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Crisis and financial contagion: new evidences and new methodological approach

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I dedicate this thesis to my family and friends.

Without their support this would not have been possible.

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Introduction

Background and motivation

Despite constant attempts to eradicate the financial crisis throughout history, unfortunately, the financial crises have not only happened, but have been pervasive for the last decades.[1] The financial crises can now easily spread across countries like contagious diseases, so that they may be a threat to maintain the global financial system stable. This situation is provoked by a highly globalized world and shocks that occur in one part of the world are transmitted fastly and efficiently to another part of the world. The fact is that the economy is more global. In finance, the significant increase of financial integration also implies that countries and markets are more interdependent on each other. This brings new advantages, but also entails new dangers for countries and policymakers. In this thesis we focus on one of these dangers: the financial contagion. In general, financial contagion is understood as the transmission or propagation of disturbances among financial markets of different countries. Consequently, finding the causes and links of international financial contagion can help policymakers to build a better global financial regulation system and thus improve its resistance to shocks and systemic risk.

The financial and monetary systems, if they are efficient, improve the resource allocation and the real economy. In theory, financial markets transmit efficiently

[1] For a historical review of crises, we recommend the book of Bordo, Eichengreen, Klingebiel, and Martinez-Peria (2001) and especially the book of Kindleberger and Aliber (2011). The Davies and Bank (1994) book is specially recommended for the finance history that dates back to 200 BC.

the resources from savers to the best investment opportunity and they share the risk with the entrepreneurs. Financial crises distort the normal behavior of financial markets and, therefore, the efficiency of the economy is affected. In international finance, financial contagion is the dangerous face of this increase of financial integration. The worst danger of this extensive interdependence is the increased probability of systemic risk, which is bound to provoke a systemic crisis. For this reason, this thesis focuses on the empirical analysis of international financial contagion, in the context of both international macroeconomy and international finance. For this purpose, we need to explain and motivate the theoretical and empirical background on contagion analysis and, finally, we will summarize the main contributions of this thesis.

Theoretical background on financial crisis

Before we explain how financial crises are transmitted, we consider necessary reviewing the main theoretical literature of financial crisis. Over the years, four generation of theoretical models have been built to characterize international financial crises.[2,3] These models guide policymakers by trying to both prevent them, with regulation and supervision – ex-ante policies – and mitigate them, with crisis management – ex-post policies. It should be noted that there are several types of crises depending on the type of financial market which suffers the crisis. These models are mainly focused on money and banking crises, although, in the financial market, you can find either banking, money, sovereign debt or stock crises. Specifically, Chapter 1 analyses contagion in all these markets for Asian crisis. Chapter 2 focuses the analysis of contagion in stock markets for the last great recession, and Chapter 3 focuses on debt markets for the last great recession. It is worth emphasizing that the literature does not give a unique definition of financial crisis. In currency crises, for example, we can see different definitions in Frankel and Rose

[2] We suggest reading the Breuer (2004), Saxena (2004) and Goldstein and Razin (2013).

[3] This taxonomy was forged by Eichengreen, Rose, and Wyplosz (1996) and has since become commonly accepted in discussing crisis.

(1996), in Kaminsky and Reinhart (1999) or in Eichengreen, Rose, and Wyplosz (1996).

First and second generation models

First generation models were motivated by Krugman (1979), who adapted the model of raw materials of Salant and Henderson (1978), explaining the relationship between fiscal deficit and currency crises. Later, Flood and Garber (1984) extended and improved the model.[4] These models are based on speculation and macroeconomic fundamentals. According to these models, a government suffering from a large budget deficit will try to monetize the deficit by money supply (the sum of domestic credit and foreign reserves), thus making it inconsistent to maintain a fixed foreign exchange rate regime. The monetization depletes the foreign reserves and, when foreign reserves fall below a certain level, speculators seize the opportunity to anticipate a depreciation of the currency and start to sell it, which then culminates with the collapse of the fixed foreign exchange rate regime.

Second generation models were pioneered by Obstfeld (1995) and Obstfeld (1996).[5] These models are usually characterized by the optimizing government where the government's choice is endogenized. These models emphasize the opposite purposes of a fixed exchange rate regime and an expansionary monetary policy, as opposed to the exogenized choice of the first generation models. An outcome of these models is that with such contradicting policy aims, the cost of maintaining a fixed exchange rate regime could exceed the benefits. Hence, in these models, there are multiple equilibria occasioned by self-fulfilling expectations that need not be lied to fundamentals. These two generation models could be presented as opposing theories. However, the economic fundamentals and the formation of investors' expectations do not seem to be incompatible.

[4] Agenor, Bhandari, and Flood (1991) and Blackburn and Sola (1993) provide reviews of these models.

