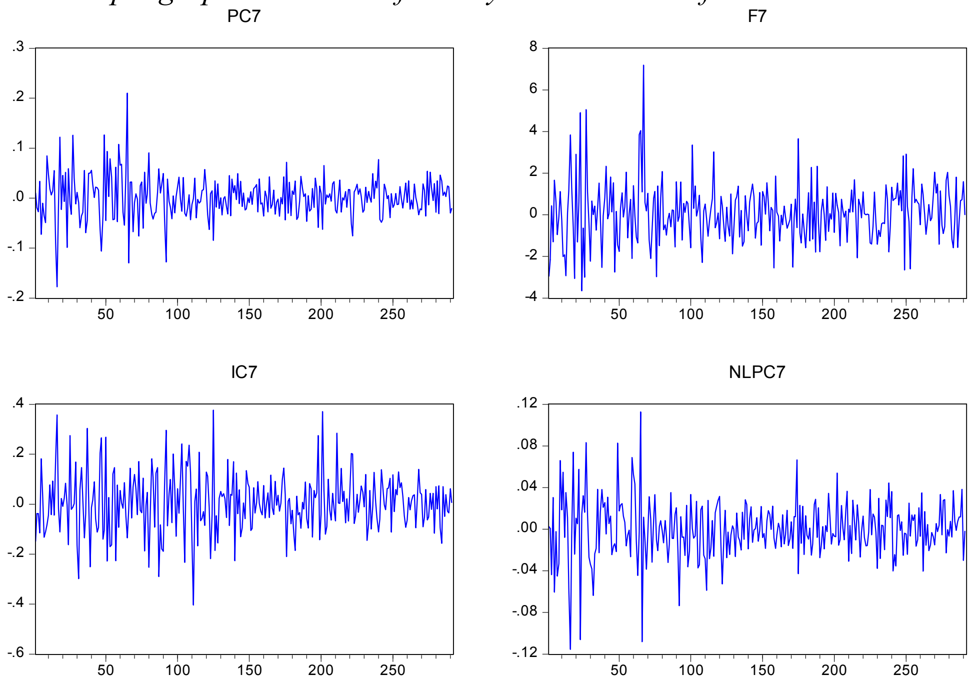


Figure 37. *Eighth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

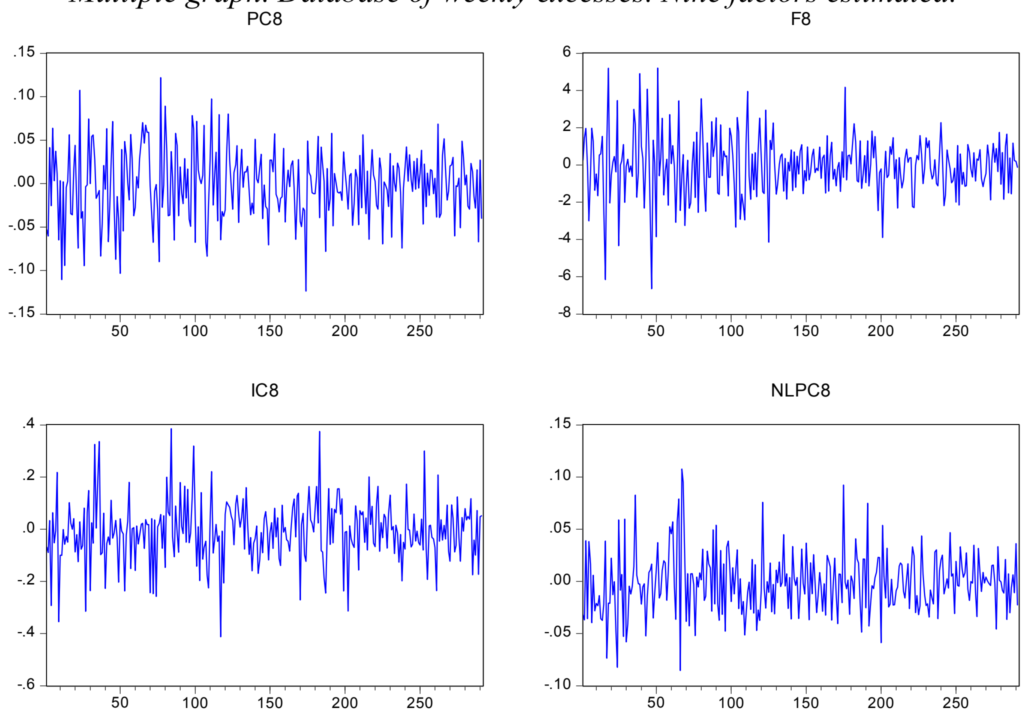


Figure 38. *Ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine factors estimated.*

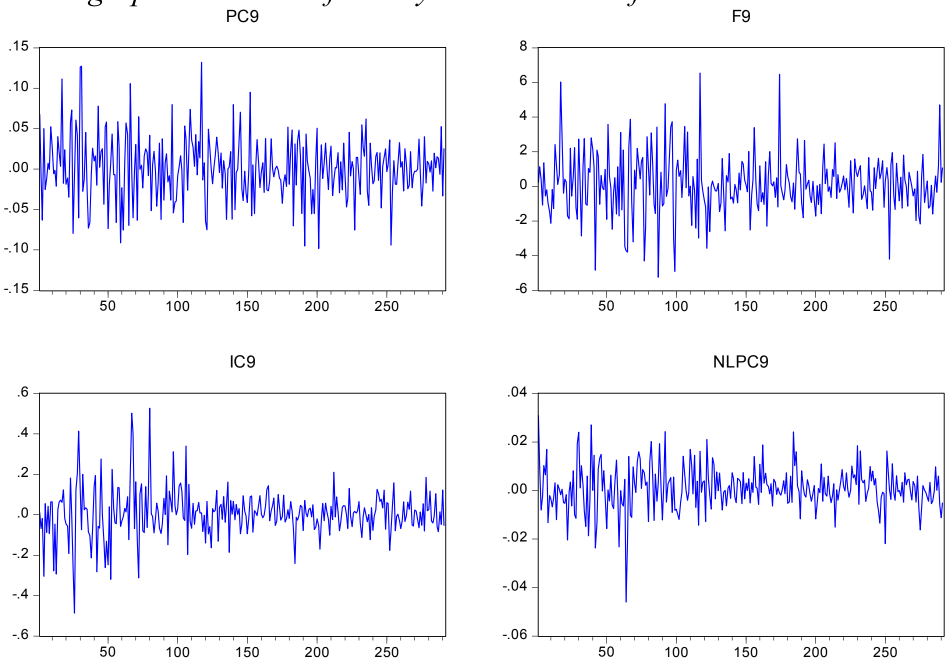


Figure 39. *First underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

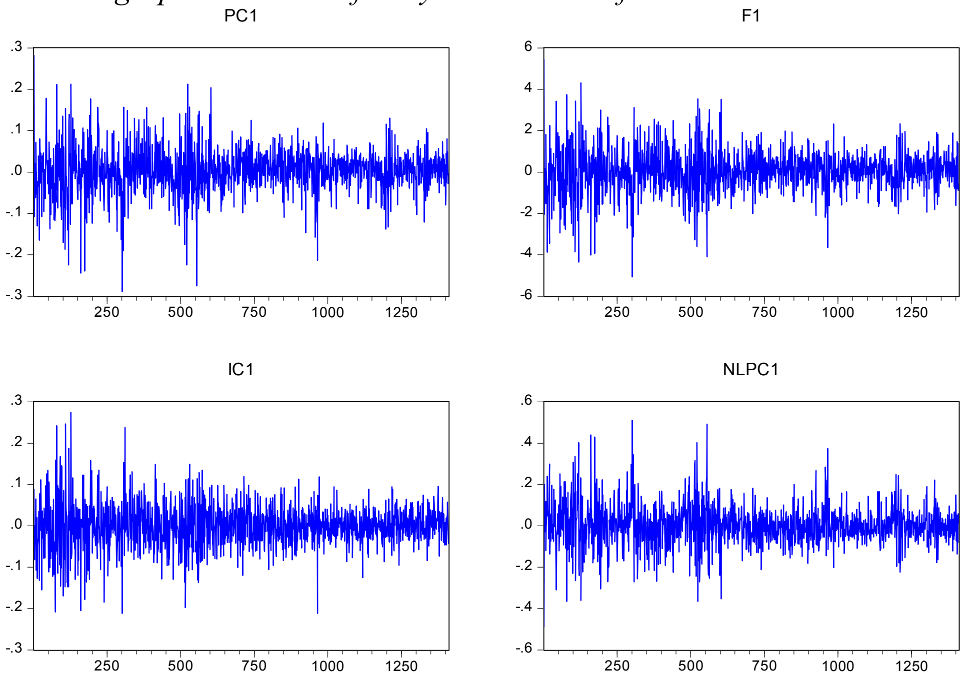


Figure 40. *Second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

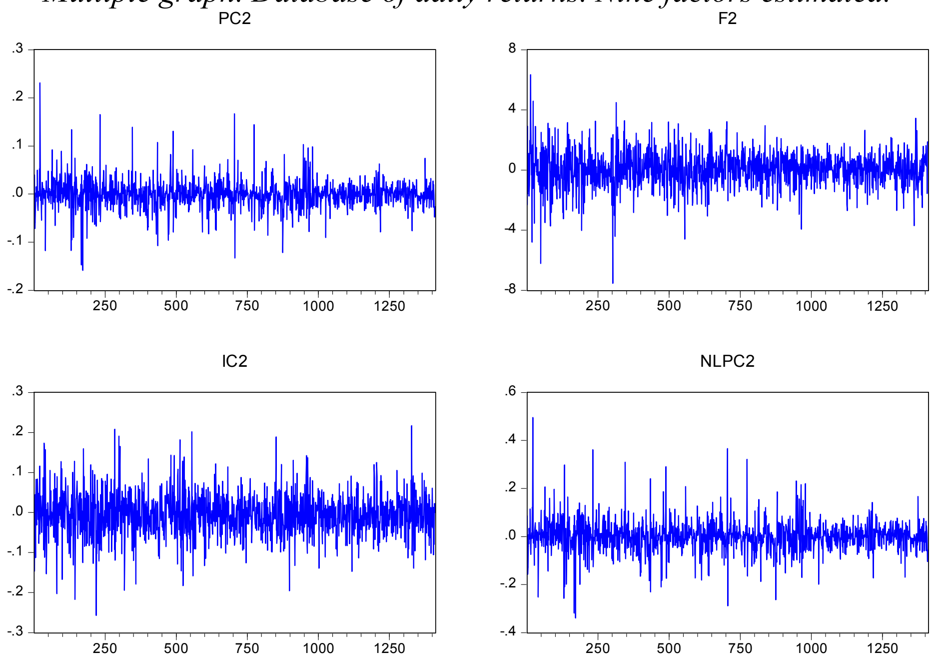


Figure 41. *Third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

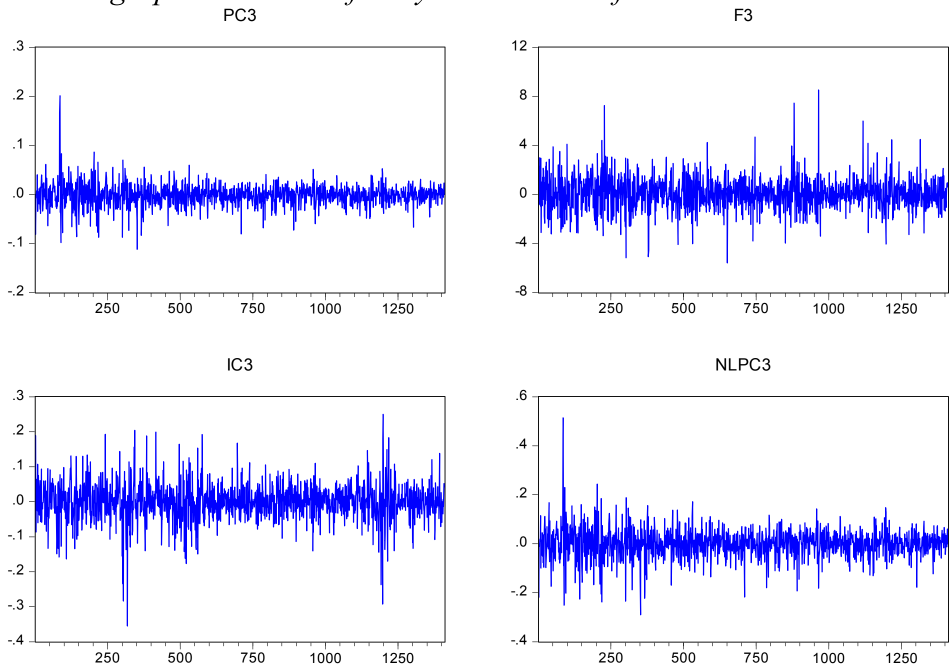


Figure 42. *Fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

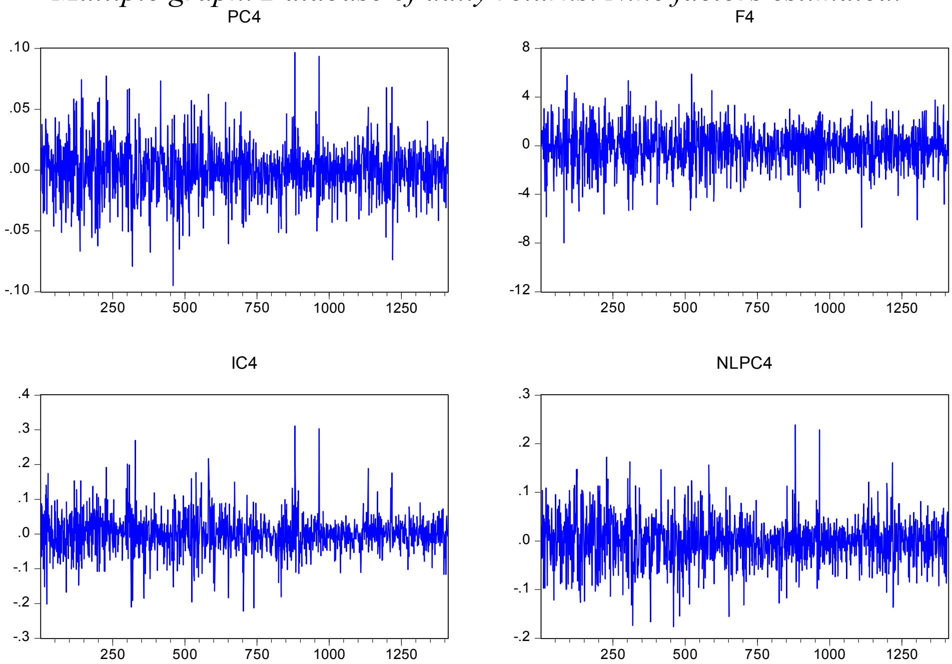


Figure 43. *Fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

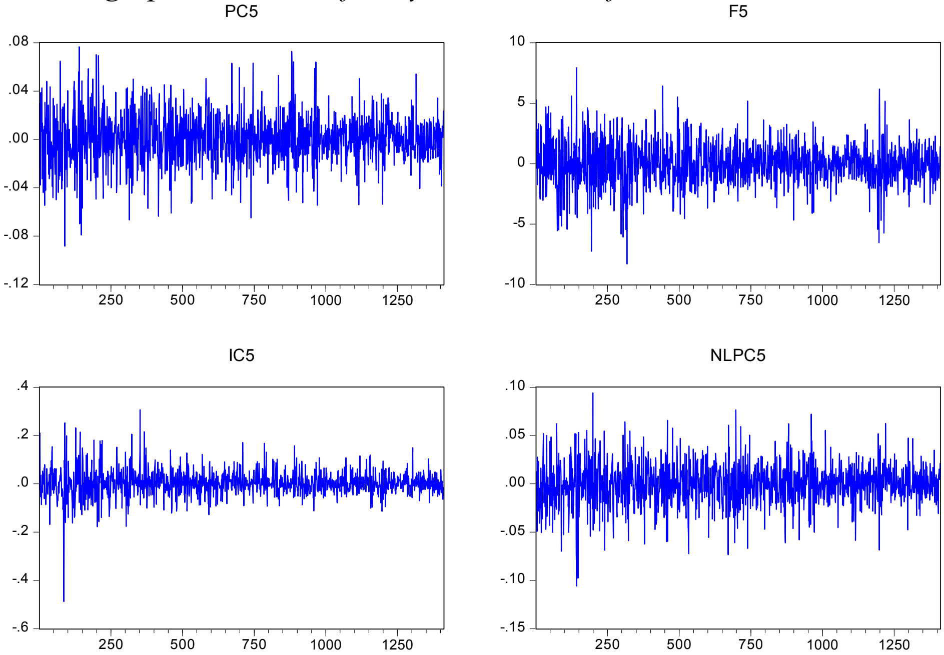


Figure 44. *Sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

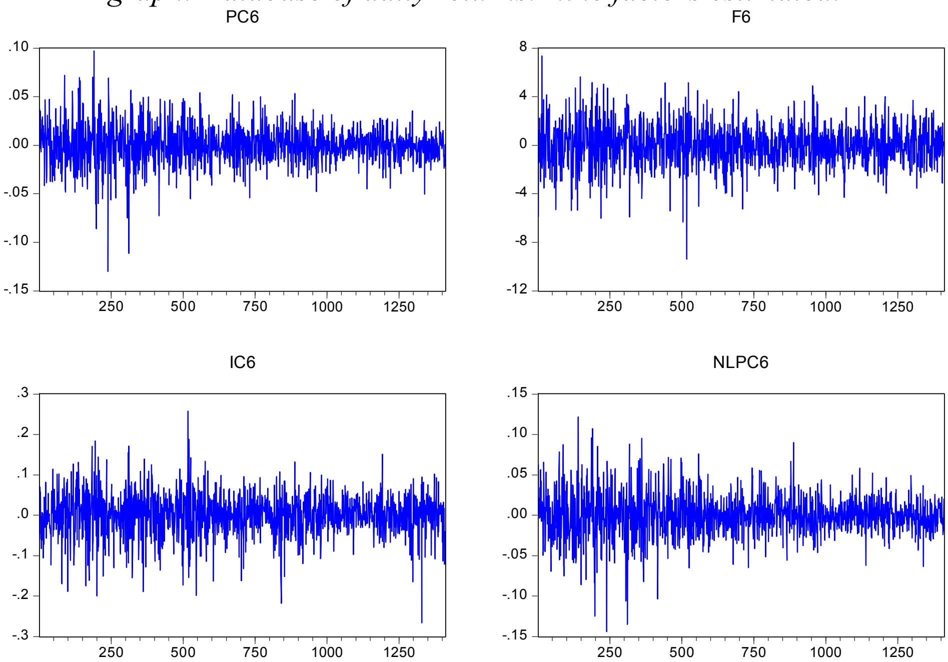


Figure 45. *Seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

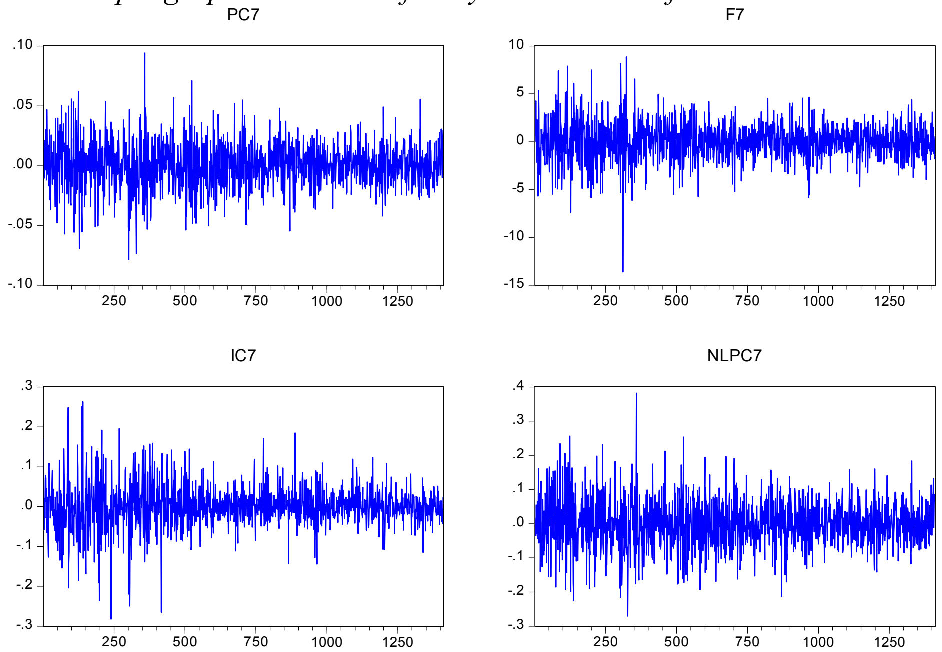


Figure 46. *Eighth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

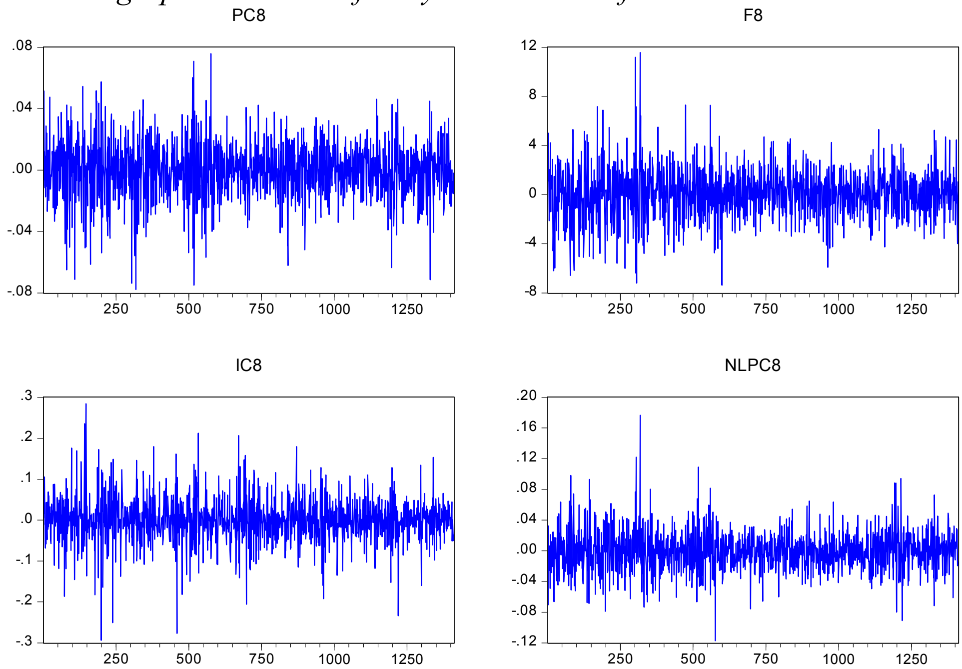


Figure 47. *Ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine factors estimated.*

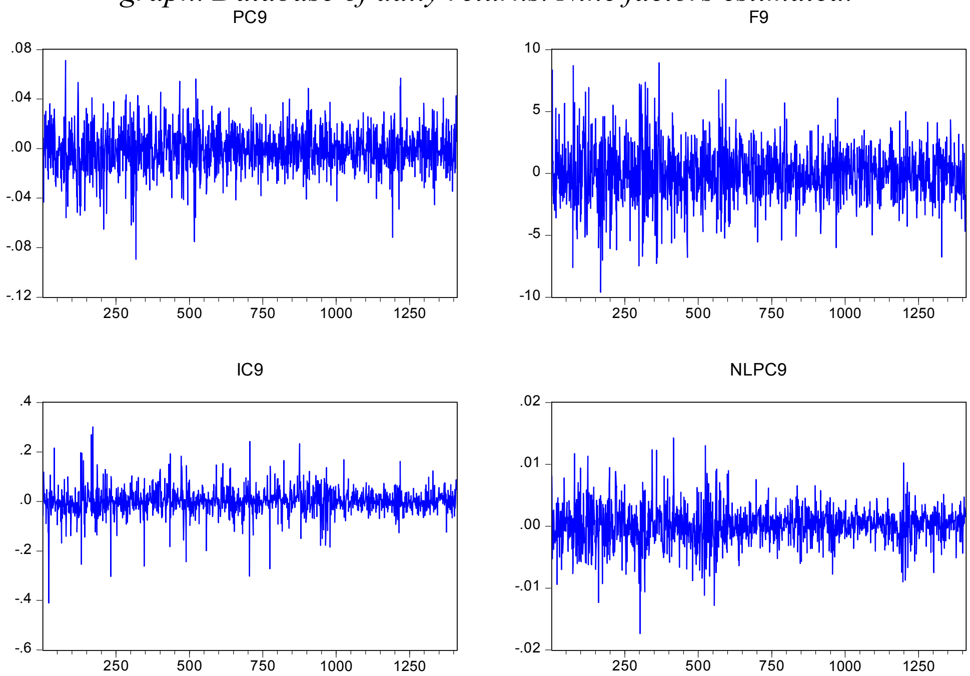


Figure 48. *First underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

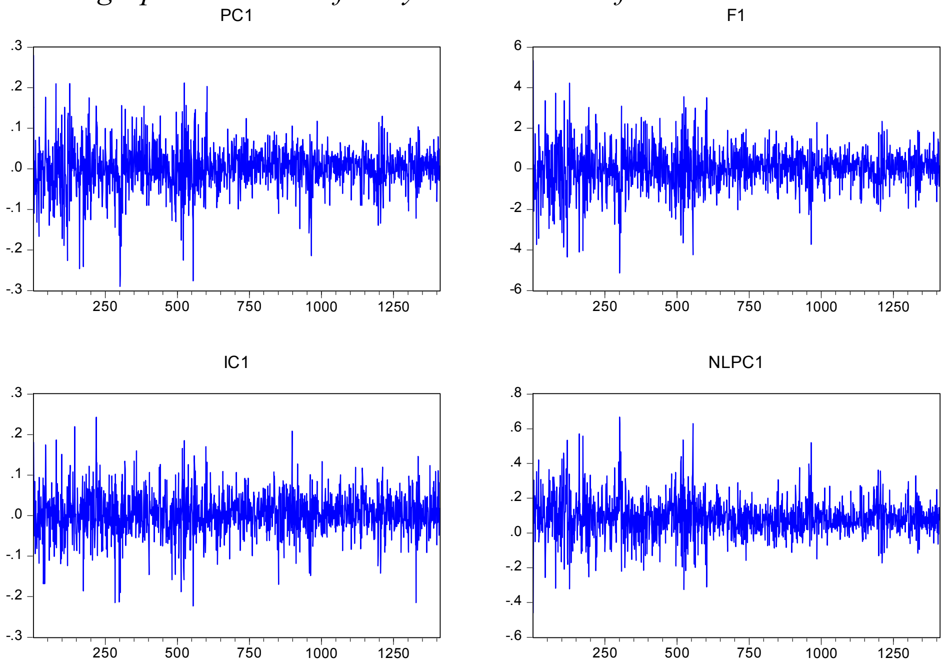


Figure 49. *Second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

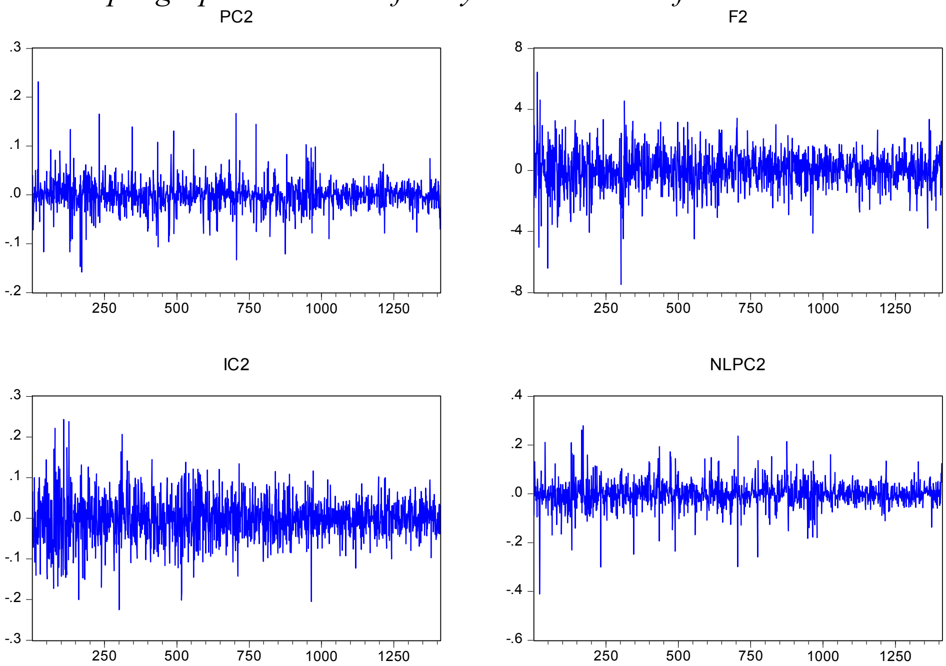


Figure 50. *Third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

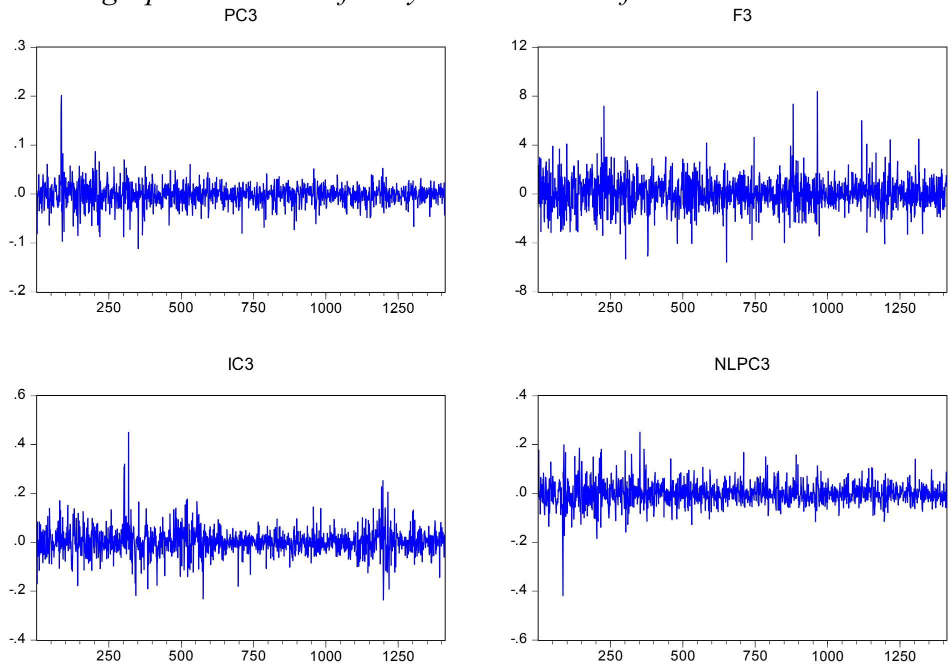


Figure 51. *Fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

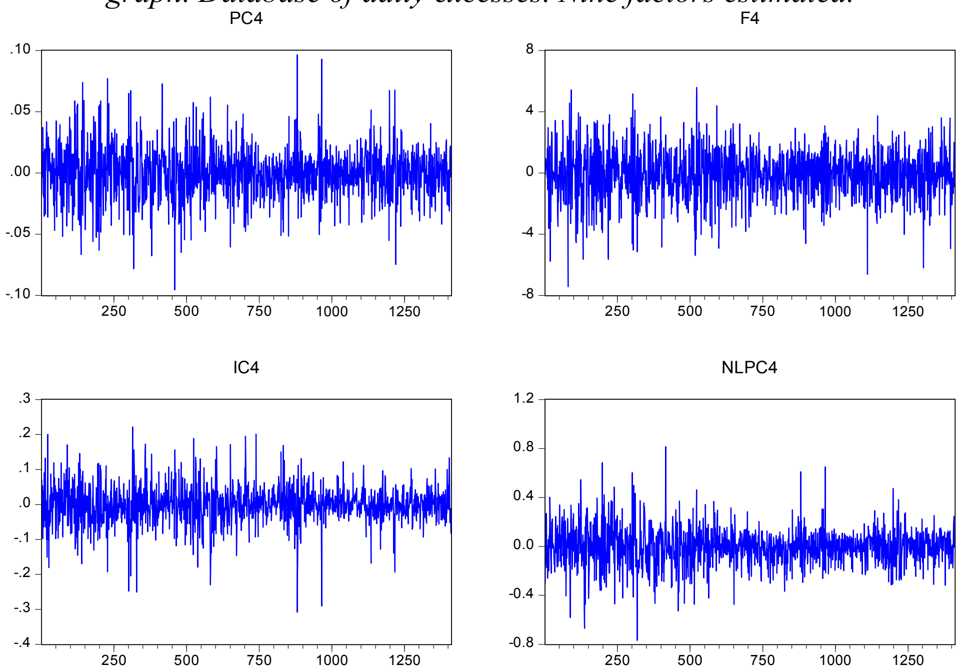


Figure 52. *Fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

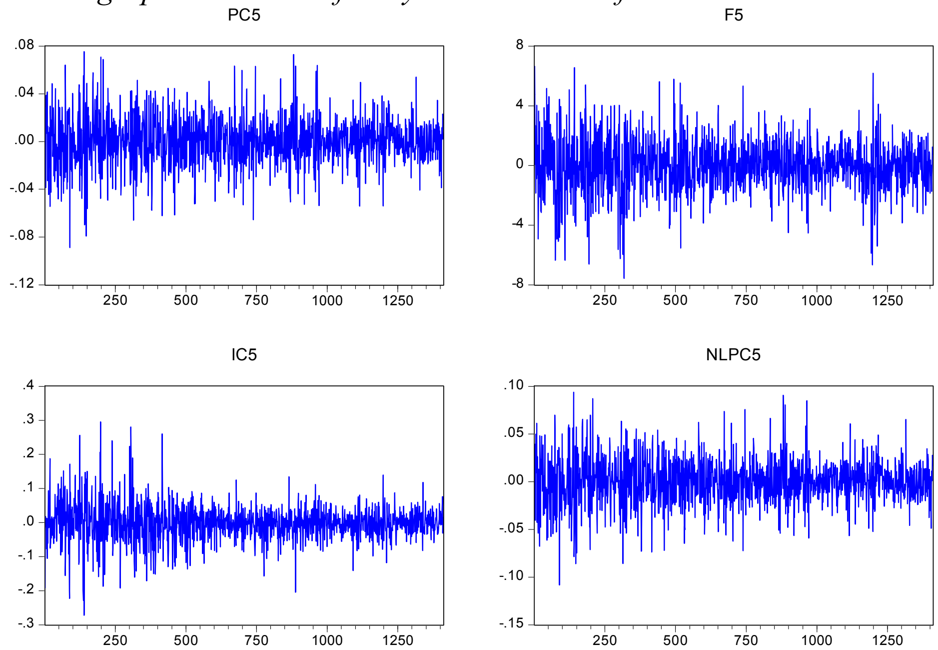


Figure 53. *Sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

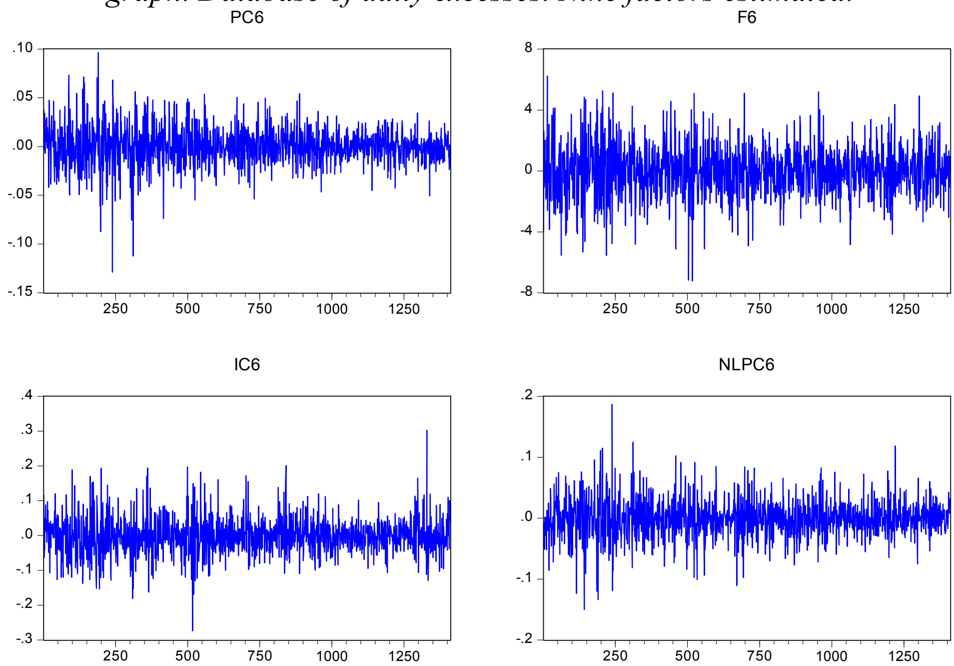


Figure 54. *Seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

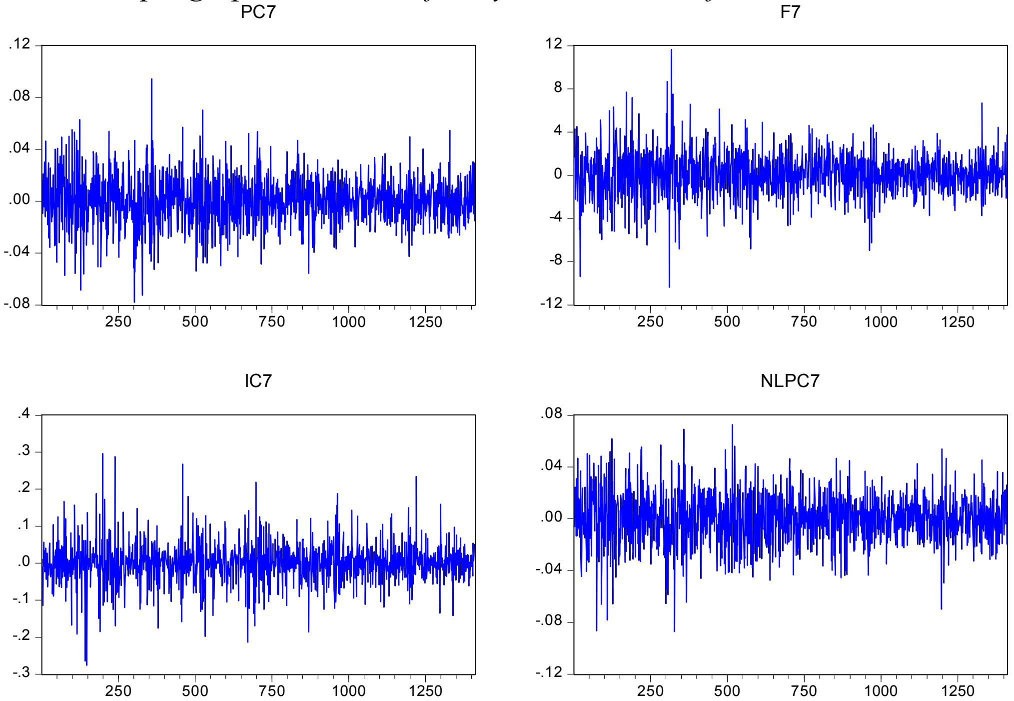


Figure 55. *Eighth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

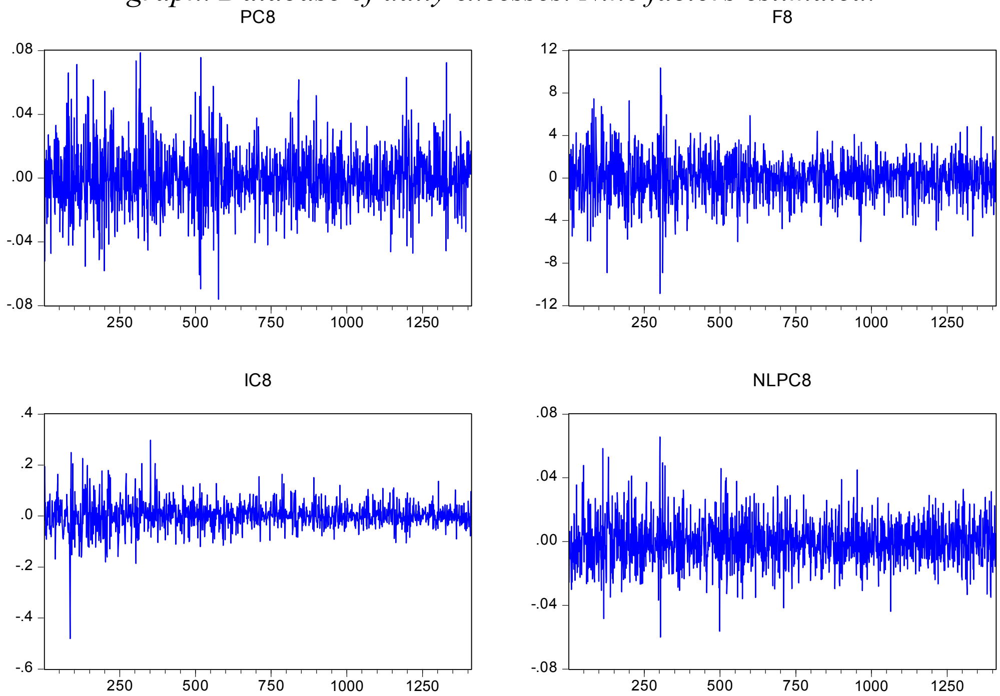


Figure 56. *Ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine factors estimated.*

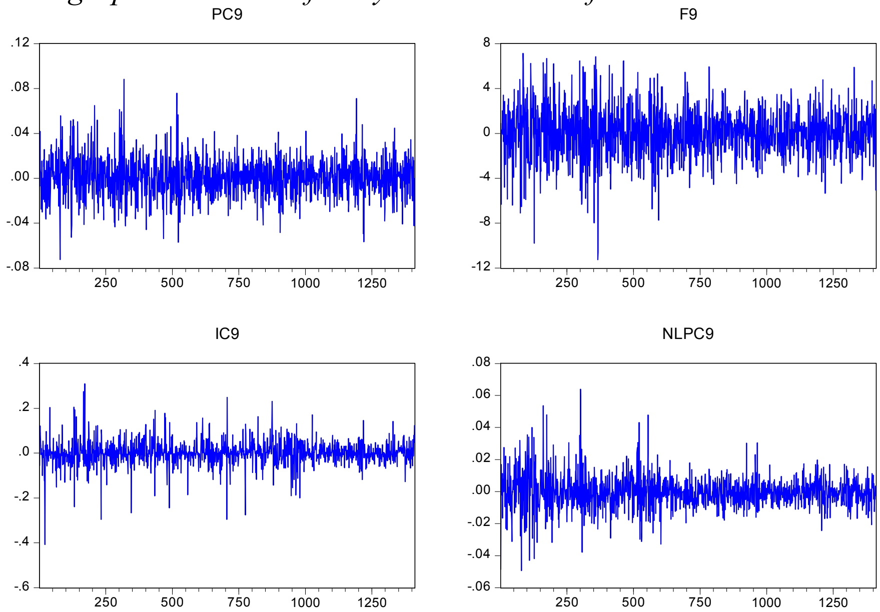


Table 56. *Descriptive Statistics. Matrix of Betas computed in Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.213618	0.018645	0.032165	-0.014136	0.012903	-0.003496	0.013655	0.002923	0.012855
Median	-0.213953	-0.058772	0.072076	-0.077736	-0.009851	0.060190	-0.018021	0.012045	-0.017317
Maximum	-0.097772	0.914825	0.318410	0.706754	0.445655	0.401360	0.588670	0.348821	0.661647
Minimum	-0.328755	-0.127194	-0.766692	-0.365744	-0.509815	-0.444461	-0.334488	-0.459446	-0.529515
Std. Dev.	0.067803	0.228617	0.227030	0.228957	0.229033	0.229388	0.228988	0.229396	0.229036
Skewness	0.020598	3.269301	-2.213245	1.627610	-0.539764	-0.426233	0.506540	-0.263241	0.551485
Kurtosis	1.999151	13.18839	8.774399	6.273850	3.430912	2.377632	3.107553	2.301330	5.536192
Jarque-Bera	0.836163	122.1305	44.11458	17.76213	1.125888	0.928367	0.864917	0.637770	6.374011
Probability	0.658309	0.000000	0.000000	0.000139	0.569530	0.628648	0.648912	0.726959	0.041295
Observations	20	20	20	20	20	20	20	20	20

Table 57. *Descriptive Statistics. Matrix of Betas computed in Factor Analysis. Database of weekly excesses. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.022544	0.011422	0.007743	0.003735	0.002379	0.000831	-6.64E-05	0.001448	0.001060
Median	0.021626	0.010748	0.008387	0.004078	0.001283	9.96E-06	-0.000285	0.000112	-2.86E-05
Maximum	0.043353	0.035217	0.030303	0.023536	0.029497	0.029144	0.015380	0.013530	0.014577
Minimum	0.009858	-0.001595	-0.008330	-0.022994	-0.019321	-0.016564	-0.014311	-0.009464	-0.007997
Std. Dev.	0.008669	0.008493	0.008564	0.007926	0.008924	0.009525	0.006503	0.006521	0.006067
Skewness	0.476575	0.768106	0.518040	-1.220873	0.738424	1.255856	0.463756	0.206923	0.886852
Kurtosis	2.891278	4.368870	3.908515	9.336240	6.824044	5.402429	4.049998	2.364219	3.326630
Jarque-Bera	0.766931	3.528126	1.582385	38.42505	14.00366	10.06697	1.635643	0.479571	2.710592
Probability	0.681496	0.171347	0.453304	0.000000	0.000910	0.006516	0.441392	0.786797	0.257871
Observations	20	20	20	20	20	20	20	20	20

Table 58. *Descriptive Statistics. Matrix of Betas computed in Independent Component Analysis. Database of weekly excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.137247	0.098974	-0.124538	-0.012394	-0.038042	-0.067917	-0.041284	0.031819	0.014986
Median	-0.140107	0.101541	-0.108194	-0.054439	-0.070025	-0.073356	-0.034232	0.021180	0.011866
Maximum	0.001794	0.329107	0.018121	0.144794	0.307902	0.080046	0.126262	0.367506	0.186462
Minimum	-0.373971	-0.120249	-0.262781	-0.137738	-0.152221	-0.354144	-0.284430	-0.114226	-0.167391
Std. Dev.	0.082626	0.094594	0.086405	0.086399	0.109293	0.084934	0.080735	0.097659	0.096045
Skewness	-0.697534	0.034277	0.047476	0.479672	1.671156	-1.549694	-0.970520	1.880488	0.011039
Kurtosis	4.940058	3.966488	1.996327	1.918160	6.014849	7.997286	5.821683	8.284079	2.441013
Jarque-Bera	4.758363	0.782332	0.846979	1.742265	16.88364	28.81590	9.774611	35.05536	0.260795
Probability	0.092626	0.676268	0.654758	0.418477	0.000216	0.000001	0.007542	0.000000	0.877746
Observations	20	20	20	20	20	20	20	20	20

Table 59. *Descriptive Statistics. Matrix of Betas computed in Neural Networks Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.144037	0.006534	0.012514	0.007574	0.086608	-0.005091	-0.003256	-0.014183	-0.161302
Median	-0.168848	-0.016567	0.014686	0.006105	-0.106972	-0.069814	-0.074214	-0.012427	0.011099
Maximum	0.216224	0.486162	0.230983	0.327174	4.095215	0.562687	1.513013	1.654952	13.61141
Minimum	-0.549244	-0.105147	-0.222991	-0.326857	-3.159456	-0.375073	-1.466123	-1.644692	-14.65570
Std. Dev.	0.202123	0.127139	0.104594	0.147370	1.973171	0.270882	0.743907	0.871323	7.309528
Skewness	0.090094	2.821949	-0.161143	-0.031310	0.239173	0.617816	0.401103	0.061453	0.016501
Kurtosis	2.588814	11.36687	3.277949	3.561855	2.682065	2.412702	2.910472	2.466058	2.610547
Jarque-Bera	0.167951	84.88170	0.150937	0.266335	0.274915	1.559753	0.542958	0.250167	0.127302
Probability	0.919454	0.000000	0.927309	0.875318	0.871572	0.458463	0.762251	0.882423	0.938332
Observations	20	20	20	20	20	20	20	20	20

Table 60. *Descriptive Statistics. Matrix of Betas computed in Principal Component Analysis. Database of daily returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.205518	-0.026812	-0.005948	0.037367	0.003264	0.002050	0.002088	-0.005036	-0.008586
Median	0.205444	0.025411	0.039499	0.068185	0.029268	-0.068253	-0.030315	0.006426	-0.018906
Maximum	0.313603	0.085528	0.258394	0.510560	0.553027	0.682432	0.551258	0.387151	0.508508
Minimum	0.117277	-0.973511	-0.891996	-0.417701	-0.510300	-0.203432	-0.322397	-0.638845	-0.399761
Std. Dev.	0.058053	0.216485	0.218133	0.214840	0.218192	0.218208	0.218207	0.218157	0.218041
Skewness	0.196386	-4.048221	-3.179878	-0.253019	-0.341232	2.085362	0.854016	-0.748609	0.122531
Kurtosis	2.206404	18.25849	13.74259	3.294214	4.581156	6.631329	3.151524	4.795651	3.142666
Jarque-Bera	0.718726	273.5095	142.8622	0.314084	2.718660	28.03302	2.695307	5.010522	0.073708
Probability	0.698121	0.000000	0.000000	0.854668	0.256833	0.000001	0.259849	0.081654	0.963817
Observations	22	22	22	22	22	22	22	22	22

Table 61. *Descriptive Statistics. Matrix of Betas computed in Factor Analysis. Database of daily returns. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.010677	0.002380	0.001147	0.000101	0.000413	9.43E-05	0.000397	0.000497	1.22E-05
Median	0.010885	0.002491	0.001842	0.000857	0.000527	-7.64E-05	0.000274	0.000792	-8.17E-05
Maximum	0.016902	0.006692	0.004317	0.003680	0.004715	0.004127	0.005437	0.003992	0.003203
Minimum	0.004406	-0.006884	-0.010784	-0.005958	-0.004371	-0.004571	-0.002680	-0.004385	-0.002796
Std. Dev.	0.003346	0.002893	0.003209	0.002477	0.002319	0.002165	0.002109	0.002084	0.001650
Skewness	0.075258	-1.620962	-2.540091	-0.681584	-0.041245	-0.080846	0.629179	-0.444208	0.325880
Kurtosis	2.352901	6.581487	9.865981	2.796291	2.386254	2.555385	2.927780	2.967787	2.472821
Jarque-Bera	0.404609	21.39236	66.87079	1.741414	0.351531	0.205175	1.456289	0.724462	0.644149
Probability	0.816846	0.000023	0.000000	0.418656	0.838815	0.902499	0.482804	0.696122	0.724644
Observations	22	22	22	22	22	22	22	22	22

Table 62. *Descriptive Statistics. Matrix of Betas computed in Independent Component Analysis. Database of daily returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.125132	-0.116101	0.066777	-0.049075	0.033456	0.000450	0.063920	0.051062	0.031444
Median	0.094508	-0.096762	0.042604	-0.025901	0.016224	0.004121	0.047740	0.036639	0.007223
Maximum	0.315097	-0.012856	0.290655	0.014193	0.419657	0.107907	0.420289	0.376939	0.545156
Minimum	-0.002412	-0.296812	-0.008843	-0.358739	-0.019655	-0.276207	0.002572	-0.038448	-0.023610
Std. Dev.	0.083025	0.059465	0.070115	0.087545	0.089333	0.072744	0.083358	0.076299	0.115508
Skewness	0.806248	-1.073562	1.974684	-2.624960	3.904274	-2.413494	3.754415	3.696723	4.268469
Kurtosis	3.034655	5.043703	6.568053	9.130191	17.45278	10.84144	16.70739	16.70546	19.52406
Jarque-Bera	2.384564	8.054628	25.96780	59.71249	247.3682	77.72240	223.9188	222.2942	317.0969
Probability	0.303528	0.017822	0.000002	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	22	22	22	22	22	22	22	22	22

Table 63. *Descriptive Statistics. Matrix of Betas computed in Neural Networks Principal Component Analysis. Database of daily returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.119893	-0.012807	-0.001845	0.019282	-0.007870	-0.004477	0.003028	0.003802	-0.172247
Median	-0.122111	0.011995	0.008987	-0.048854	0.010642	-0.054925	-0.021991	-0.004923	-0.145817
Maximum	0.309391	0.056768	0.126594	0.431654	0.298487	0.711866	0.415778	0.444057	19.54631
Minimum	-0.607666	-0.442438	-0.315774	-0.367921	-0.757126	-0.810291	-0.437547	-0.475327	-20.77902
Std. Dev.	0.247487	0.099766	0.094423	0.193479	0.211303	0.420271	0.205113	0.213034	10.49282
Skewness	-0.103990	-3.847167	-1.602713	0.379405	-2.057010	0.015676	0.061142	0.144390	-0.034435
Kurtosis	2.463291	17.18474	6.661458	2.693511	8.414006	2.208827	2.774900	3.088573	2.755183
Jarque-Bera	0.303703	238.7089	21.70761	0.613918	42.38357	0.574692	0.060155	0.083636	0.059289
Probability	0.859116	0.000000	0.000019	0.735681	0.000000	0.750252	0.970370	0.959044	0.970791
Observations	22	22	22	22	22	22	22	22	22

Table 64. *Descriptive Statistics. Matrix of Betas computed in Principal Component Analysis. Database of daily excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.205540	-0.026666	-0.006038	0.037381	0.003131	0.001901	0.002352	0.005226	0.008298
Median	0.205552	0.023935	0.040631	0.068637	0.030312	-0.066245	-0.030811	-0.008722	0.013215
Maximum	0.313559	0.085533	0.261388	0.516046	0.539109	0.694619	0.549216	0.642165	0.393722
Minimum	0.117683	-0.972958	-0.888977	-0.417046	-0.519924	-0.194530	-0.319764	-0.390327	-0.502186
Std. Dev.	0.057972	0.216504	0.218130	0.214838	0.218194	0.218209	0.218205	0.218152	0.218053
Skewness	0.197833	-4.041332	-3.143075	-0.230206	-0.434586	2.097280	0.830105	0.778501	-0.110605
Kurtosis	2.202977	18.22104	13.56084	3.317536	4.519788	6.742978	3.079893	4.874525	3.117541
Jarque-Bera	0.725814	272.2588	138.4598	0.286741	2.809780	28.97053	2.532459	5.443260	0.057521
Probability	0.695651	0.000000	0.000000	0.866433	0.245394	0.000001	0.281893	0.065767	0.971649
Observations	22	22	22	22	22	22	22	22	22

Table 65. *Descriptive Statistics. Matrix of Betas computed in Factor Analysis. Database of daily excesses. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.010746	0.002076	0.001164	0.000152	0.000366	0.000262	0.000622	4.79E-05	-3.34E-05
Median	0.010974	0.002269	0.001806	0.000860	0.000295	0.000250	0.000305	-0.000410	0.000207
Maximum	0.017049	0.006459	0.004402	0.003967	0.004426	0.003953	0.007124	0.003250	0.002382
Minimum	0.004509	-0.006993	-0.010730	-0.006111	-0.004465	-0.005231	-0.004171	-0.002835	-0.004135
Std. Dev.	0.003342	0.002899	0.003211	0.002479	0.002265	0.002249	0.002350	0.001904	0.001763
Skewness	0.076609	-1.565711	-2.497213	-0.751624	-0.207834	-0.325778	0.687129	0.324049	-0.719137
Kurtosis	2.369068	6.327439	9.719117	3.061907	2.578481	3.050174	4.217956	1.839652	2.824028
Jarque-Bera	0.386422	19.13785	64.24992	2.074957	0.321253	0.391456	3.091002	1.619234	1.924634
Probability	0.824308	0.000070	0.000000	0.354347	0.851610	0.822236	0.213205	0.445029	0.382007
Observations	22	22	22	22	22	22	22	22	22

Table 66. *Descriptive Statistics. Matrix of Betas computed in Independent Component Analysis. Database of daily excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	0.147800	0.099561	-0.076087	0.051725	-0.037076	0.016234	-0.045470	0.023507	0.040329
Median	0.144840	0.086432	-0.065400	0.027037	-0.025403	0.013372	-0.030621	0.007860	0.016475
Maximum	0.320216	0.278503	-0.003832	0.371244	0.040032	0.313429	0.029971	0.410121	0.549238
Minimum	0.031453	-0.014624	-0.348008	-0.009987	-0.386188	-0.077354	-0.382361	-0.043782	-0.003813
Std. Dev.	0.059802	0.080791	0.070664	0.090617	0.082854	0.073110	0.077497	0.088956	0.114223
Skewness	0.735317	0.697162	-2.663075	2.666694	-3.549238	3.119452	-3.939217	3.954645	4.294559
Kurtosis	4.570998	2.861136	11.12761	9.119144	15.80892	13.80057	17.86903	17.82951	19.66242
Jarque-Bera	4.244902	1.799802	86.55704	60.39820	196.5853	142.6116	259.5613	258.9319	322.1252
Probability	0.119738	0.406610	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	22	22	22	22	22	22	22	22	22

Table 67. *Descriptive Statistics. Matrix of Betas computed in Neural Networks Principal Component Analysis. Database of daily excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
Mean	-0.153356	-0.000188	0.003934	0.011566	0.005673	0.011585	-0.113363	-0.190890	0.604049
Median	-0.023482	0.069230	-0.027525	-0.035161	0.031529	-0.084985	0.110835	0.076830	-0.886506
Maximum	2.772315	0.706448	0.479473	0.602297	0.486563	2.257217	6.806987	10.82161	56.29629
Minimum	-4.645785	-1.187565	-0.179648	-0.415274	-0.393025	-1.350791	-10.66053	-16.90248	-36.12472
Std. Dev.	1.910751	0.513759	0.133741	0.249862	0.187730	0.946124	4.552608	6.994788	23.58244
Skewness	-0.578208	-0.623105	2.001670	0.570823	-0.244804	0.649418	-0.558019	-0.595869	0.581020
Kurtosis	2.749818	2.608357	8.363808	2.846333	4.469168	2.871715	2.687833	2.828300	2.773077
Jarque-Bera	1.283231	1.564222	41.06408	1.216386	2.198323	1.561479	1.231075	1.328909	1.285011
Probability	0.526441	0.457439	0.000000	0.544333	0.333150	0.458067	0.540350	0.514554	0.525973
Observations	22	22	22	22	22	22	22	22	22

Table 68 *Correlation matrix. Betas computed in Principal Component Analysis. Database of weekly returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.274319	1.000000							
	1.210263	-----							
	0.2418	-----							
B3	0.471119	-0.012441	1.000000						
	2.266020	-0.052786	-----						
	0.0360	0.9585	-----						
B4	-0.204519	0.005401	0.009275	1.000000					
	-0.886437	0.022914	0.039354	-----					
	0.3871	0.9820	0.9690	-----					
B5	0.186645	-0.004929	-0.008465	0.003675	1.000000				
	0.806031	-0.020911	-0.035914	0.015590	-----				
	0.4307	0.9835	0.9717	0.9877	-----				
B6	-0.050418	0.001331	0.002287	-0.000993	0.000906	1.000000			
	-0.214179	0.005649	0.009701	-0.004211	0.003843	-----			
	0.8328	0.9956	0.9924	0.9967	0.9970	-----			
B7	0.198168	-0.005233	-0.008987	0.003902	-0.003561	0.000962	1.000000		
	0.857768	-0.022202	-0.038131	0.016553	-0.015106	0.004081	-----		
	0.4023	0.9825	0.9700	0.9870	0.9881	0.9968	-----		
B8	0.042616	-0.001125	-0.001933	0.000839	-0.000766	0.000207	-0.000813	1.000000	
	0.180967	-0.004774	-0.008200	0.003560	-0.003249	0.000878	-0.003449	-----	
	0.8584	0.9962	0.9935	0.9972	0.9974	0.9993	0.9973	-----	
B9	0.185540	-0.004900	-0.008415	0.003653	-0.003334	0.000901	-0.003539	-0.000761	1.000000
	0.801089	-0.020787	-0.035701	0.015498	-0.014144	0.003821	-0.015017	-0.003229	-----
	0.4335	0.9836	0.9719	0.9878	0.9889	0.9970	0.9882	0.9975	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 69 *Correlation matrix. Betas computed in Factor Analysis. Database of weekly returns. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	-0.176560	1.000000							
	-0.761038	-----							
	0.4565	-----							
B3	-0.043950	-0.115967	1.000000						
	-0.186646	-0.495349	-----						
	0.8540	0.6263	-----						
B4	0.193799	-0.049381	0.165280	1.000000					
	0.838107	-0.209760	0.711004	-----					
	0.4130	0.8362	0.4862	-----					
B5	0.417522	0.059878	0.105560	-0.086326	1.000000				
	1.949442	0.254497	0.450370	-0.367622	-----				
	0.0670	0.8020	0.6578	0.7174	-----				
B6	-0.075838	-0.127475	0.296413	0.067045	0.128165	1.000000			
	-0.322682	-0.545280	1.316750	0.285091	0.548279	-----			
	0.7507	0.5923	0.2044	0.7788	0.5902	-----			
B7	0.165454	0.108284	-0.130134	-0.130138	0.139718	-0.080446	1.000000		
	0.711773	0.462127	-0.556845	-0.556863	0.598645	-0.342415	-----		
	0.4857	0.6495	0.5845	0.5845	0.5569	0.7360	-----		
B8	-0.312901	-0.186321	-0.101715	0.007030	-0.049518	0.112593	-0.135558	1.000000	
	-1.397710	-0.804584	-0.433791	0.029825	-0.210344	0.480747	-0.580483	-----	
	0.1792	0.4316	0.6696	0.9765	0.8358	0.6365	0.5688	-----	
B9	0.244735	0.063382	-0.097131	0.000293	0.065954	-0.069757	0.064657	-0.004408	1.000000
	1.070886	0.269449	-0.414051	0.001244	0.280429	-0.296678	0.274891	-0.018700	-----
	0.2984	0.7906	0.6837	0.9990	0.7823	0.7701	0.7865	0.9853	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 70. *Correlation matrix. Betas computed in Independent Component Analysis. Database of weekly returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000 ----- -----								
B2	0.101359 0.432254 0.6707	1.000000 ----- -----							
B3	-0.084303 -0.358945 0.7238	-0.159021 -0.683365 0.5031	1.000000 ----- -----						
B4	-0.134654 -0.576537 0.5714	0.023895 0.101405 0.9204	0.146417 0.627963 0.5379	1.000000 ----- -----					
B5	0.055462 0.235667 0.8164	0.010325 0.043806 0.9655	0.073410 0.312296 0.7584	-0.028163 -0.119531 0.9062	1.000000 ----- -----				
B6	-0.337940 -1.523382 0.1450	-0.319723 -1.431615 0.1694	0.118984 0.508416 0.6173	0.022365 0.094910 0.9254	0.090293 0.384653 0.7050	1.000000 ----- -----			
B7	0.075702 0.322100 0.7511	0.119232 0.509493 0.6166	-0.030562 -0.129723 0.8982	0.184804 0.797798 0.4354	0.062287 0.264777 0.7942	-0.019100 -0.081049 0.9363	1.000000 ----- -----		
B8	0.121964 0.521343 0.6085	0.093902 0.400161 0.6937	-0.124976 -0.534420 0.5996	-0.017293 -0.073378 0.9423	0.009422 0.039975 0.9686	0.204540 0.886530 0.3870	0.114150 0.487483 0.6318	1.000000 ----- -----	
B9	0.231060 1.007572 0.3270	0.253417 1.111436 0.2810	-0.228061 -0.993771 0.3335	-0.107586 -0.459114 0.6516	-0.192894 -0.834046 0.4152	-0.078164 -0.332641 0.7432	-0.212978 -0.924808 0.3673	-0.043897 -0.186418 0.8542	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 71. *Correlation matrix. Betas computed in Neural Networks Principal Component Analysis. Database of weekly returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000 ----- -----								
B2	0.987092 26.14941 0.0000	1.000000 ----- -----							
B3	-0.997698 -62.41914 0.0000	-0.982196 -22.18221 0.0000	1.000000 ----- -----						
B4	0.972338 17.66139 0.0000	0.960348 14.61393 0.0000	-0.968428 -16.48143 0.0000	1.000000 ----- -----					
B5	0.950406 12.96488 0.0000	0.933671 11.06085 0.0000	-0.945090 -12.26914 0.0000	0.921097 10.03739 0.0000	1.000000 ----- -----				
B6	0.600766 3.188335 0.0051	0.599271 3.175949 0.0052	-0.605925 -3.231492 0.0046	0.585187 3.061716 0.0067	0.562715 2.888035 0.0098	1.000000 ----- -----			
B7	-0.172991 -0.745172 0.4658	-0.163441 -0.702871 0.4911	0.173804 0.748786 0.4637	-0.164966 -0.709613 0.4870	-0.169491 -0.729648 0.4750	-0.119766 -0.511806 0.6150	1.000000 ----- -----		
B8	0.986664 25.71731 0.0000	0.973560 18.08182 0.0000	-0.984811 -24.06376 0.0000	0.959100 14.37500 0.0000	0.936476 11.32812 0.0000	0.596771 3.155342 0.0055	-0.179408 -0.773719 0.4491	1.000000 ----- -----	
B9	-0.999558 -142.6458 0.0000	-0.985840 -24.94200 0.0000	0.996753 52.51934 0.0000	-0.972190 -17.61224 0.0000	-0.948457 -12.69761 0.0000	-0.605253 -3.225832 0.0047	0.172549 0.743212 0.4669	-0.987415 -26.48879 0.0000	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 72. *Correlation matrix. Betas computed in Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.270470	1.000000							
	1.191934	-----							
	0.2488	-----							
B3	0.469853	-0.012163	1.000000						
	2.258202	-0.051606	-----						
	0.0366	0.9594	-----						
B4	-0.204761	0.005301	0.009208	1.000000					
	-0.887532	0.022488	0.039067	-----					
	0.3865	0.9823	0.9693	-----					
B5	0.186830	-0.004836	-0.008402	0.003661	1.000000				
	0.806859	-0.020519	-0.035646	0.015534	-----				
	0.4303	0.9839	0.9720	0.9878	-----				
B6	-0.050544	0.001308	0.002273	-0.000991	0.000904	1.000000			
	-0.214716	0.005551	0.009643	-0.004203	0.003834	-----			
	0.8324	0.9956	0.9924	0.9967	0.9970	-----			
B7	0.197768	-0.005119	-0.008893	0.003876	-0.003536	0.000957	1.000000		
	0.855964	-0.021720	-0.037733	0.016443	-0.015003	0.004059	-----		
	0.4033	0.9829	0.9703	0.9871	0.9882	0.9968	-----		
B8	0.042261	-0.001094	-0.001900	0.000828	-0.000756	0.000204	-0.000800	1.000000	
	0.179460	-0.004641	-0.008063	0.003514	-0.003206	0.000867	-0.003394	-----	
	0.8596	0.9963	0.9937	0.9972	0.9975	0.9993	0.9973	-----	
B9	0.186140	-0.004818	-0.008371	0.003648	-0.003328	0.000900	-0.003523	-0.000753	1.000000
	0.803771	-0.020443	-0.035514	0.015477	-0.014121	0.003820	-0.014948	-0.003194	-----
	0.4320	0.9839	0.9721	0.9878	0.9889	0.9970	0.9882	0.9975	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 73. *Correlation matrix. Betas computed in Factor Analysis. Database of weekly excesses. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	-0.176639	1.000000							
	-0.761388	-----							
	0.4563	-----							
B3	-0.041388	-0.115492	1.000000						
	-0.175746	-0.493290	-----						
	0.8625	0.6278	-----						
B4	0.193432	-0.048646	0.164474	1.000000					
	0.836458	-0.206631	0.707440	-----					
	0.4139	0.8386	0.4884	-----					
B5	0.418025	0.060689	0.105945	-0.087294	1.000000				
	1.952288	0.257958	0.452032	-0.371777	-----				
	0.0666	0.7994	0.6566	0.7144	-----				
B6	-0.075164	-0.125914	0.301730	0.065792	0.124229	1.000000			
	-0.319798	-0.538494	1.342711	0.279737	0.531175	-----			
	0.7528	0.5968	0.1961	0.7829	0.6018	-----			
B7	0.163485	0.104010	-0.124207	-0.129450	0.142388	-0.070778	1.000000		
	0.703068	0.443684	-0.531077	-0.553870	0.610319	-0.301042	-----		
	0.4910	0.6626	0.6019	0.5865	0.5493	0.7668	-----		
B8	-0.310870	-0.186121	-0.099413	0.007031	-0.049650	0.114926	-0.132105	1.000000	
	-1.387666	-0.803688	-0.423873	0.029832	-0.210907	0.490844	-0.565429	-----	
	0.1822	0.4321	0.6767	0.9765	0.8353	0.6295	0.5788	-----	
B9	0.246515	0.062910	-0.097371	-0.000397	0.067688	-0.070072	0.063289	-0.004714	1.000000
	1.079180	0.267435	-0.415083	-0.001683	0.287836	-0.298023	0.269051	-0.020000	-----
	0.2948	0.7922	0.6830	0.9987	0.7768	0.7691	0.7910	0.9843	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 74. *Correlation matrix. Betas computed in Independent Component Analysis. Database of weekly excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000 ----- -----								
B2	0.331284 1.489637 0.1536	1.000000 ----- -----							
B3	-0.012450 -0.052827 0.9585	-0.090017 -0.383468 0.7059	1.000000 ----- -----						
B4	0.082262 0.350195 0.7303	0.076745 0.326564 0.7478	0.136017 0.582485 0.5675	1.000000 ----- -----					
B5	-0.208394 -0.903986 0.3779	-0.247634 -1.084398 0.2925	0.162011 0.696558 0.4950	-0.131783 -0.564029 0.5797	1.000000 ----- -----				
B6	-0.250603 -1.098265 0.2866	0.056186 0.238755 0.8140	0.026159 0.111022 0.9128	0.021364 0.090659 0.9288	-0.045040 -0.191282 0.8504	1.000000 ----- -----			
B7	-0.240207 -1.049852 0.3077	0.224975 0.979598 0.3403	-0.233752 -1.019984 0.3213	0.016730 0.070990 0.9442	-0.234559 -1.023711 0.3195	-0.122939 -0.525571 0.6056	1.000000 ----- -----		
B8	0.007380 0.031310 0.9754	-0.112380 -0.479829 0.6371	0.293267 1.301452 0.2095	-0.062674 -0.266428 0.7929	0.317006 1.418082 0.1732	0.031413 0.133339 0.8954	-0.187004 -0.807639 0.4298	1.000000 ----- -----	
B9	-0.181921 -0.784925 0.4427	0.039776 0.168887 0.8678	-0.177716 -0.766182 0.4535	-0.170458 -0.733933 0.4724	0.182573 0.787832 0.4410	-0.043925 -0.186539 0.8541	0.004296 0.018228 0.9857	-0.001160 -0.004920 0.9961	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 75. *Correlation matrix. Betas computed in Neural Networks Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.408412	1.000000							
	1.898277	-----							
	0.0738	-----							
B3	0.744706	0.256418	1.000000						
	4.734128	1.125518	-----						
	0.0002	0.2752	-----						
B4	0.392949	0.175917	0.202180	1.000000					
	1.812979	0.758175	0.875865	-----					
	0.0865	0.4582	0.3926	-----					
B5	-0.933612	-0.350757	-0.651582	-0.367507	1.000000				
	-11.05534	-1.589096	-3.644224	-1.676522	-----				
	0.0000	0.1294	0.0019	0.1109	-----				
B6	0.780729	0.266903	0.533160	0.288334	-0.761729	1.000000			
	5.300875	1.174999	2.673718	1.277558	-4.988057	-----			
	0.0000	0.2553	0.0155	0.2176	0.0001	-----			
B7	0.875718	0.312794	0.600988	0.321644	-0.853947	0.698676	1.000000		
	7.695087	1.397183	3.190183	1.441204	-6.962468	4.143240	-----		
	0.0000	0.1793	0.0051	0.1667	0.0000	0.0006	-----		
B8	0.917697	0.337290	0.643601	0.339808	-0.919649	0.757884	0.824615	1.000000	
	9.800255	1.520075	3.567689	1.532901	-9.934612	4.928702	6.184508	-----	
	0.0000	0.1459	0.0022	0.1427	0.0000	0.0001	0.0000	-----	
B9	0.973534	0.359258	0.670145	0.364225	-0.970300	0.786086	0.888631	0.939512	1.000000
	18.07262	1.633243	3.830591	1.659248	-17.01751	5.395554	8.220578	11.63750	-----
	0.0000	0.1198	0.0012	0.1144	0.0000	0.0000	0.0000	0.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 76. *Correlation matrix. Betas computed in Principal Component Analysis. Database of daily returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.459336	1.000000							
	2.312619	-----							
	0.0315	-----							
B3	0.101126	-0.003538	1.000000						
	0.454578	-0.015822	-----						
	0.6543	0.9875	-----						
B4	-0.645063	0.022567	0.004968	1.000000					
	-3.775291	0.100948	0.022219	-----					
	0.0012	0.9206	0.9825	-----					
B5	-0.055473	0.001941	0.000427	-0.002725	1.000000				
	-0.248465	0.008679	0.001911	-0.012188	-----				
	0.8063	0.9932	0.9985	0.9904	-----				
B6	-0.034849	0.001219	0.000268	-0.001712	-0.000147	1.000000			
	-0.155946	0.005452	0.001200	-0.007657	-0.000658	-----			
	0.8776	0.9957	0.9991	0.9940	0.9995	-----			
B7	-0.035492	0.001242	0.000273	-0.001744	-0.000150	-9.42E-05	1.000000		
	-0.158823	0.005553	0.001222	-0.007798	-0.000671	-0.000421	-----		
	0.8754	0.9956	0.9990	0.9939	0.9995	0.9997	-----		
B8	0.085607	-0.002995	-0.000659	0.004206	0.000362	0.000227	0.000231	1.000000	
	0.384257	-0.013394	-0.002949	0.018809	0.001618	0.001016	0.001035	-----	
	0.7048	0.9894	0.9977	0.9852	0.9987	0.9992	0.9992	-----	
B9	0.146052	-0.005109	-0.001125	0.007175	0.000617	0.000388	0.000395	-0.000952	1.000000
	0.660243	-0.022851	-0.005031	0.032090	0.002760	0.001734	0.001766	-0.004259	-----
	0.5166	0.9820	0.9960	0.9747	0.9978	0.9986	0.9986	0.9966	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 77. *Correlation matrix. Betas computed in Factor Analysis. Database of daily returns. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.051407	1.000000							
	0.230201	-----							
	0.8203	-----							
B3	-0.632639	-0.187459	1.000000						
	-3.653248	-0.853472	-----						
	0.0016	0.4035	-----						
B4	-0.164877	-0.097116	0.015083	1.000000					
	-0.747585	-0.436379	0.067460	-----					
	0.4634	0.6672	0.9469	-----					
B5	-0.335864	0.138137	0.092591	0.057809	1.000000				
	-1.594665	0.623745	0.415865	0.258964	-----				
	0.1265	0.5398	0.6819	0.7983	-----				
B6	-0.344291	-0.104240	-0.039180	0.166107	0.064101	1.000000			
	-1.639979	-0.468727	-0.175353	0.753321	0.287258	-----			
	0.1166	0.6443	0.8626	0.4600	0.7769	-----			
B7	-0.516958	0.037349	0.025315	0.093873	0.114412	0.150616	1.000000		
	-2.700795	0.167147	0.113248	0.421674	0.515048	0.681346	-----		
	0.0138	0.8689	0.9110	0.6778	0.6122	0.5035	-----		
B8	-0.150863	-0.004591	-0.020708	-0.004024	0.137991	0.051068	0.209536	1.000000	
	-0.682490	-0.020532	-0.092629	-0.017994	0.623073	0.228683	0.958349	-----	
	0.5028	0.9838	0.9271	0.9858	0.5403	0.8214	0.3493	-----	
B9	-0.071158	-0.085551	0.040333	-0.067123	0.106448	0.084468	-0.020974	-0.002352	1.000000
	-0.319039	-0.384002	0.180522	-0.300860	0.478770	0.379107	-0.093821	-0.010520	-----
	0.7530	0.7050	0.8586	0.7666	0.6373	0.7086	0.9262	0.9917	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 78. *Correlation matrix. Betas computed in Independent Component Analysis. Database of daily returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000 ----- -----								
B2	0.204708 0.935287 0.3608	1.000000 ----- -----							
B3	-0.146504 -0.662333 0.5153	0.224511 1.030348 0.3151	1.000000 ----- -----						
B4	-0.188798 -0.859791 0.4001	0.011276 0.050430 0.9603	0.033970 0.152007 0.8807	1.000000 ----- -----					
B5	-0.074587 -0.334493 0.7415	0.025930 0.116000 0.9088	-0.046371 -0.207599 0.8376	-0.012539 -0.056078 0.9558	1.000000 ----- -----				
B6	0.117817 0.530588 0.6015	-0.013304 -0.059504 0.9531	0.028349 0.126831 0.9003	-0.049340 -0.220923 0.8274	0.020604 0.092163 0.9275	1.000000 ----- -----			
B7	0.068120 0.305353 0.7633	0.041481 0.185667 0.8546	-0.083115 -0.372993 0.7131	-0.110199 -0.495845 0.6254	-0.002477 -0.011078 0.9913	0.056326 0.252298 0.8034	1.000000 ----- -----		
B8	-0.223099 -1.023527 0.3183	0.367854 1.769137 0.0921	-0.114033 -0.513320 0.6134	0.036075 0.161435 0.8734	-0.080679 -0.361988 0.7212	-0.017438 -0.077999 0.9386	-0.115642 -0.520659 0.6083	1.000000 ----- -----	
B9	-0.299097 -1.401770 0.1763	0.233850 1.075636 0.2949	-0.142224 -0.642576 0.5278	0.054208 0.242783 0.8106	-0.027997 -0.125254 0.9016	-0.023612 -0.105625 0.9169	-0.131656 -0.593955 0.5592	-0.021267 -0.095129 0.9252	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 79. *Correlation matrix. Betas computed in Neural Networks Principal Component Analysis. Database of daily returns. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000 ----- -----								
B2	-0.267883 -1.243455 0.2281	1.000000 ----- -----							
B3	-0.532361 -2.812455 0.0108	0.098841 0.444206 0.6617	1.000000 ----- -----						
B4	-0.818624 -6.374378 0.0000	0.191732 0.873661 0.3927	0.458337 2.306250 0.0319	1.000000 ----- -----					
B5	-0.089761 -0.403050 0.6912	0.010140 0.045348 0.9643	0.040436 0.180982 0.8582	0.055142 0.246977 0.8074	1.000000 ----- -----				
B6	0.916032 10.21332 0.0000	-0.189898 -0.864988 0.3973	-0.482286 -2.462116 0.0230	-0.798855 -5.939238 0.0000	-0.065508 -0.293593 0.7721	1.000000 ----- -----			
B7	-0.949251 -13.49734 0.0000	0.200266 0.914134 0.3715	0.502591 2.599877 0.0171	0.831793 6.701465 0.0000	0.069107 0.309799 0.7599	-0.881585 -8.352435 0.0000	1.000000 ----- -----		
B8	0.705007 4.445688 0.0002	-0.135012 -0.609373 0.5491	-0.366648 -1.762437 0.0933	-0.601014 -3.362969 0.0031	-0.055322 -0.247787 0.8068	0.634762 3.673761 0.0015	-0.665064 -3.982745 0.0007	1.000000 ----- -----	
B9	0.990995 33.09836 0.0000	-0.207318 -0.947748 0.3546	-0.524345 -2.753878 0.0122	-0.868305 -7.828500 0.0000	-0.072531 -0.325227 0.7484	0.920490 10.53457 0.0000	-0.958772 -15.08839 0.0000	0.695595 4.329961 0.0003	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 80. *Correlation matrix. Betas computed in Principal Component Analysis. Database of daily excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.457482	1.000000							
	2.300807	-----							
	0.0323	-----							
B3	0.102816	-0.003572	1.000000						
	0.462255	-0.015973	-----						
	0.6489	0.9874	-----						
B4	-0.646280	0.022451	0.005046	1.000000					
	-3.787508	0.100429	0.022565	-----					
	0.0012	0.9210	0.9822	-----					
B5	-0.053300	0.001852	0.000416	-0.002616	1.000000				
	-0.238706	0.008281	0.001861	-0.011698	-----				
	0.8138	0.9935	0.9985	0.9908	-----				
B6	-0.032367	0.001124	0.000253	-0.001588	-0.000131	1.000000			
	-0.144825	0.005028	0.001130	-0.007104	-0.000586	-----			
	0.8863	0.9960	0.9991	0.9944	0.9995	-----			
B7	-0.040036	0.001391	0.000313	-0.001965	-0.000162	-9.84E-05	1.000000		
	-0.179191	0.006220	0.001398	-0.008787	-0.000725	-0.000440	-----		
	0.8596	0.9951	0.9989	0.9931	0.9994	0.9997	-----		
B8	-0.088981	0.003091	0.000695	-0.004367	-0.000360	-0.000219	-0.000271	1.000000	
	-0.399522	0.013824	0.003107	-0.019529	-0.001611	-0.000978	-0.001210	-----	
	0.6937	0.9891	0.9976	0.9846	0.9987	0.9992	0.9990	-----	
B9	-0.141352	0.004910	0.001104	-0.006937	-0.000572	-0.000347	-0.000430	-0.000955	1.000000
	-0.638555	0.021960	0.004935	-0.031023	-0.002558	-0.001554	-0.001922	-0.004271	-----
	0.5304	0.9827	0.9961	0.9756	0.9980	0.9988	0.9985	0.9966	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 81. *Correlation matrix. Betas computed in Factor Analysis. Database of daily excesses. Nine factors estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.07E-05								

B2	5.28E-07	8.02E-06							
	0.255687	-----							
	0.8008	-----							
B3	-6.50E-06	-1.53E-06	9.84E-06						
	-3.669593	-0.782075	-----						
	0.0015	0.4433	-----						
B4	-1.24E-06	-7.10E-07	5.49E-08	5.87E-06					
	-0.708422	-0.465366	0.032315	-----					
	0.4869	0.6467	0.9745	-----					
B5	-1.55E-06	1.02E-06	7.47E-07	4.14E-08	4.90E-06				
	-0.979042	0.736220	0.483962	0.034508	-----				
	0.3393	0.4701	0.6337	0.9728	-----				
B6	-3.18E-06	-3.24E-07	-9.23E-08	9.25E-07	4.94E-07	4.83E-06			
	-2.210376	-0.232935	-0.059885	0.789191	0.456134	-----			
	0.0389	0.8182	0.9528	0.4393	0.6532	-----			
B7	-2.71E-06	2.53E-07	1.08E-07	1.06E-07	7.49E-07	9.32E-07	5.27E-06		
	-1.735881	0.174375	0.066797	0.085083	0.665996	0.840341	-----		
	0.0980	0.8633	0.9474	0.9330	0.5130	0.4107	-----		
B8	-2.45E-06	1.81E-07	2.57E-07	4.24E-07	1.28E-08	5.31E-07	3.95E-07	3.46E-06	
	-1.968580	0.153349	0.197043	0.422865	0.013948	0.586278	0.415428	-----	
	0.0630	0.8797	0.8458	0.6769	0.9890	0.5642	0.6823	-----	
B9	1.97E-07	1.75E-07	-3.32E-07	4.98E-07	-4.58E-07	-4.13E-07	-2.70E-07	-5.42E-09	2.97E-06
	0.156645	0.160255	-0.275364	0.537167	-0.541198	-0.491315	-0.305945	-0.007562	-----
	0.8771	0.8743	0.7859	0.5971	0.5943	0.6286	0.7628	0.9940	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 82. *Correlation matrix. Betas computed in Independent Component Analysis. Database of daily excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000 ----- -----								
B2	-0.078607 -0.352634 0.7281	1.000000 ----- -----							
B3	0.181189 0.823938 0.4197	0.073497 0.329580 0.7451	1.000000 ----- -----						
B4	0.159493 0.722523 0.4783	0.201969 0.922239 0.3674	-0.031257 -0.139852 0.8902	1.000000 ----- -----					
B5	-0.066672 -0.298831 0.7682	-0.055605 -0.249060 0.8059	-0.019957 -0.089269 0.9298	-0.096992 -0.435815 0.6676	1.000000 ----- -----				
B6	-0.069052 -0.309548 0.7601	-0.121957 -0.549511 0.5887	0.060619 0.271598 0.7887	-0.028915 -0.129366 0.8984	0.015731 0.070359 0.9446	1.000000 ----- -----			
B7	0.397473 1.937150 0.0670	0.165598 0.750946 0.4614	-0.106993 -0.481249 0.6356	0.037780 0.169077 0.8674	-0.063518 -0.284635 0.7789	0.027174 0.121570 0.9045	1.000000 ----- -----		
B8	-0.000952 -0.004259 0.9966	-0.075429 -0.338291 0.7387	0.027292 0.122097 0.9040	-0.005453 -0.024387 0.9808	-0.001163 -0.005199 0.9959	0.024519 0.109684 0.9138	0.063101 0.282758 0.7803	1.000000 ----- -----	
B9	-0.459519 -2.313789 0.0314	-0.242764 -1.119151 0.2763	0.152617 0.690615 0.4977	-0.101749 -0.457407 0.6523	0.047831 0.214151 0.8326	0.011941 0.053407 0.9579	0.036316 0.162516 0.8725	0.009892 0.044243 0.9651	1.000000 ----- -----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Table 83. *Correlation matrix. Betas computed in Neural Networks Principal Component Analysis. Database of daily excesses. Nine components estimated.*

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1.000000								

B2	0.973128	1.000000							
	18.89966	-----							
	0.0000	-----							
B3	0.656782	0.642634	1.000000						
	3.895102	3.751044	-----						
	0.0009	0.0013	-----						
B4	-0.992263	-0.964984	-0.649807	1.000000					
	-35.74116	-16.45225	-3.823219	-----					
	0.0000	0.0000	0.0011	-----					
B5	-0.153220	-0.150892	-0.110651	0.159135	1.000000				
	-0.693410	-0.682626	-0.497902	0.720858	-----				
	0.4960	0.5027	0.6240	0.4793	-----				
B6	-0.989462	-0.961391	-0.650968	0.980939	0.152257	1.000000			
	-30.56116	-15.62388	-3.835065	22.57612	0.688946	-----			
	0.0000	0.0000	0.0010	0.0000	0.4988	-----			
B7	0.998950	0.970945	0.654462	-0.992522	-0.156657	-0.987451	1.000000		
	97.51314	18.14515	3.871004	-36.36277	-0.709349	-27.96276	-----		
	0.0000	0.0000	0.0010	0.0000	0.4863	0.0000	-----		
B8	0.999317	0.971324	0.653242	-0.992476	-0.151825	-0.988859	0.998283	1.000000	
	120.9454	18.27019	3.858405	-36.25078	-0.686947	-29.70895	76.21442	-----	
	0.0000	0.0000	0.0010	0.0000	0.5000	0.0000	0.0000	-----	
B9	-0.999897	-0.971950	-0.654941	0.993284	0.155273	0.988792	-0.998999	-0.999370	1.000000
	-312.1752	-18.48173	-3.875959	38.39377	0.702929	29.61881	-99.88091	-125.9642	-----
	0.0000	0.0000	0.0009	0.0000	0.4902	0.0000	0.0000	0.0000	-----

Notes: Number for each factor represent the Correlation, the value of the t-statistic and its corresponding p-value, respectively.

Figure 57. *Plot of the Betas computed in Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

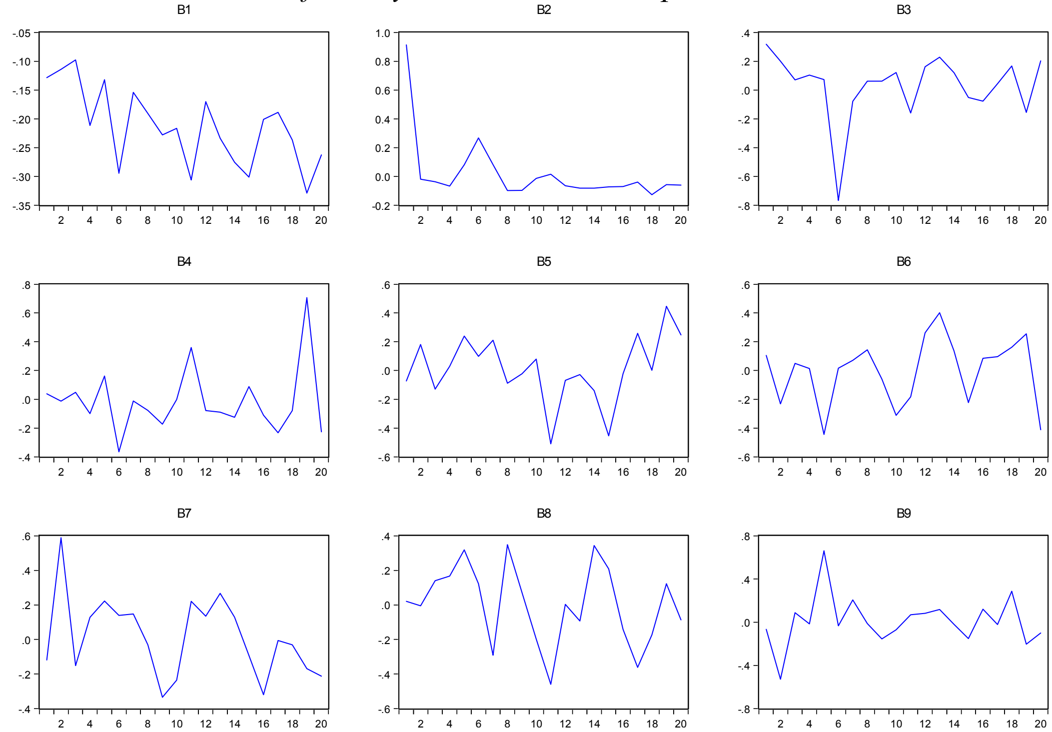


Figure 58. *Plot of the Betas computed in Factor Analysis. Database of weekly excesses. Nine components estimated.*

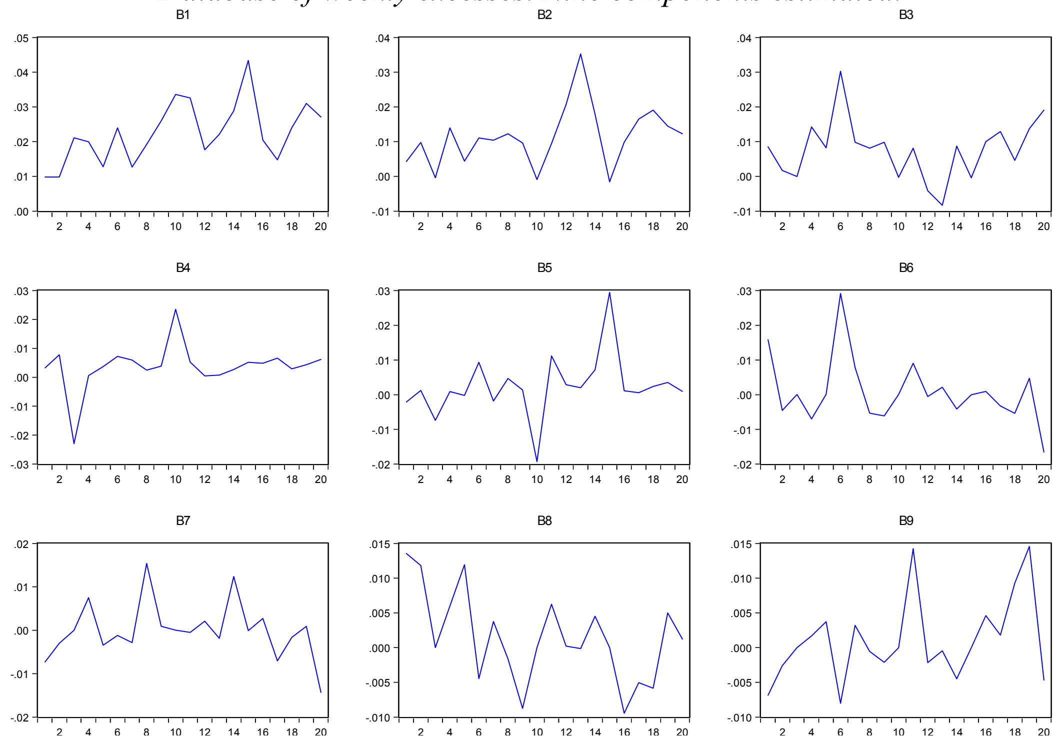


Figure 59. *Plot of the Betas computed in Independent Component Analysis. Database of weekly excesses. Nine components estimated.*

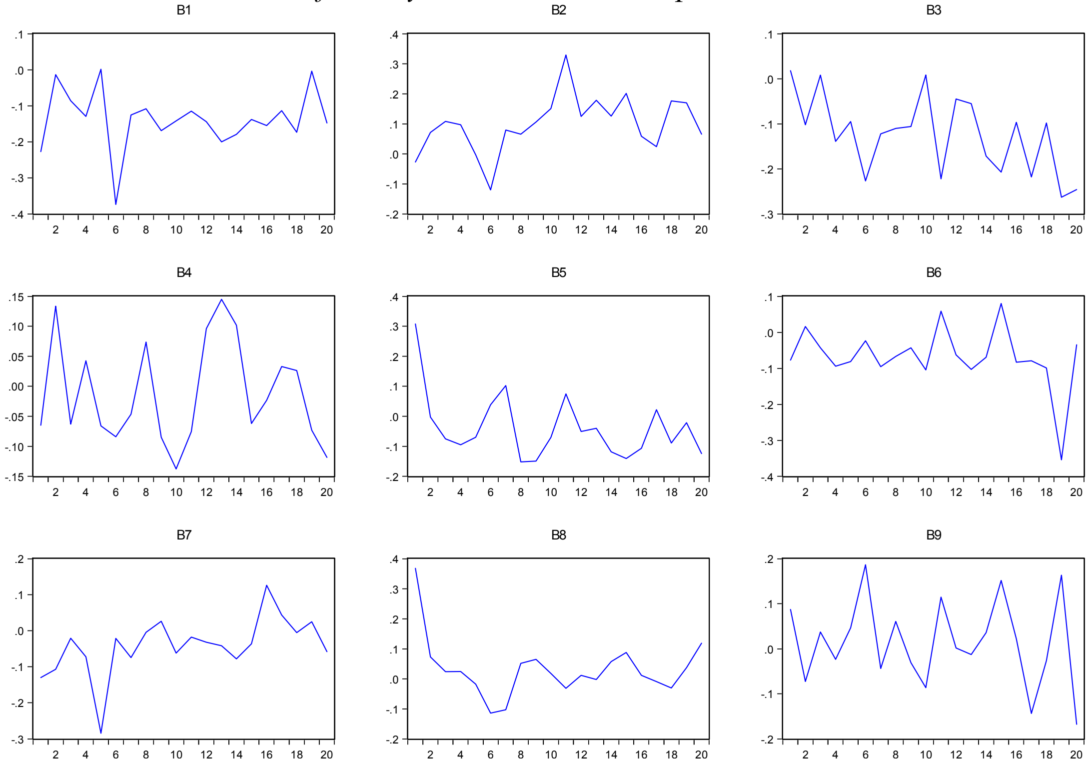


Figure 60. *Plot of the Betas computed in Neural Networks Principal Component Analysis. Database of weekly excesses. Nine components estimated.*

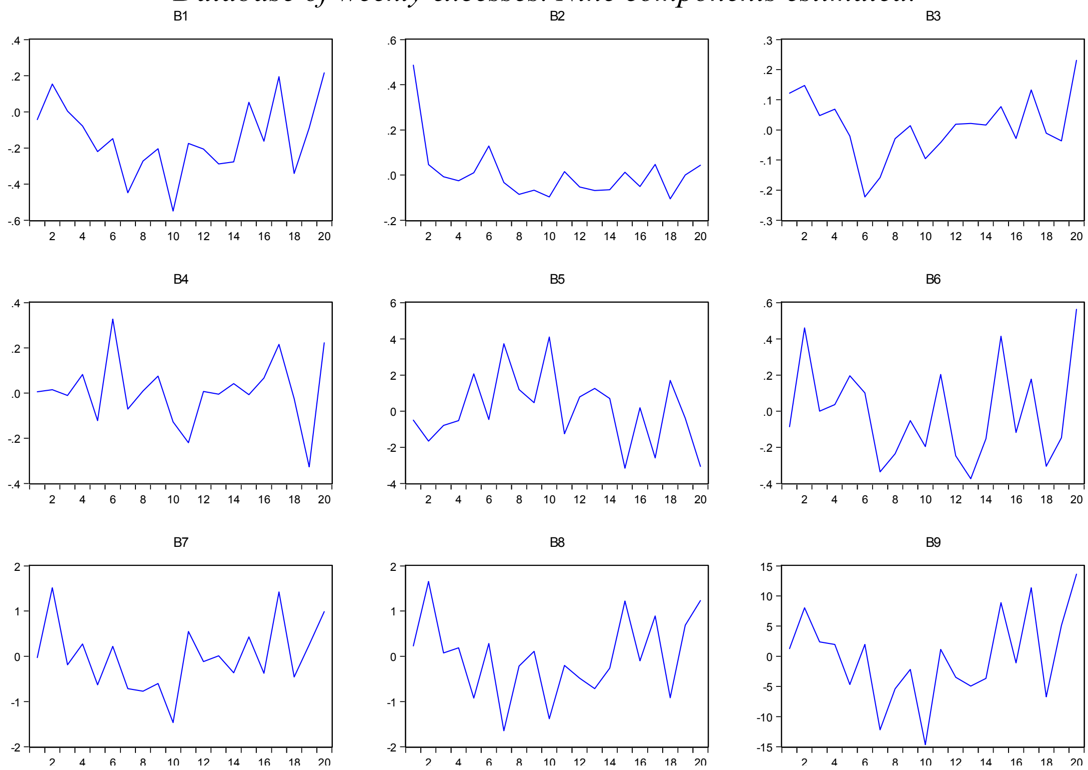


Figure 61. *Plot of the Betas computed in Principal Component Analysis. Database of daily returns. Nine components estimated.*

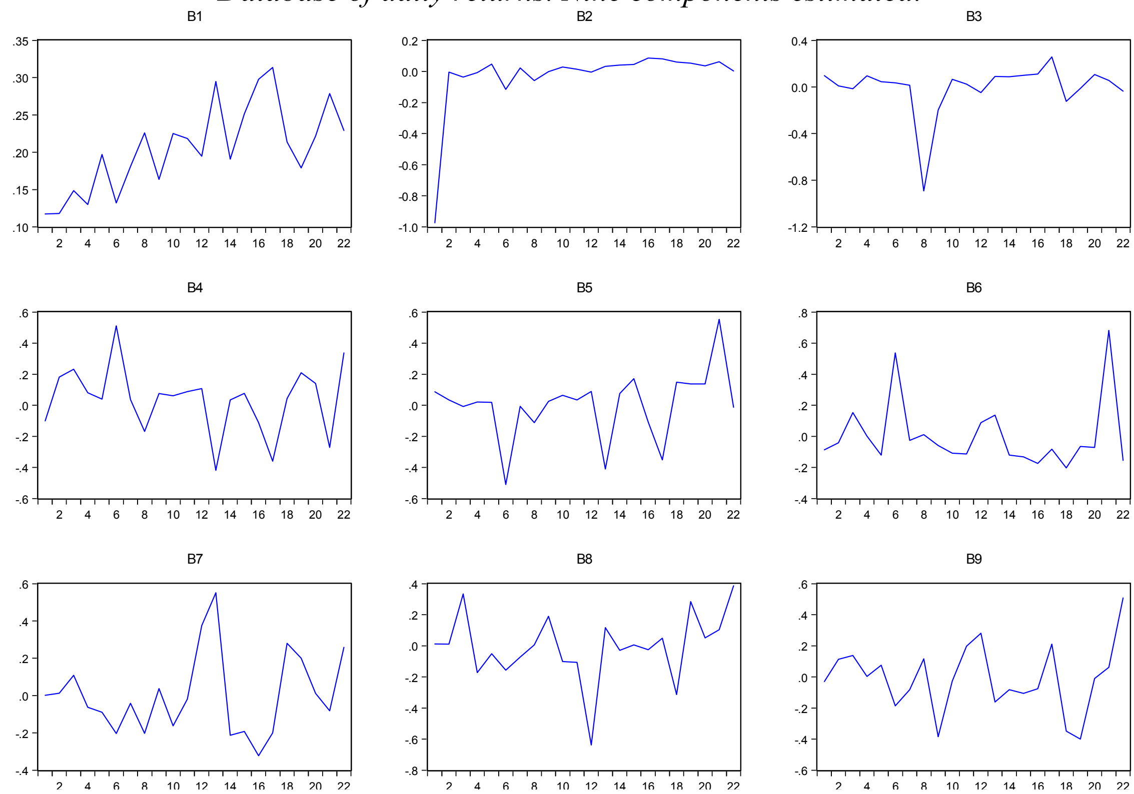


Figure 62. *Plot of the Betas computed in Factor Analysis. Database of daily returns. Nine components estimated.*

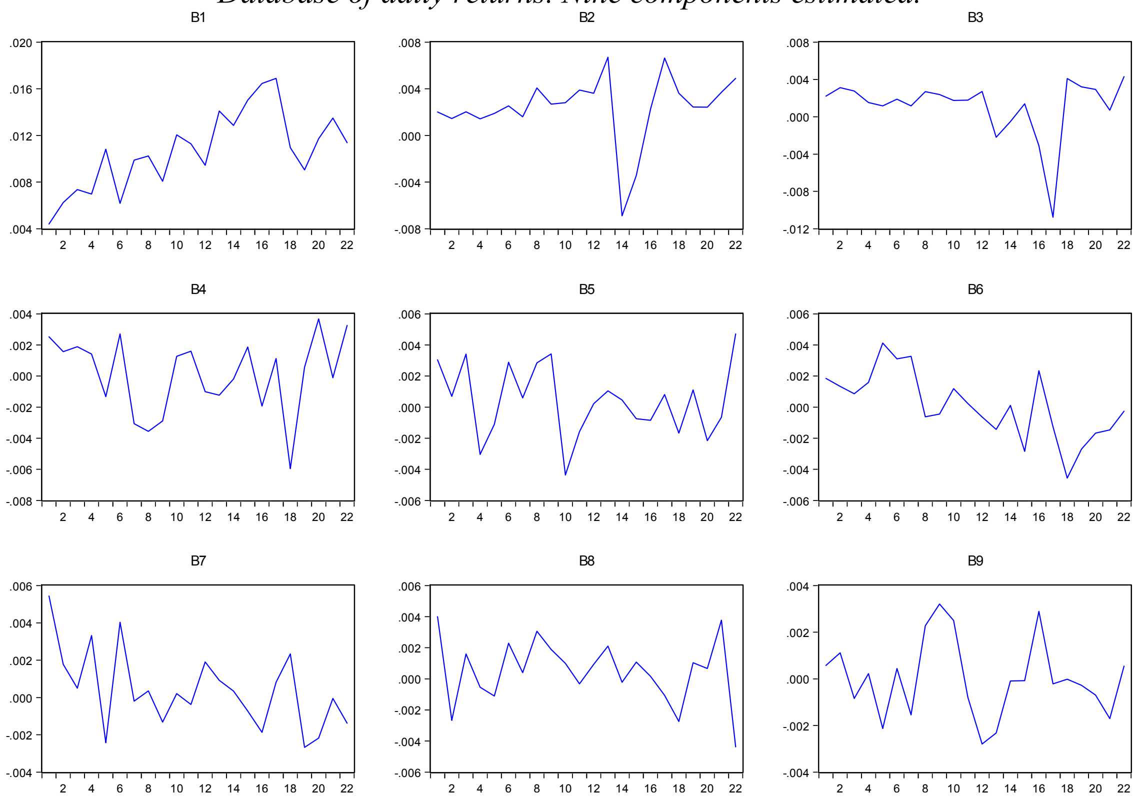


Figure 63. *Plot of the Betas computed in Independent Component Analysis. Database of daily returns. Nine components estimated.*

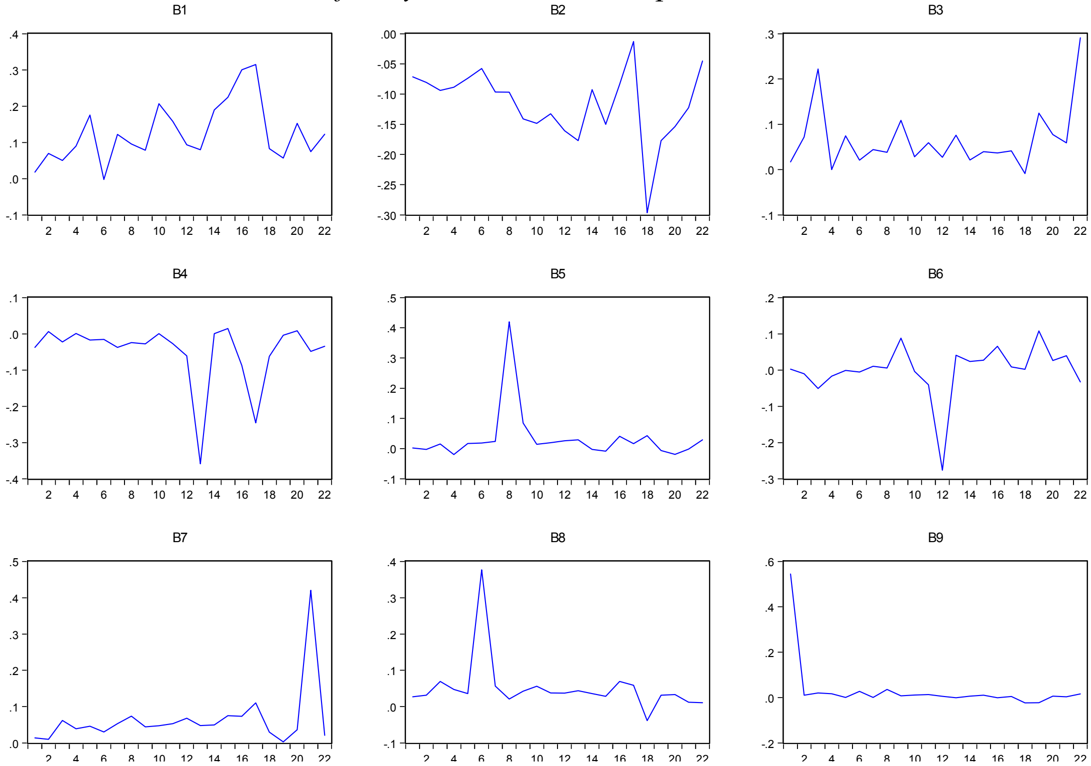


Figure 64. *Plot of the Betas computed in Neural Networks Principal Component Analysis. Database of daily returns. Nine components estimated.*

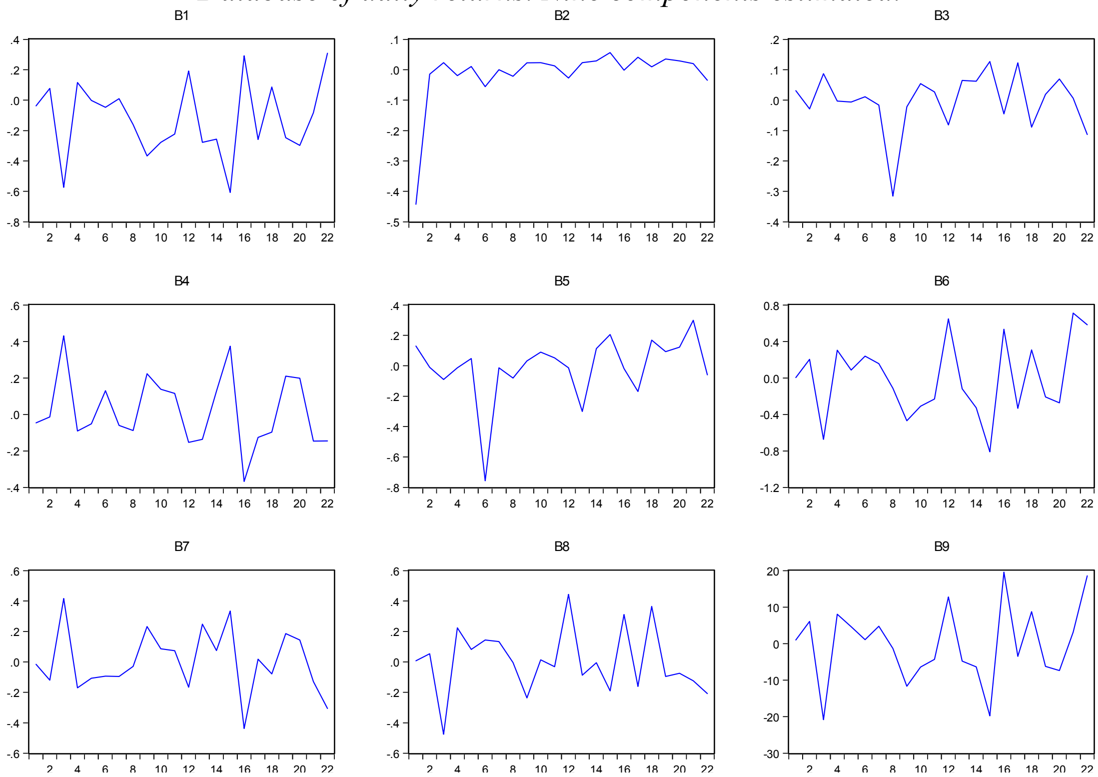


Figure 65. *Plot of the Betas computed in Principal Component Analysis. Database of daily excesses. Nine components estimated.*

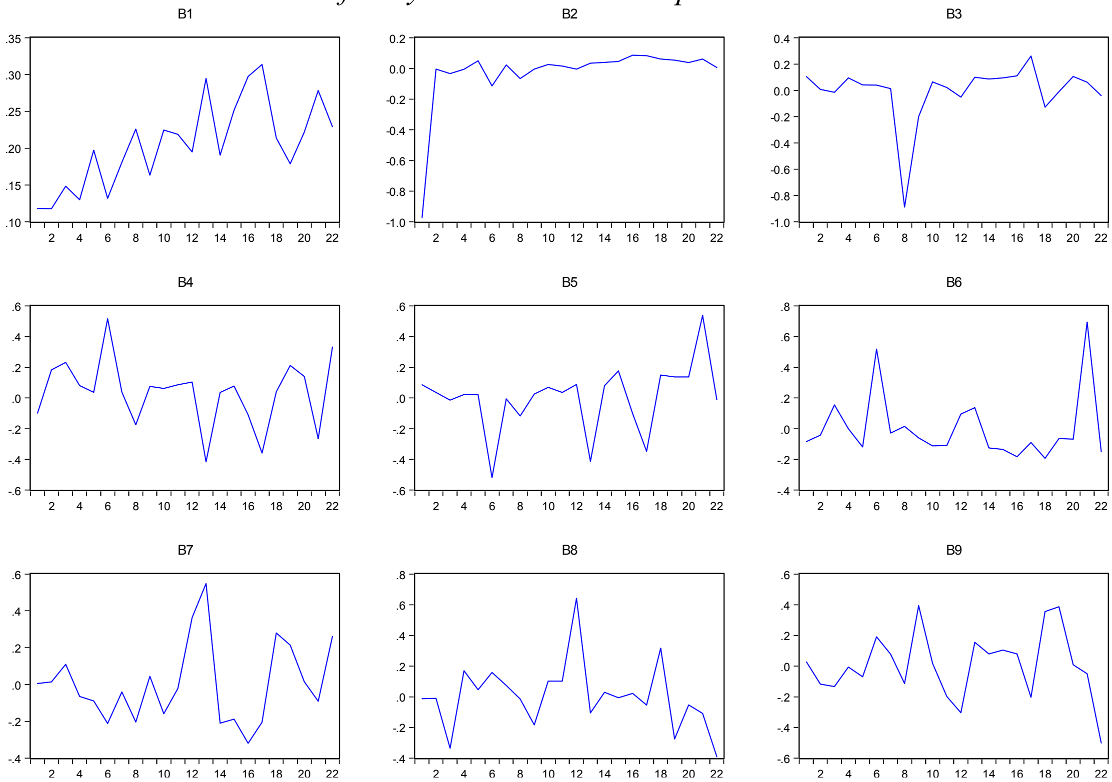


Figure 66. *Plot of the Betas computed in Factor Analysis. Database of daily excesses. Nine components estimated.*

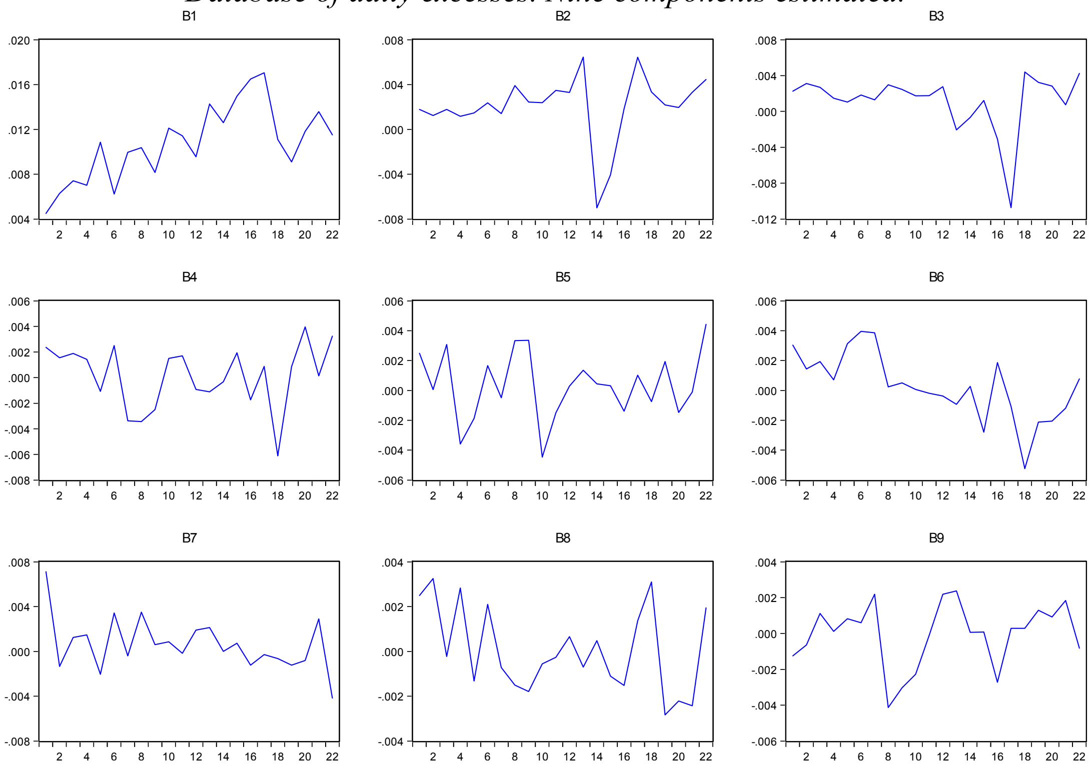


Figure 67. *Plot of the Betas computed in Independent Component Analysis. Database of daily excesses. Nine components estimated.*

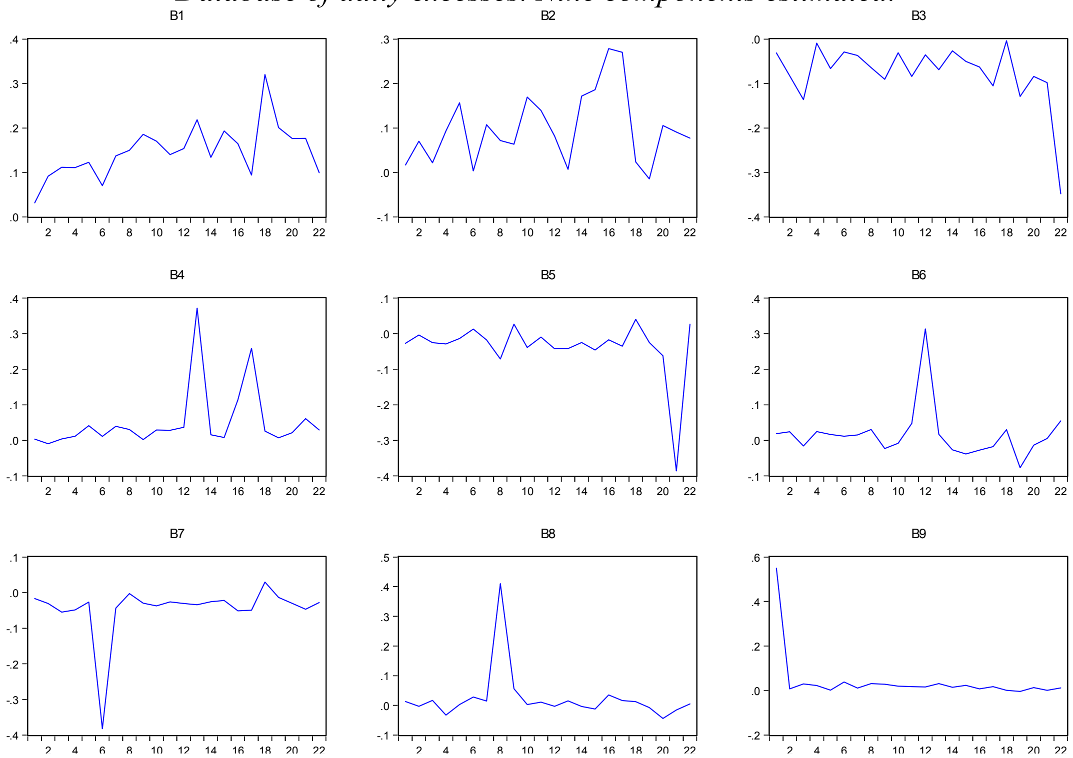


Figure 68. *Plot of the Betas computed in Neural Networks Principal Component Analysis. Database of daily excesses. Nine components estimated.*

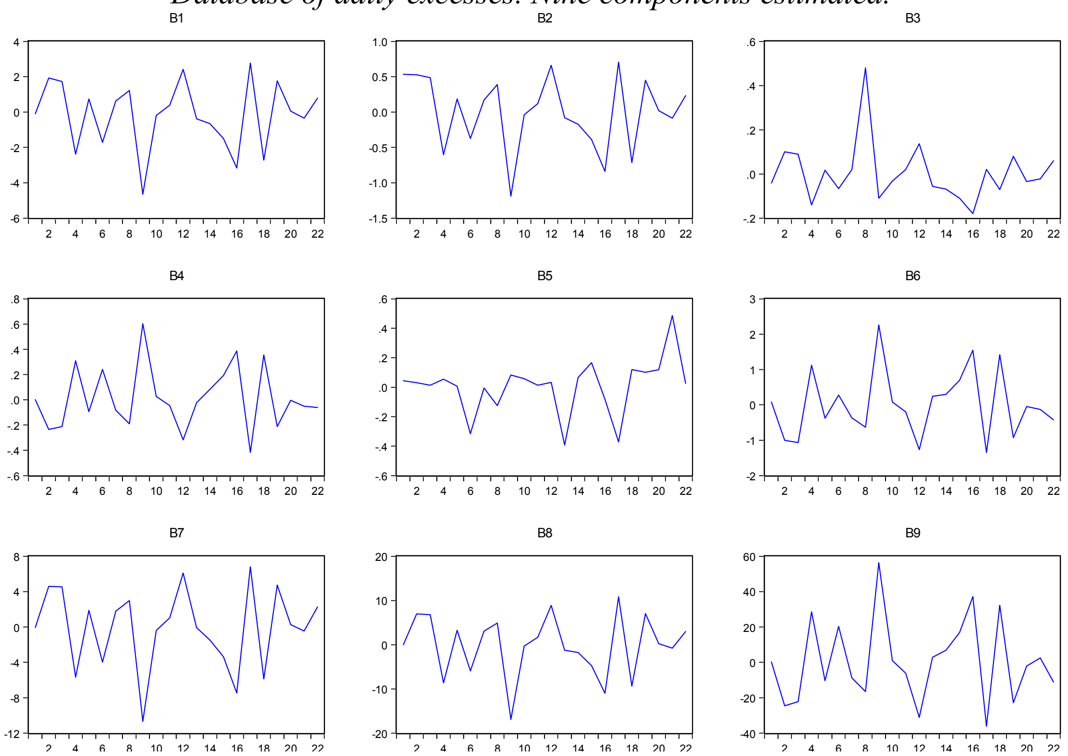


Figure 69. *Plot of the Betas computed in Principal Component Analysis. Database of daily excesses. Nine components estimated.*

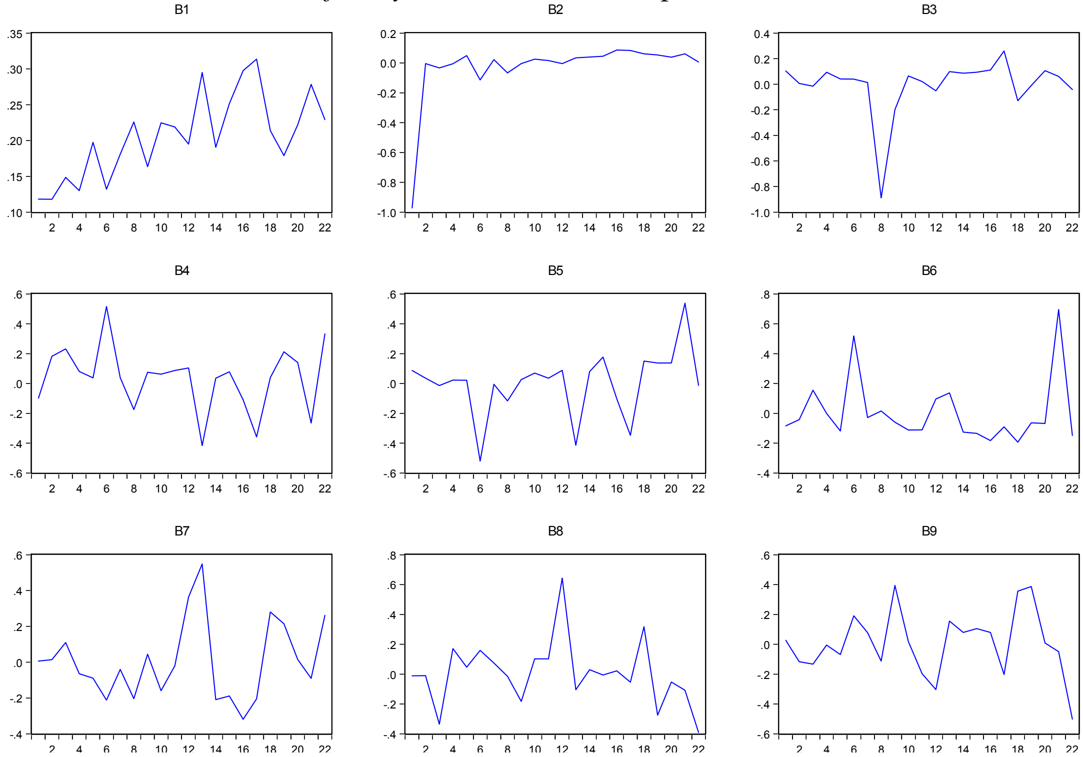


Figure 70. *Plot of the Betas computed in Factor Analysis. Database of daily excesses. Nine components estimated.*

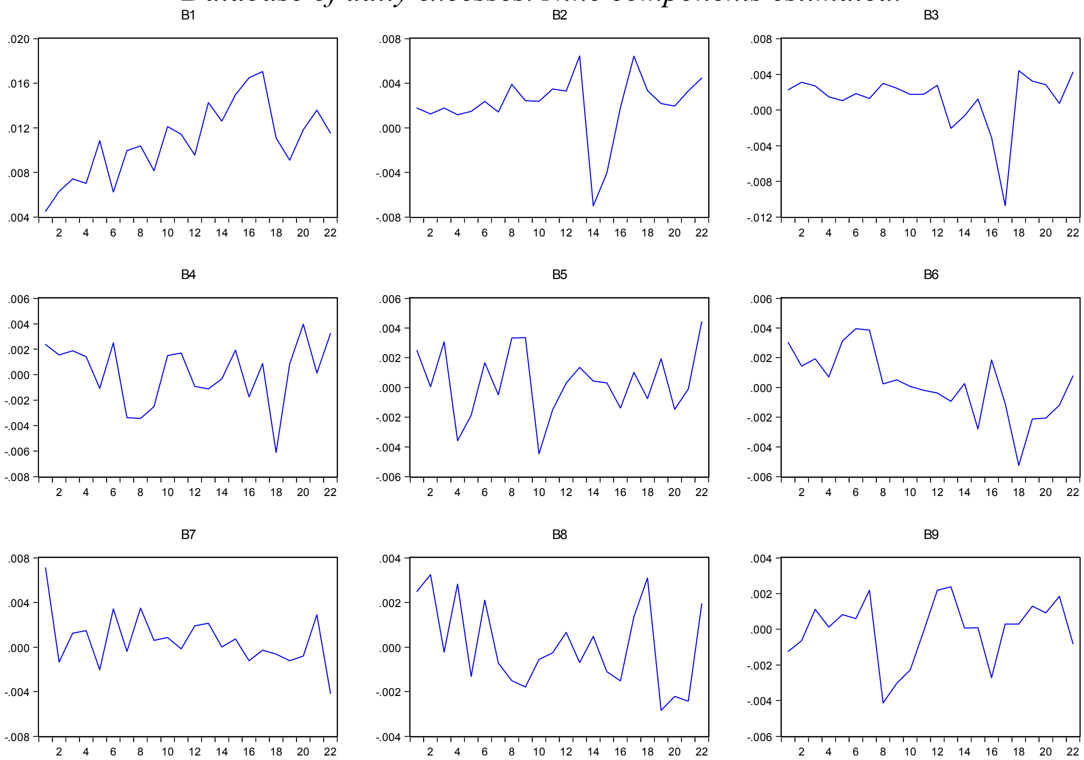


Figure 71. *Plot of the Betas computed in Independent Component Analysis. Database of daily excesses. Nine components estimated.*

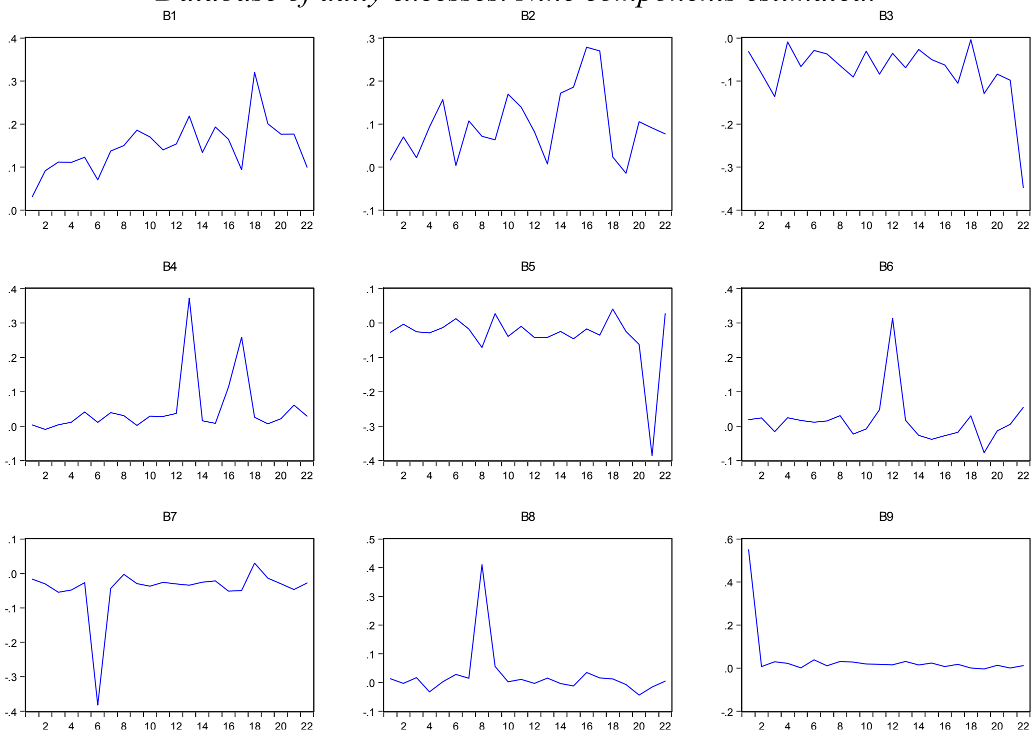


Figure 72. *Plot of the Betas computed in Neural Networks Principal Component Analysis. Database of daily excesses. Nine components estimated.*

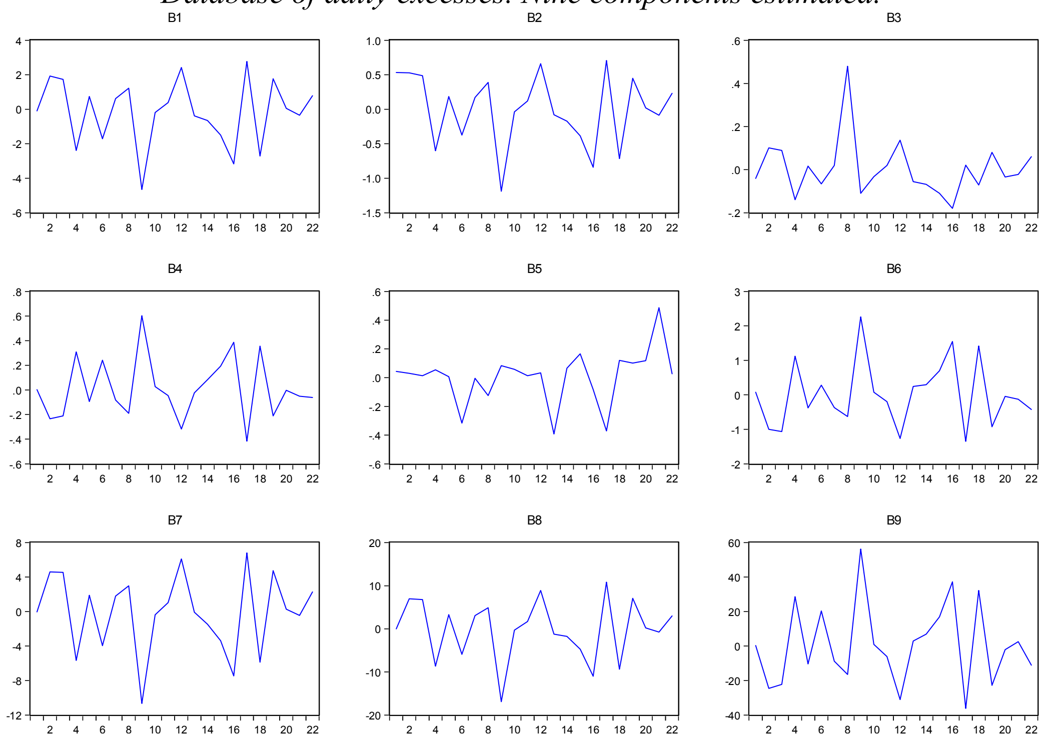


Figure 73. *Betas to the first underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

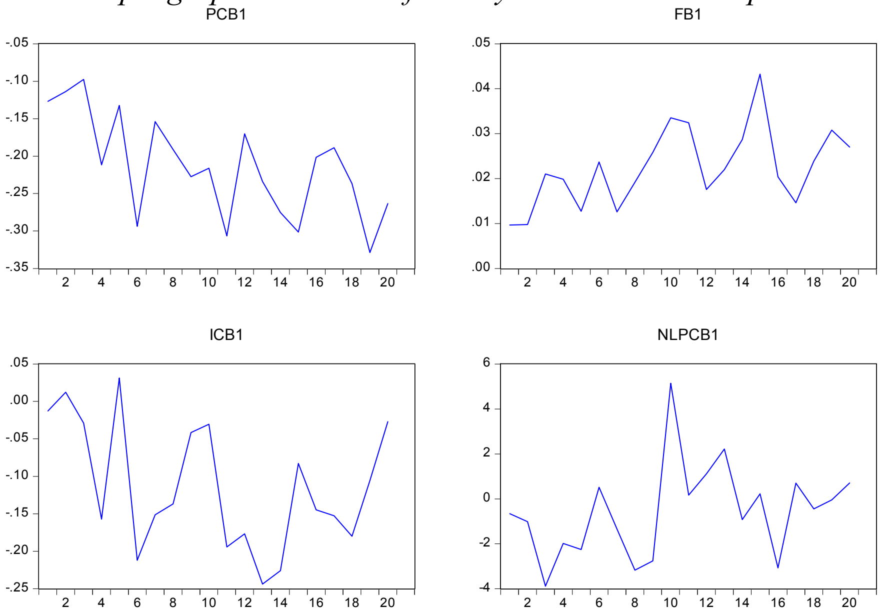


Figure 74. *Betas to the second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

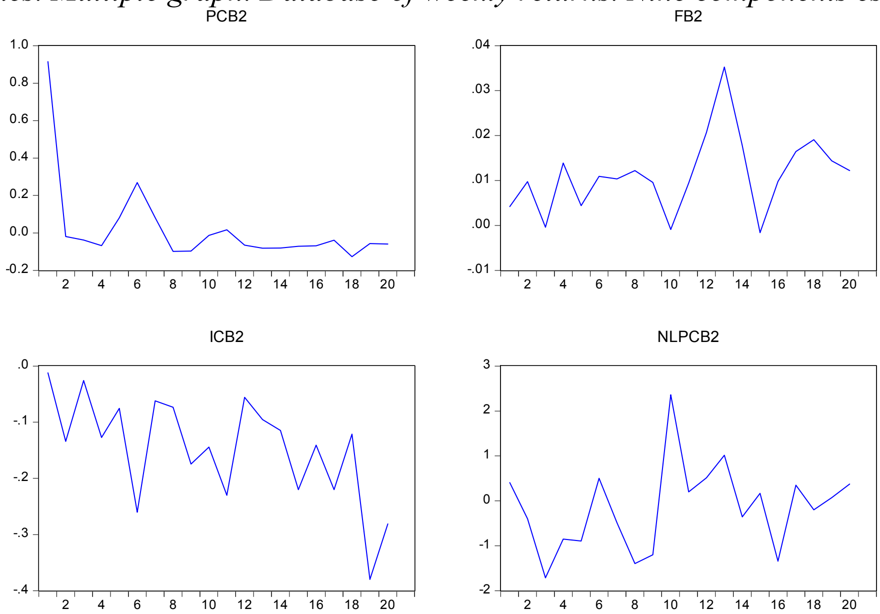


Figure 75. *Betas to the third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

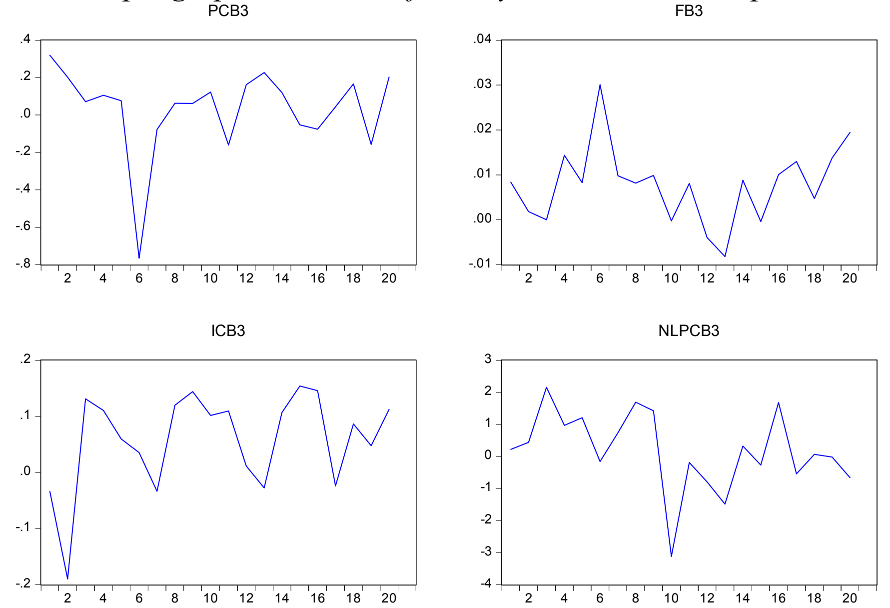


Figure 76. *Betas to the fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

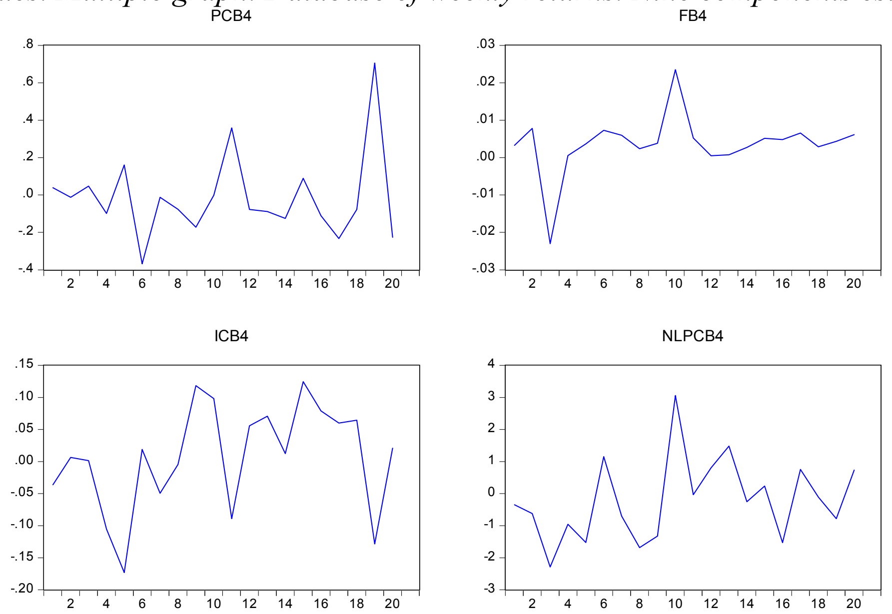


Figure 77. *Betas to the fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

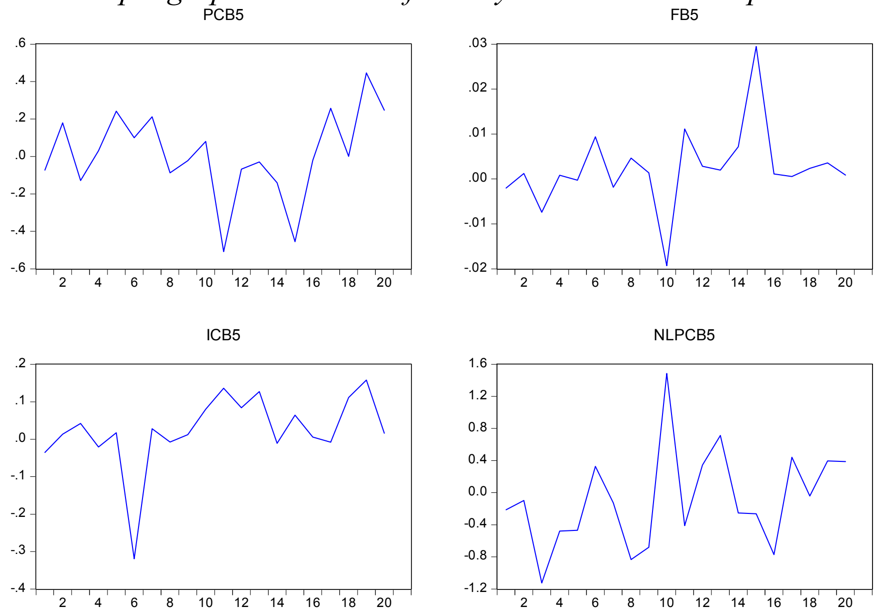


Figure 78. *Betas to the sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

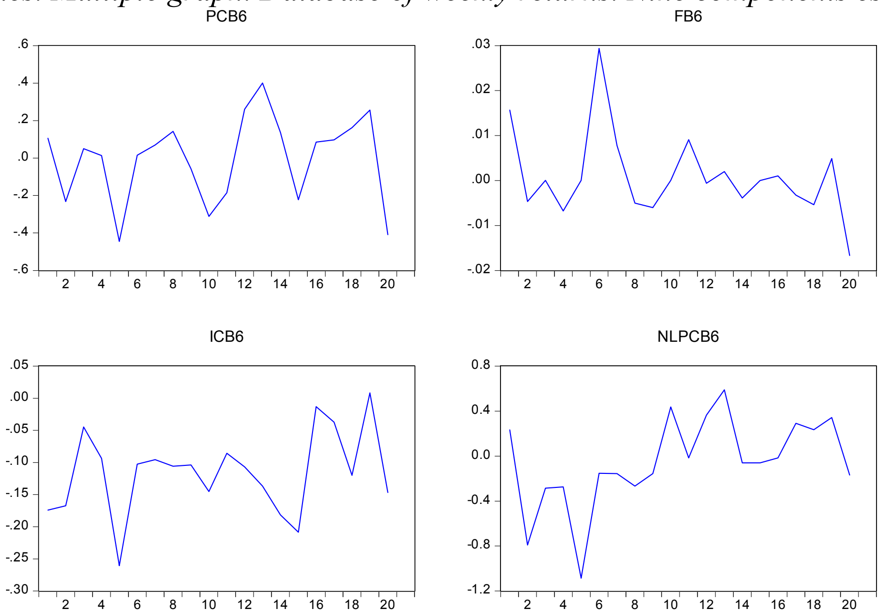


Figure 79. *Betas to the seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

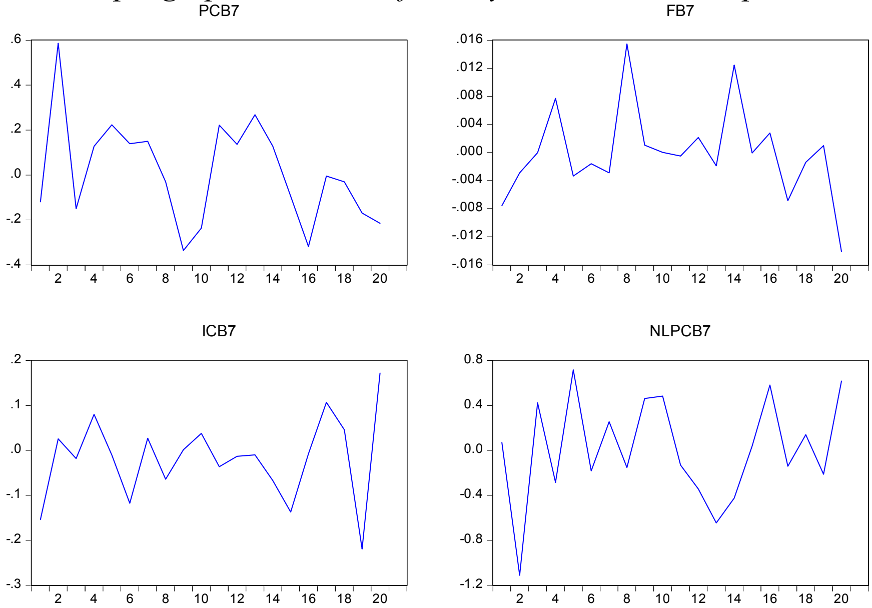


Figure 80. *Betas to the eight underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

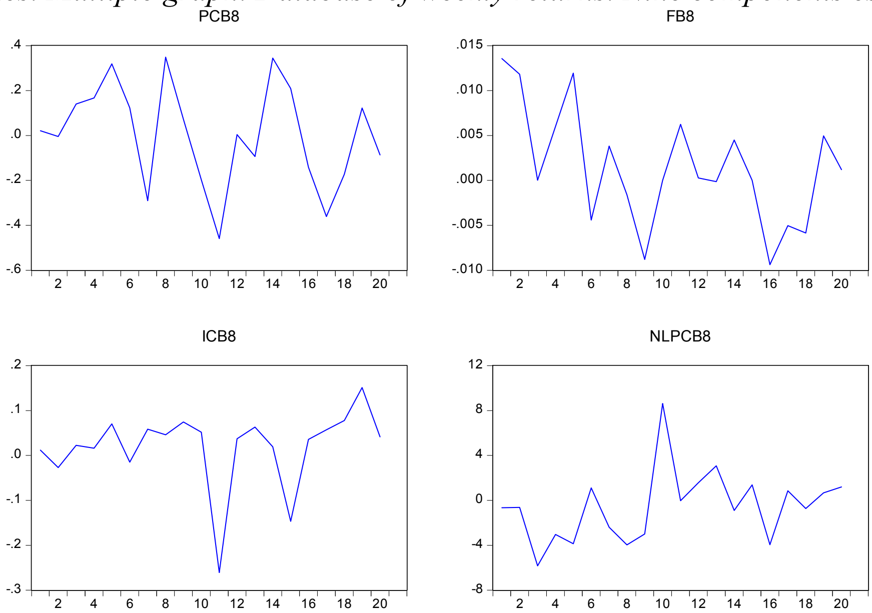


Figure 81. *Betas to the ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly returns. Nine components estimated.*

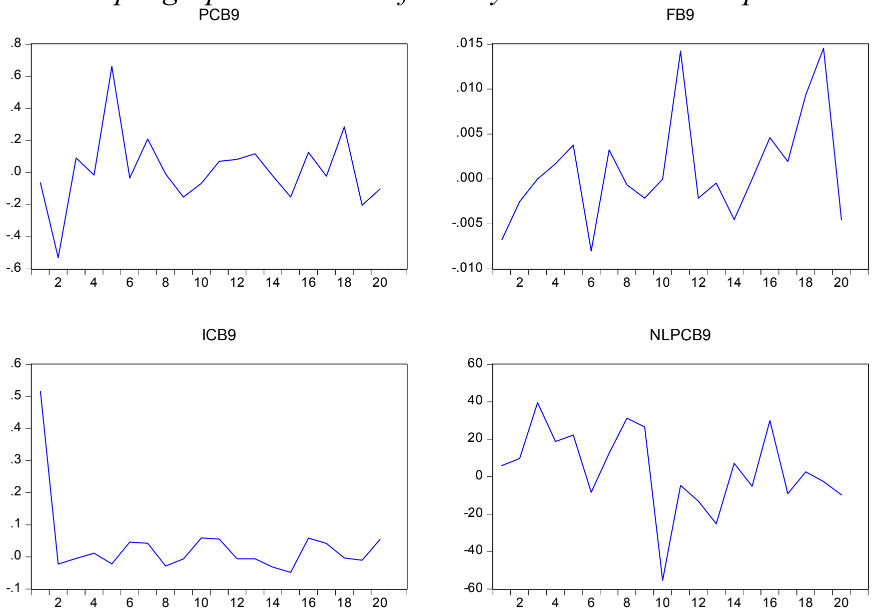


Figure 82. *Betas to the first underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

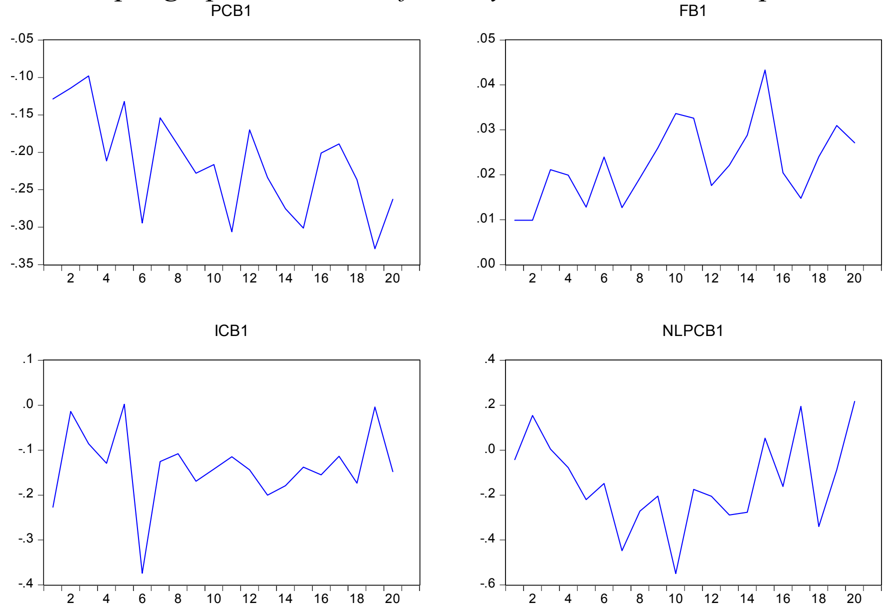


Figure 83. *Betas to the second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

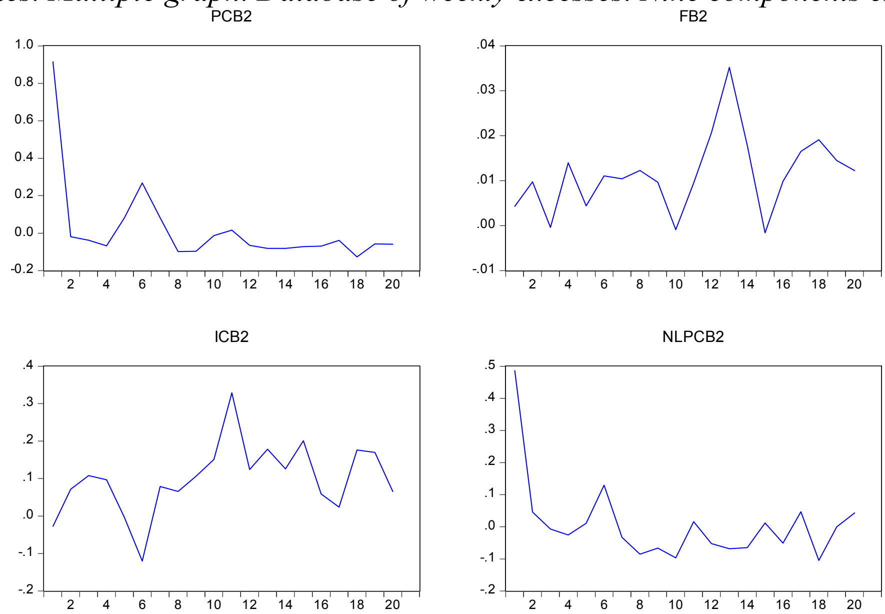


Figure 84. *Betas to the third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

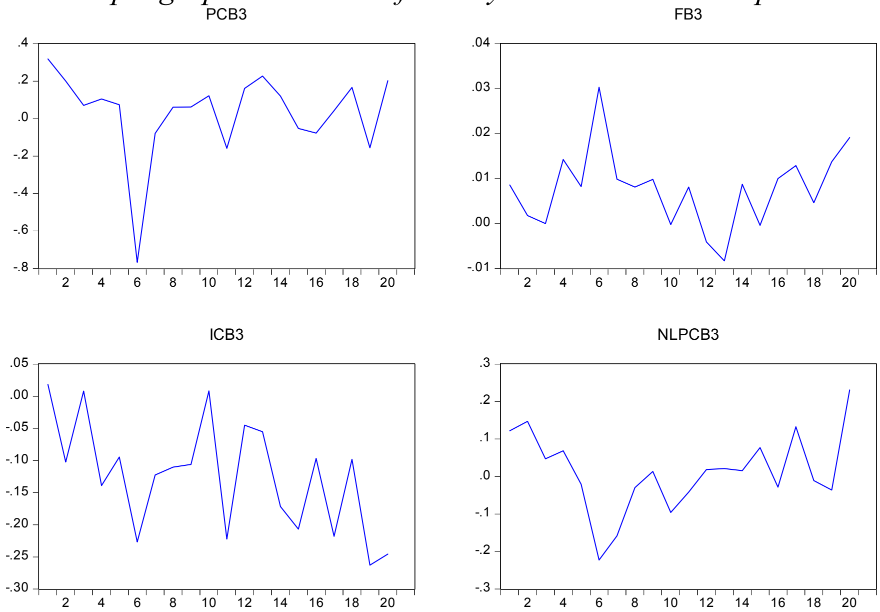


Figure 85. *Betas to the fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

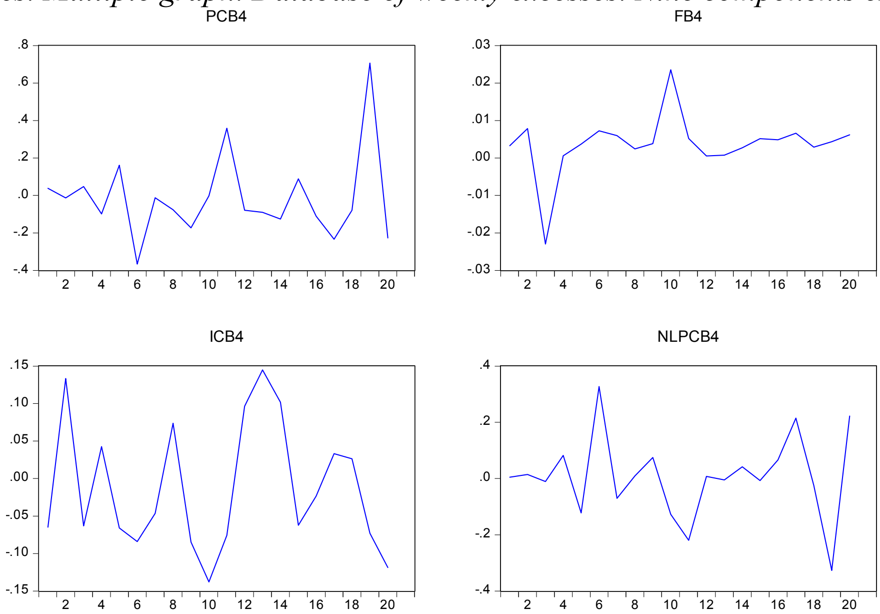


Figure 86. *Betas to the fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

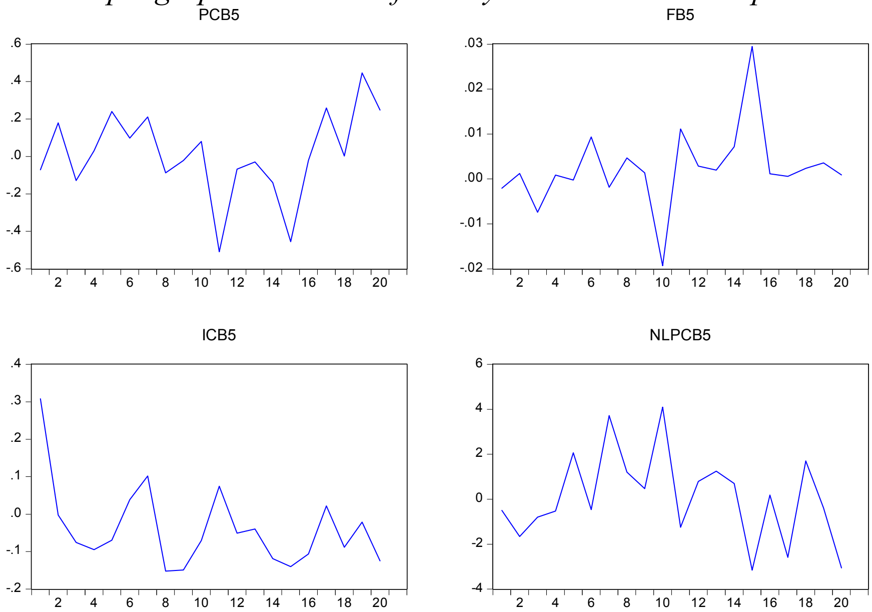


Figure 87. *Betas to the sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

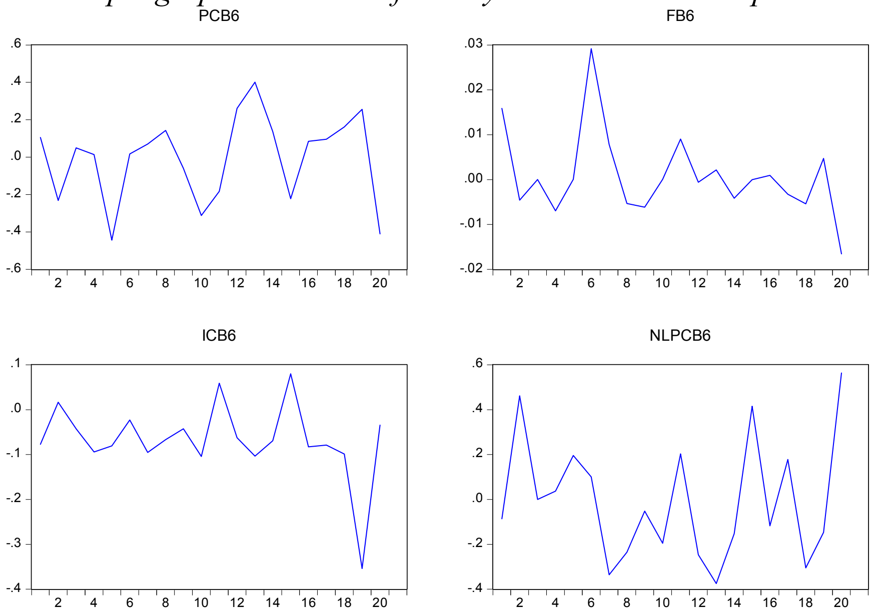


Figure 88. *Beta to the seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

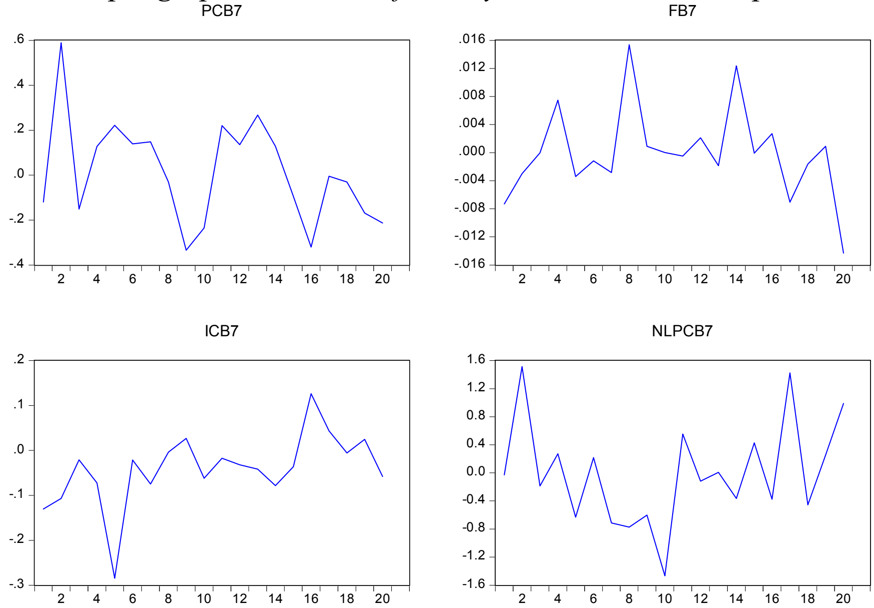


Figure 89. *Betas to the eight underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

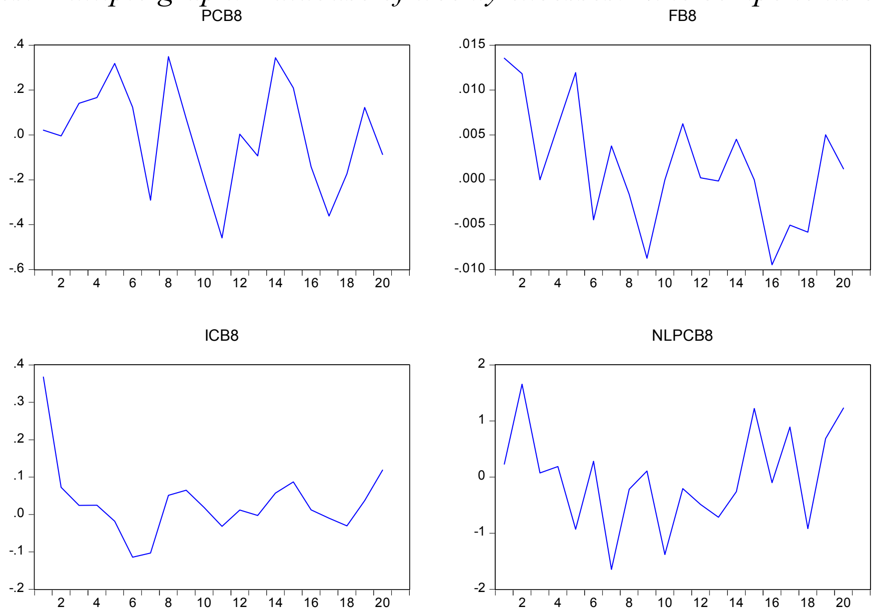


Figure 90. *Betas to the ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of weekly excesses. Nine components estimated.*

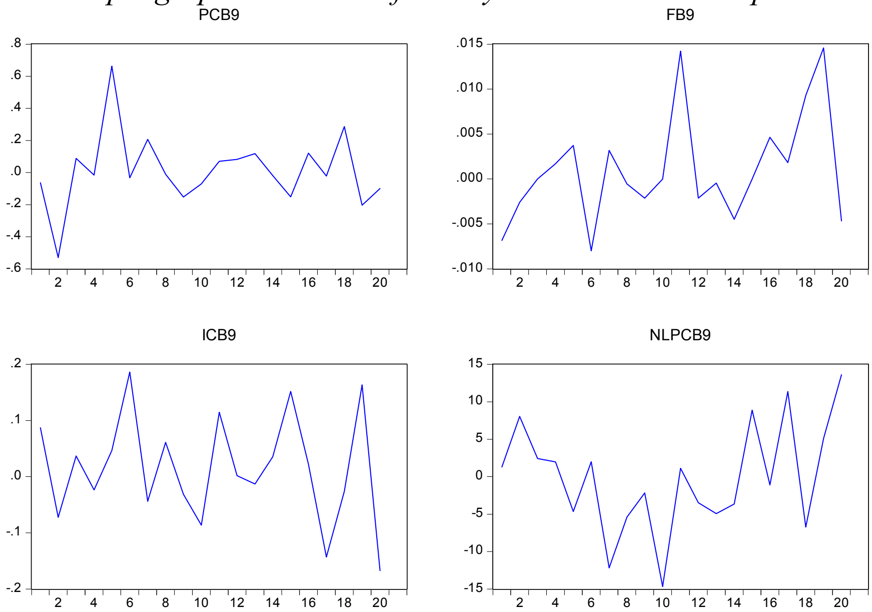


Figure 91. *Betas to the first underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

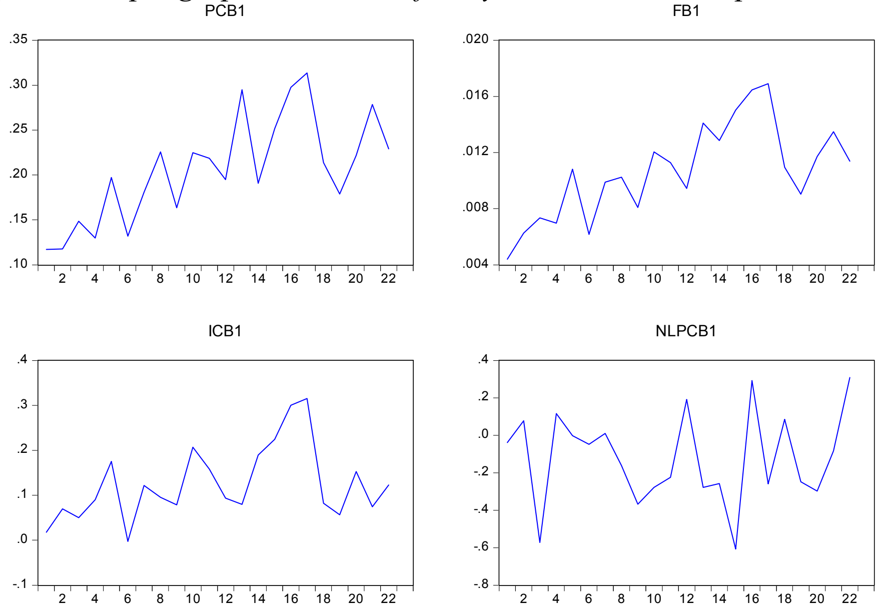


Figure 92. *Beta to the second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

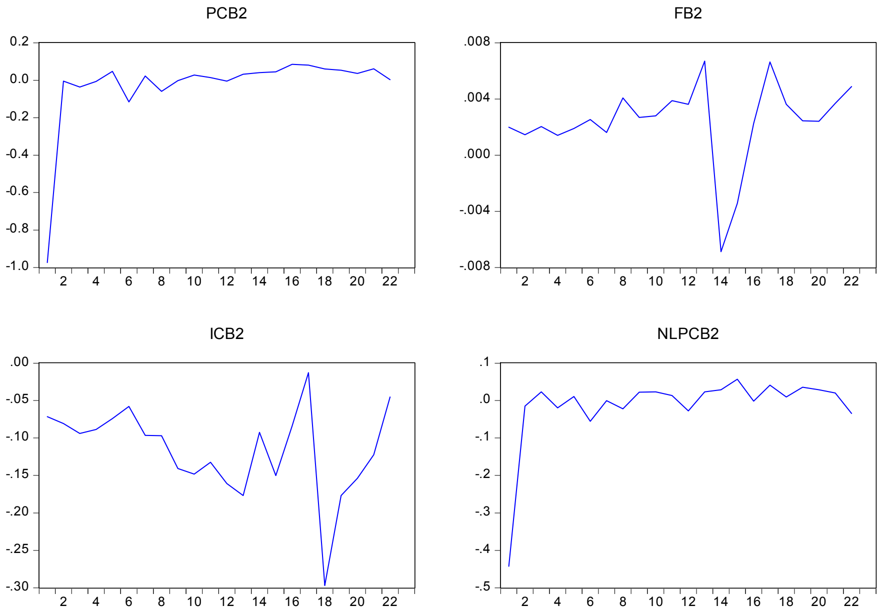


Figure 93. *Betas to the third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

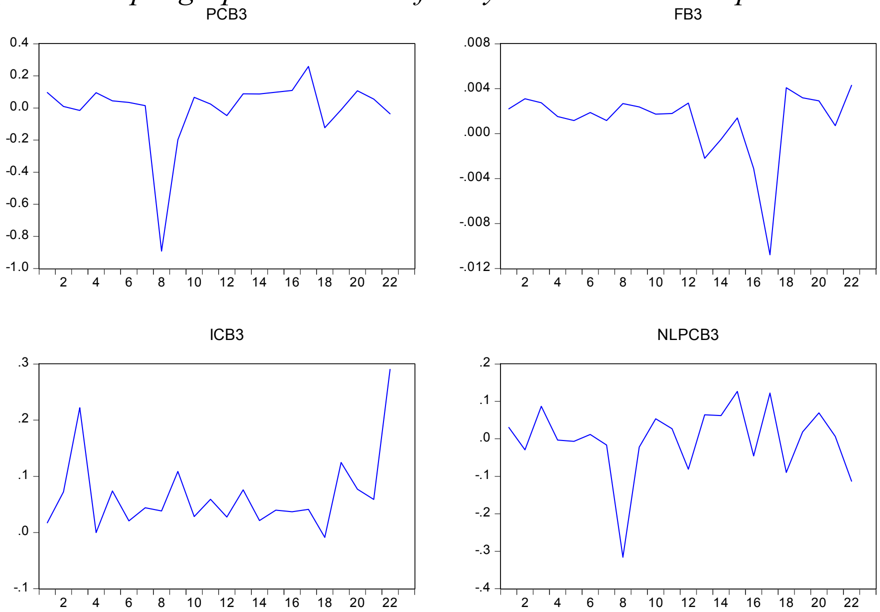


Figure 94. *Betas to the fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

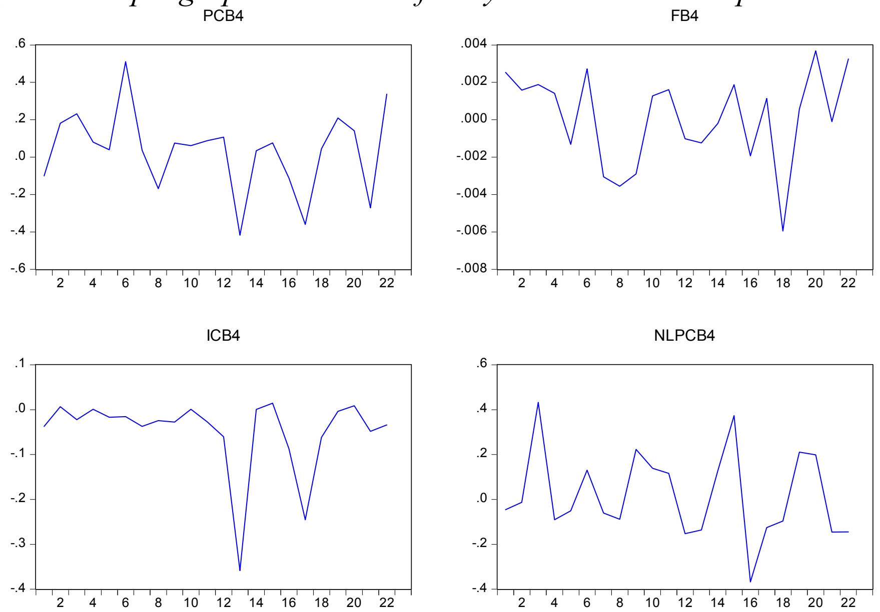


Figure 95. *Betas to the fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

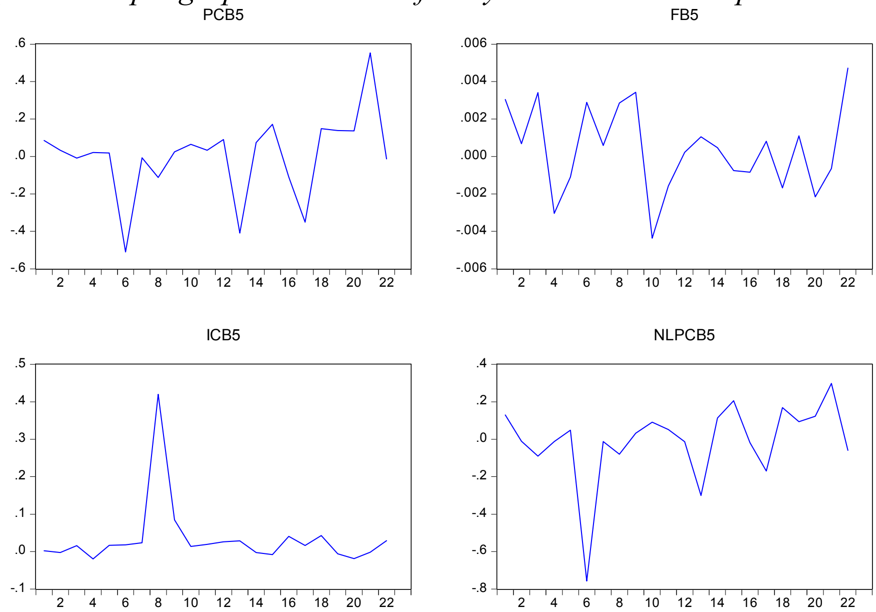


Figure 96. *Betas to the sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

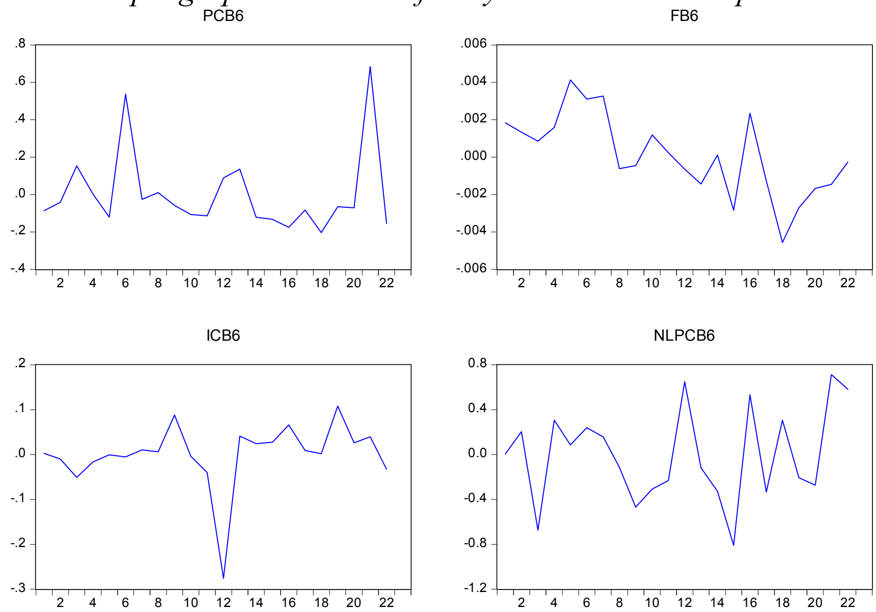


Figure 97. *Betas to the seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

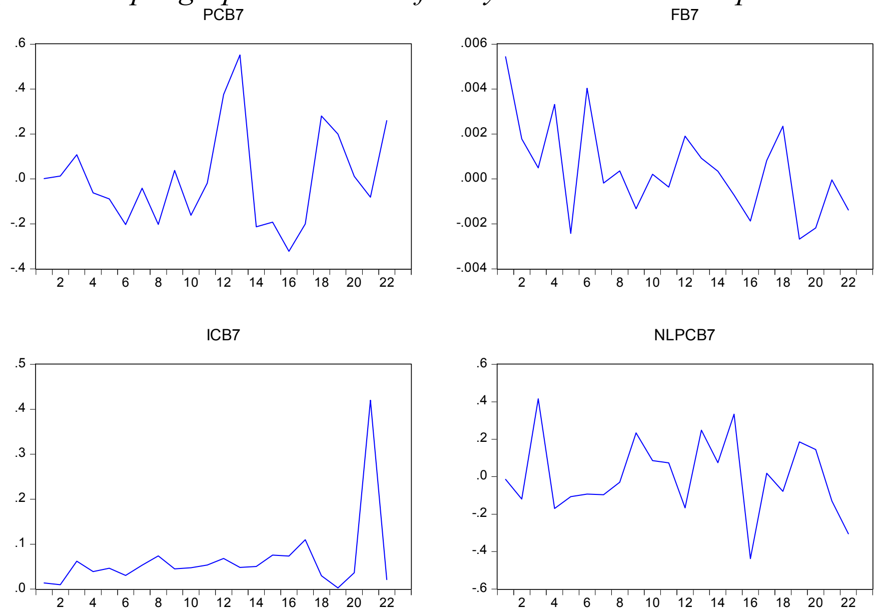


Figure 98. *Betas to the eight underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

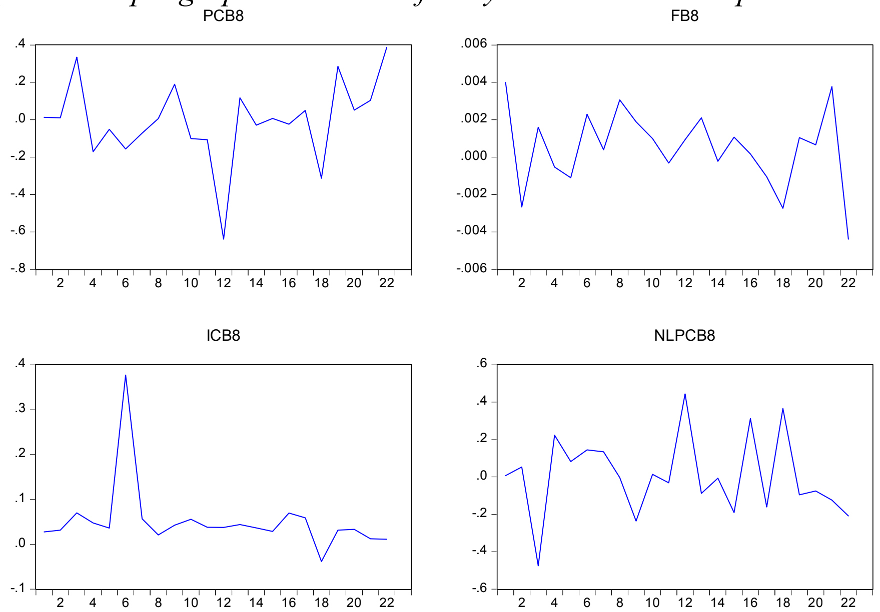


Figure 99. *Betas to the ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily returns. Nine components estimated.*

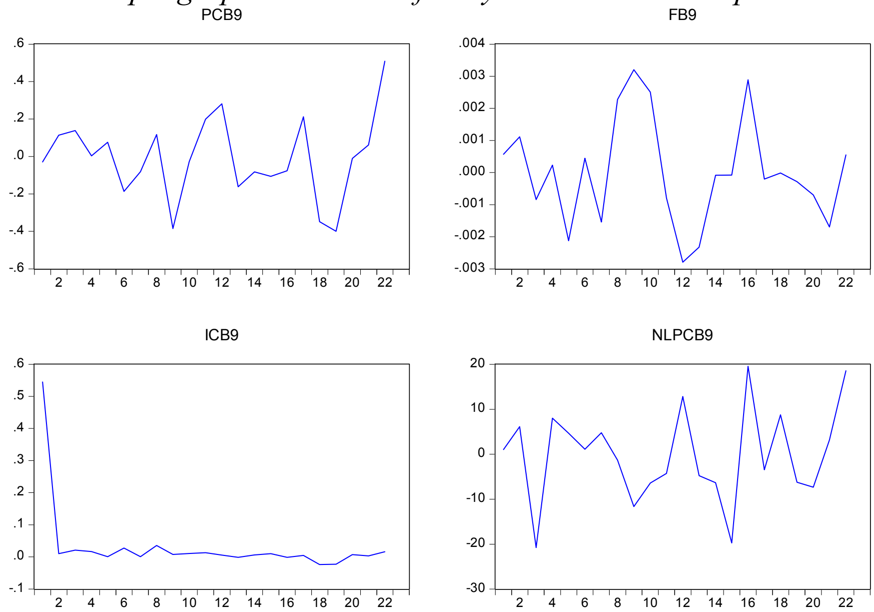


Figure 100. *Betas to the first underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

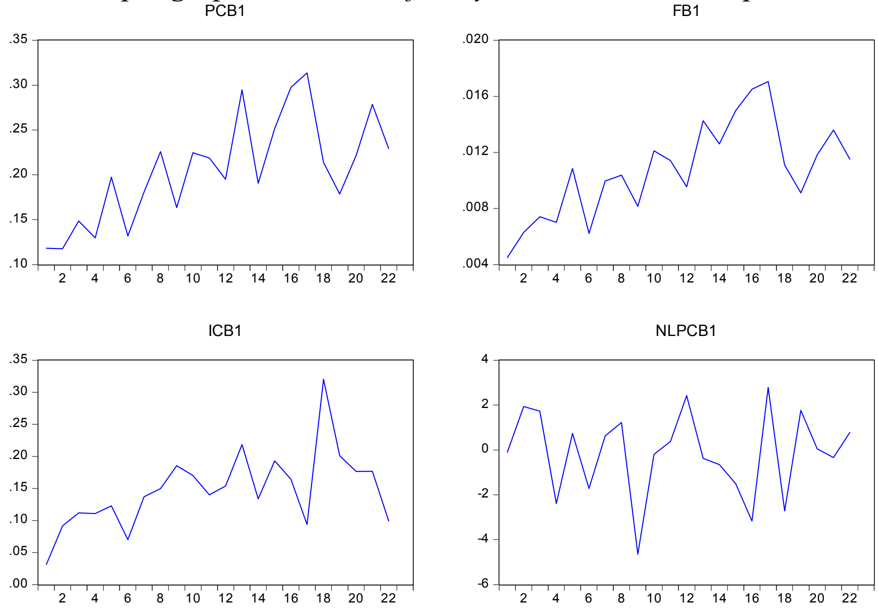


Figure 101. *Betas to the second underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

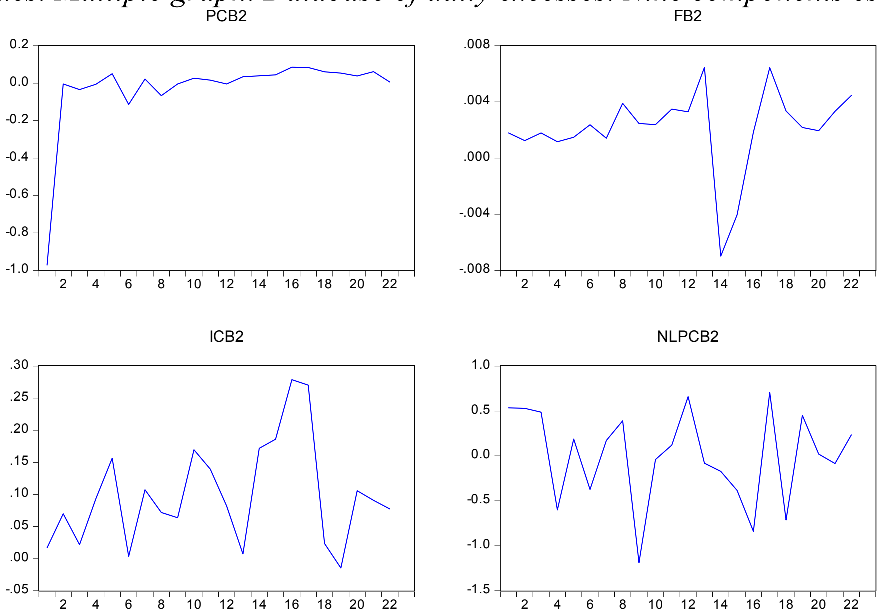


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Figure 102. *Betas to the third underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

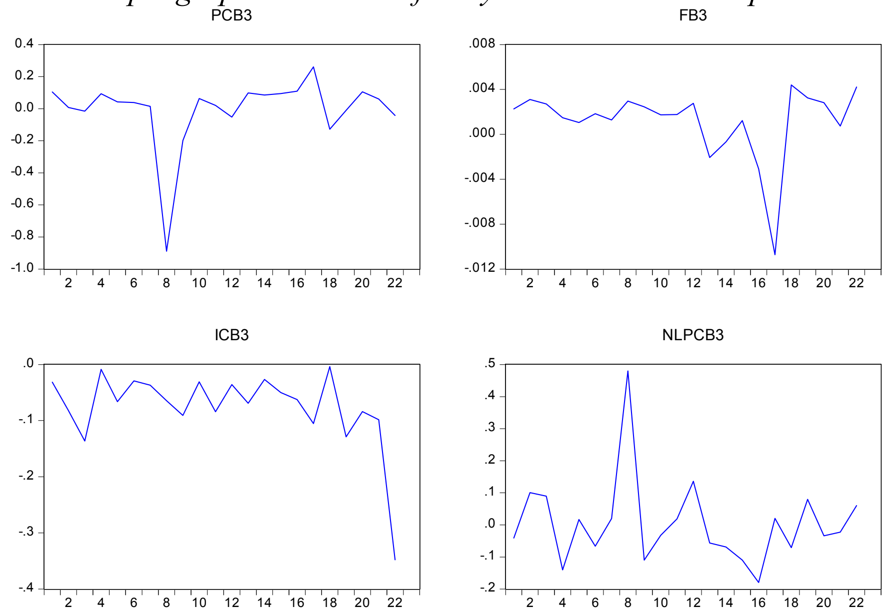

Figure 103. *Betas to the fourth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

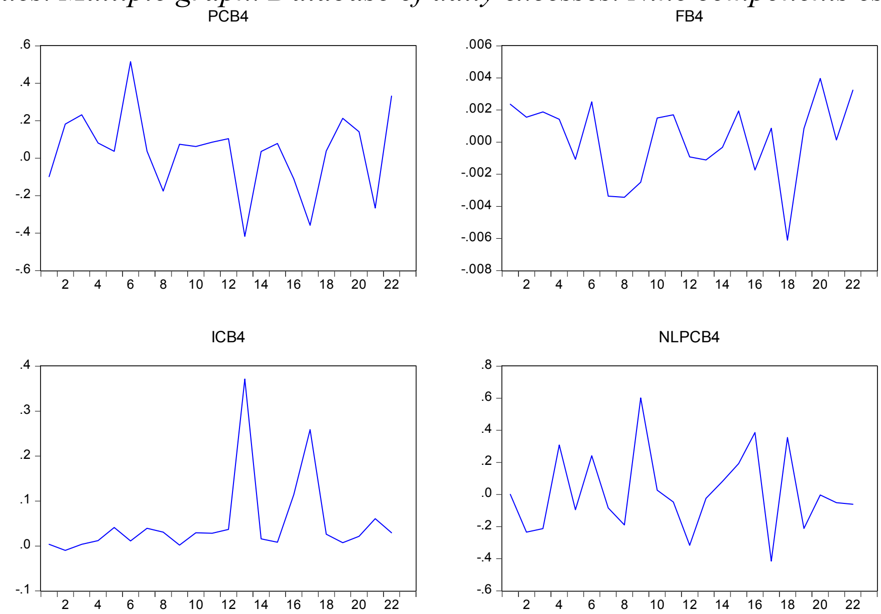

Figure 104. *Betas to the fifth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

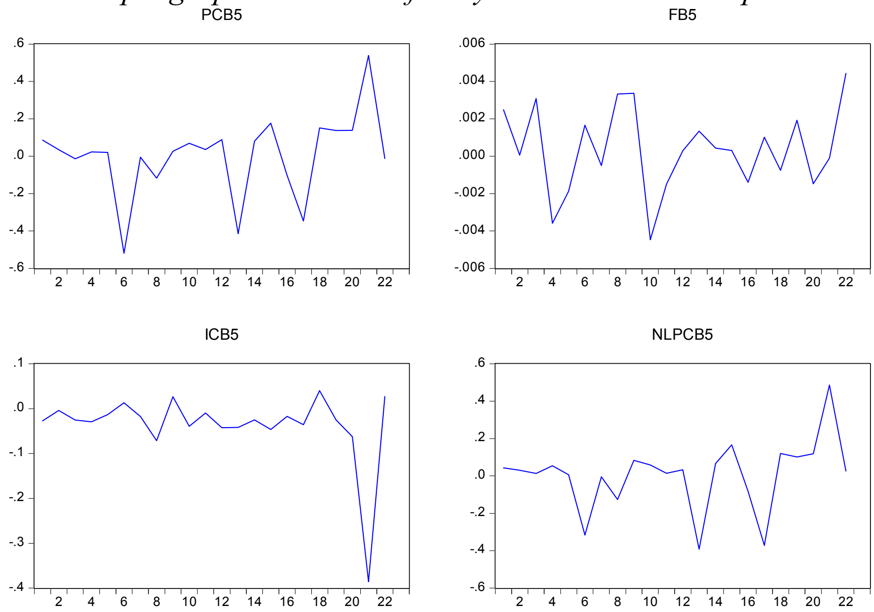

Figure 105. *Betas to the sixth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

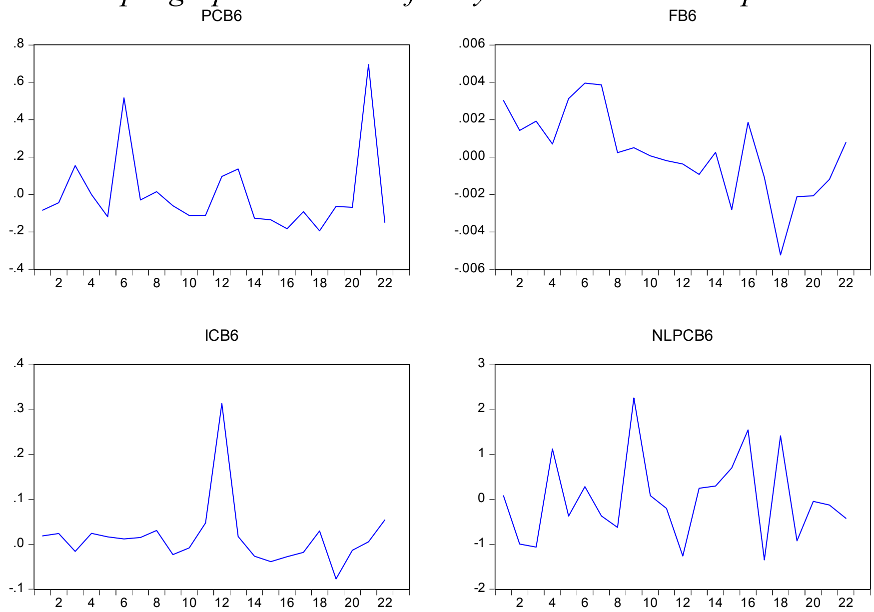

Figure 106. *Betas to the seventh underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

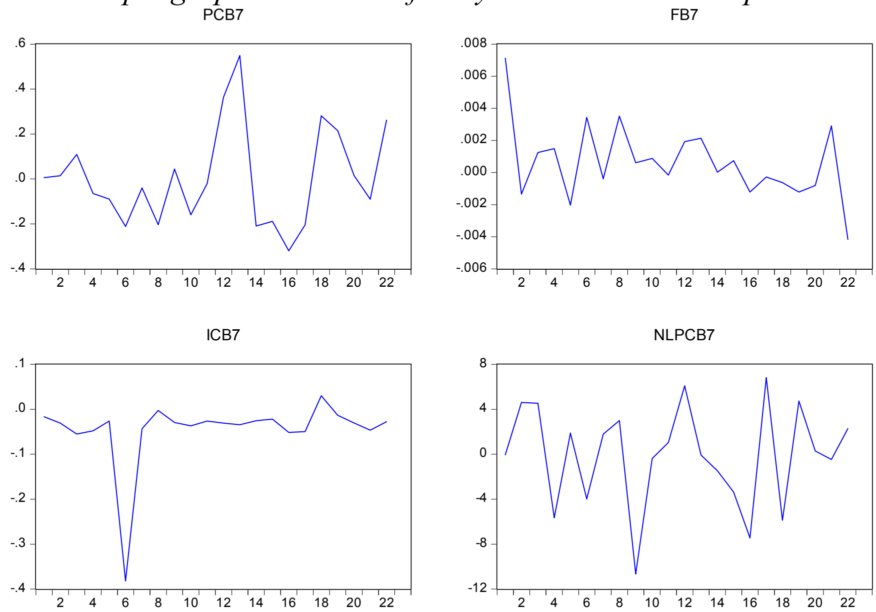

Figure 107. *Betas to the eight underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

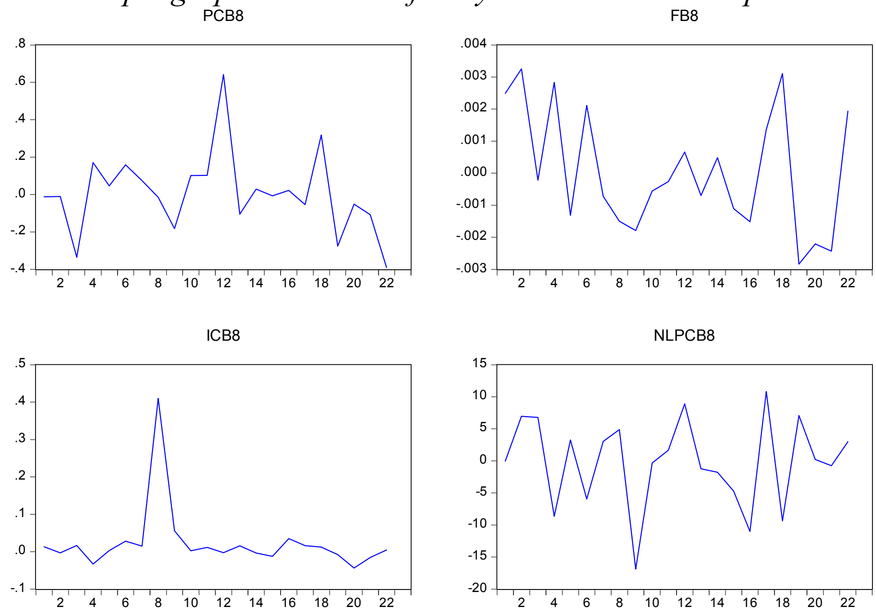

Figure 108. *Betas to the ninth underlying systematic risk factor extracted by the four techniques. Multiple graph. Database of daily excesses. Nine components estimated.*

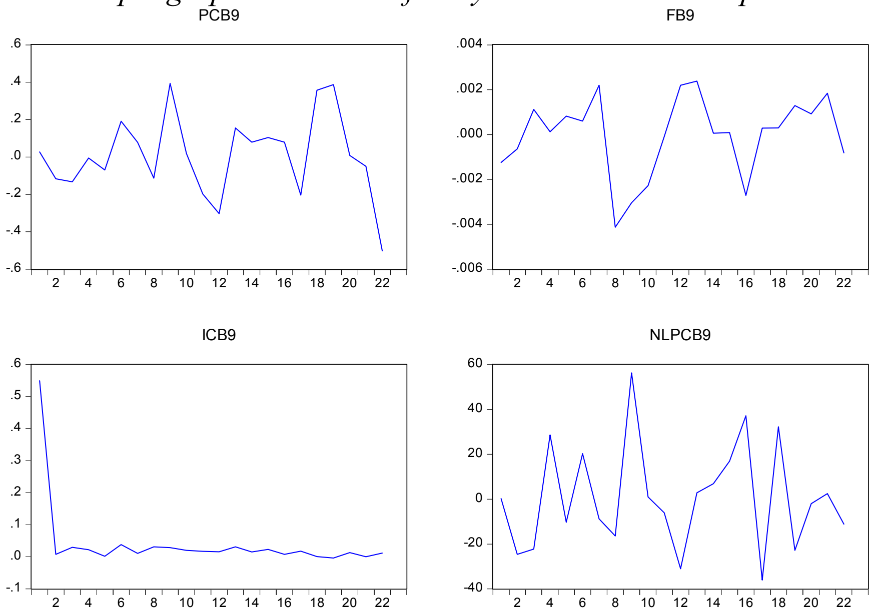

Figure 109. *Loadings matrices. Diagram for interpretation of extracted factors. Principal Component Analysis. Database of weekly excesses. Nine components.*

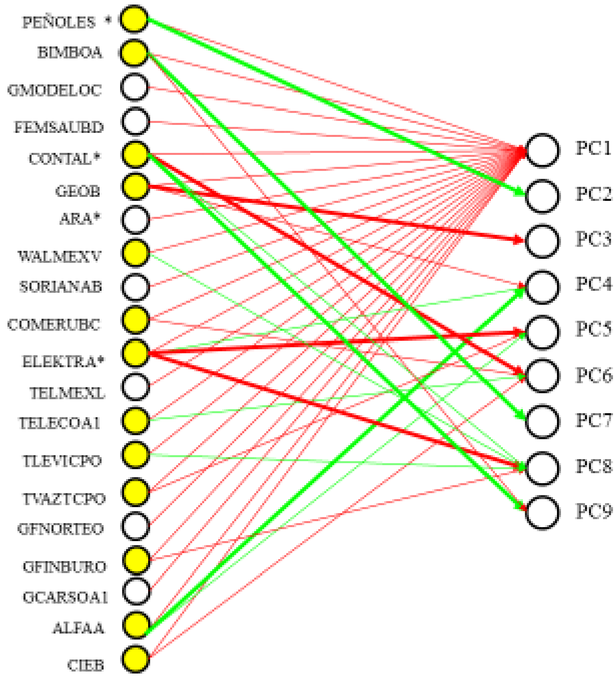

Figure 110. *Loadings matrices. Diagram for interpretation of extracted factors. Factor Analysis. Database of weekly excesses. Nine components.*

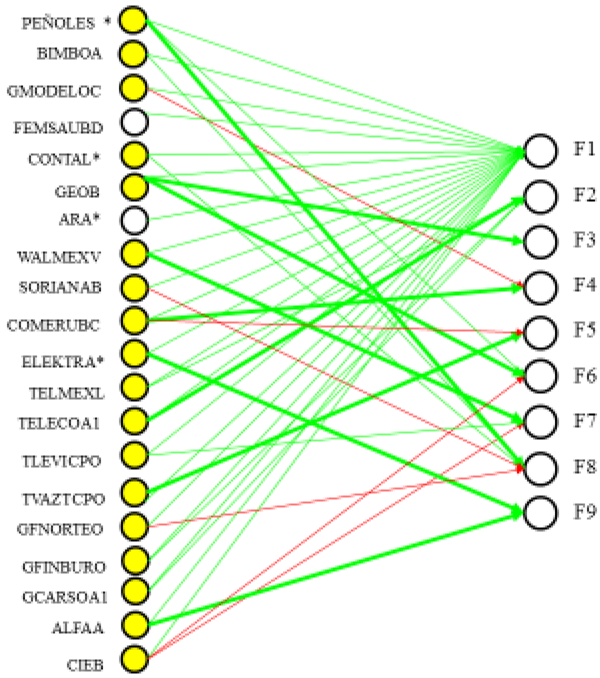

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Figure 111. *Loadings matrices. Diagram for interpretation of extracted factors. Independent Component Analysis. Database of weekly excesses. Nine components.*

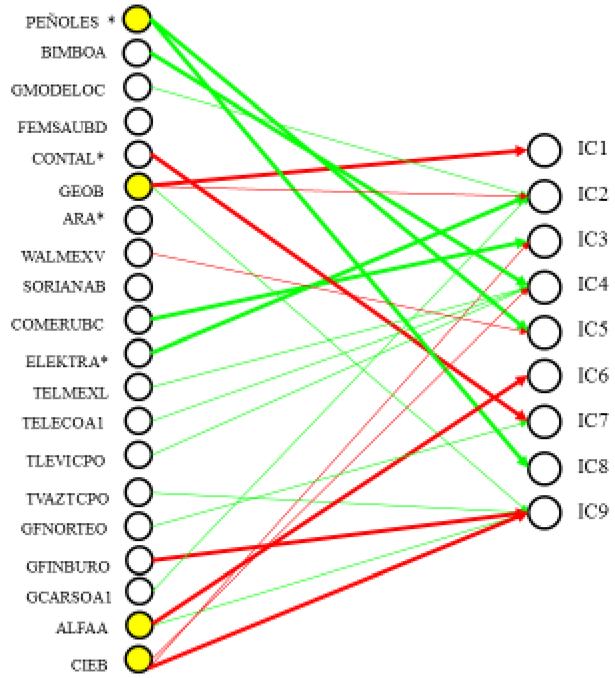

Figure 112. *Loadings matrices. Diagram for interpretation of extracted factors. Neural Networks Principal Component Analysis. Database of weekly excesses. Nine components.*

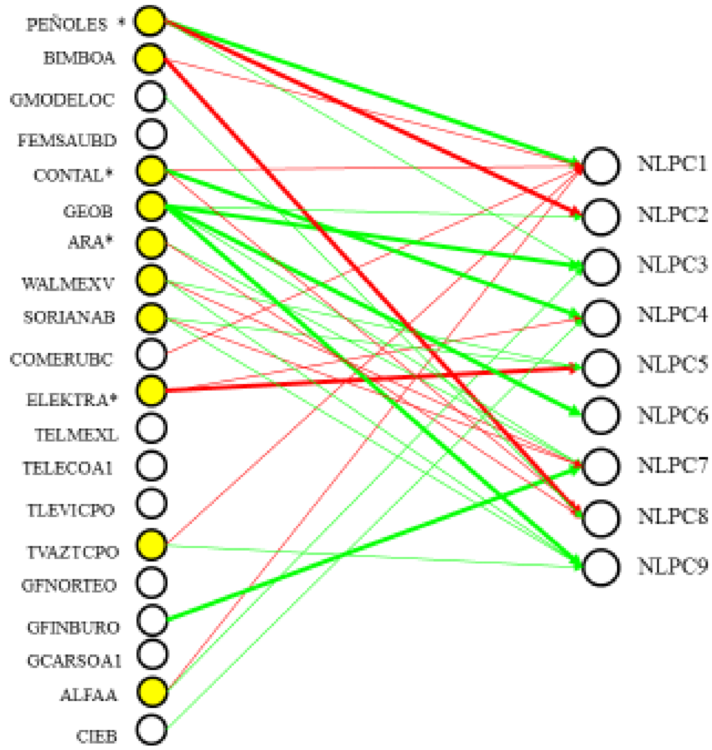

Figure 113. *Loadings matrices. Diagram for interpretation of extracted factors. Principal Component Analysis. Database of daily excesses. Nine components.*

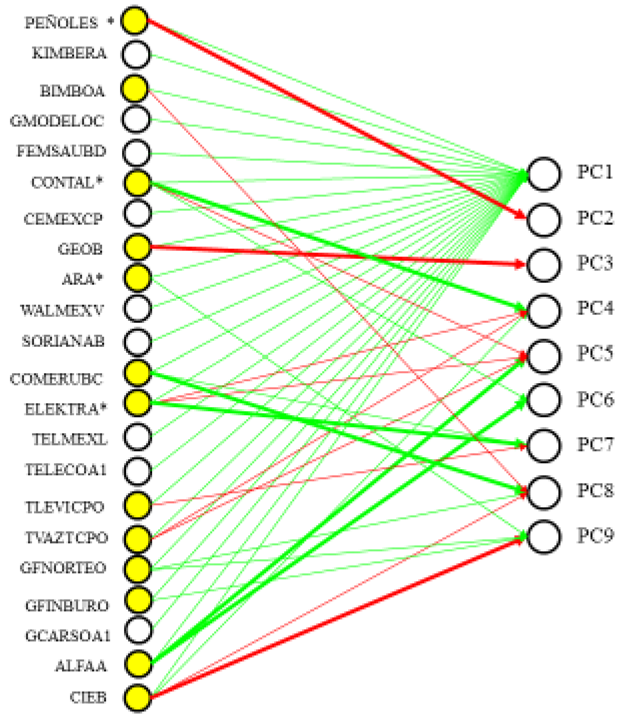

Figure 114. *Loadings matrices. Diagram for interpretation of extracted factors. Factor Analysis. Database of daily excesses. Nine components.*

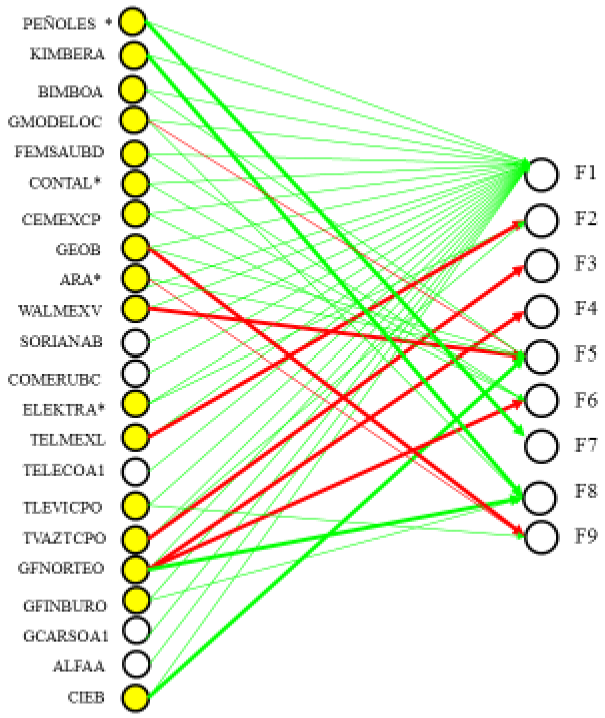

Figure 115. *Loadings matrices. Diagram for interpretation of extracted factors. Independent Component Analysis. Database of daily excesses. Nine components.*

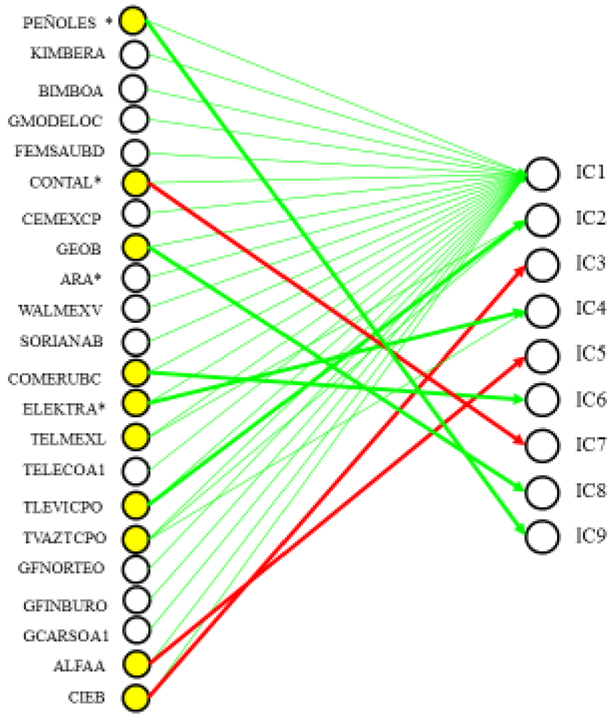

Figure 116. *Loadings matrices. Diagram for interpretation of extracted factors. Neural Networks Principal Component Analysis. Database of daily excesses. Nine components.*