[5] Rangvid (2001b) reviews these models.

Third and fourth generation models

While the first and second generation models focused on the currency crisis, the third generation models connect currency crises to models of banking crises and credit frictions, helping to unify into a common theory of "financial crisis" the various models of crisis that existed. The third generation models emphasize the importance of the financial sector and capital flows in currency crises. Specifically, two causes of banking crises are mainly introduced as models of the monetary crisis. The first was the moral hazard – one of the first models to capture the moral hazard was proposed Krugman (1999). The second one was illiquidity in bank run – Chang and Velasco (2001) put international illiquidity and bank runs at the centre of the analysis of currency crisis.

Finally, the fourth generation models consider the role of institutional factors. These models are important because institutional factors impact information, uncertainty, and transactions costs and can affect the efficiency of decision-making.

Theoretical background on financial contagion

Once the literature of financial crisis has been briefly reviewed, the following question is how crises can be transmitted. The origin of the contagion theories can be found in the bank runs literature on domestic banking crises. In fact, the study of contagion is a natural question in the international context of crises. Theoretical models of contagion are an extension to the international context of the models of financial crises. There are several theoretical models that explain the transmission of financial crisis. Similar to the theoretical generation models that focus on financial crises, contagion models could classify the transmission of crisis through the economic fundamentals or investors' expectations, as they explain how the crisis is transmitted. There are models that explain the crisis transmission through "fundamental channels" as common shocks,[6] trade channels,[7] and financial links.

[6] See Calvo and Reinhart (1996).
[7] See Calvo and Reinhart (1996).

These channels are often called "fundamental" since many (although not all) are based on economic fundamentals. Others would explain the transmission of crises through investors' practices – problems of liquidity and incentives,[8] problems of information asymmetry,[9] moral hazard[10] and market coordination – or multiple equilibrium. The Diamond and Dybvig (1983) multiple equilibrium model was extended to international contagion, among others, by Chang and Velasco (2001).

However, there is disagreement on what exactly contagion means, as we already saw in the definition of crisis above. The disagreement appears when it has to classify the transmission mechanisms of crisis between contagion and no contagion. A good theoretical definition of contagion has to allow the definition of an appropriate empirical strategy to test the presence of contagion and guide policymakers to useful policies. There are several taxonomies to define contagion. Specifically, some authors define contagion only as the transmission of the most extreme negative events. Another definition of contagion focuses just on the residual transmission of shocks after controlling for "fundamentals".[11] Finally, other authors argue that contagion only appears when there exist "irrational" investor behavior through financial markets. These stricter definitions of contagion and the disagreement on what constituted "fundamental linkages" or "rational behavior" are extremely difficult to measure and, hence, is hard to test the existence of contagion. Pericoli and Sbracia (2003) find five different definitions of contagion classifying them, from the less to more restrictive definitions.

Despite all this disagreement about the precise definition of contagion, Pericoli and Sbracia (2003) point out that two important and useful questions in the literature of contagion have remarkable policy implications. Firstly, what are the channels for the international transmission of area-specific shocks? This question defines contagion depending on the channels of transmission that have been used to spread the crisis. Chapter 1 analyses the main channels of contagion for the

[8] See Valdés (2000).
[9] See Calvo and Mendoza (2000).
[10] See Dooley (2000).
[11] Kaminsky and Reinhart (2000) define "fundamentals-based contagion" and "non-fundamentals-based contagion".

Asian crisis. Second, it would be interesting to check whether there has been discontinuities in the international transmission mechanism of the crises. From this point of view, contagion is defined according to the stability of the transmission mechanisms, which reduces the analysis to distinguish between the so-called "shift-contagion" versus interdependence relationship. This definition is extremely useful to measure and test contagion, and is the one that is used in Chapters 2 and 3 to study the last great recession.[12]

The literature of "shift-contagion" can be classified into two major groups of contributions according to the channels of transmission of crises, i.e., explaining how shocks are propagated: (i) crisis-contingent and (ii) non-crisis-contingent channels. Crisis contingent channels imply that the crisis causes a structural shift and transmission mechanisms change between calm and crisis periods. Therefore, the transmission mechanism during or right after the crisis is inherently different from any that existed before the crisis. The crisis-contingent channels can have three different mechanisms: multiple equilibria based on investor psychology,[13] endogenous liquidity shocks that cause a portfolio recomposition,[14] and political economy.[15]

The non-crisis-contingent channels imply that transmission mechanisms are stable during both crises and tranquil periods and therefore cross-market linkages do not change after a shock. Forbes and Rigobon (2000) point out that the non-crisis-contingent channels are based in the role of trade, monetary policy coordination, learning, and aggregate shocks – such as international interest rates, aggregate shifts in risk aversion, random liquidity shocks, and world demand. These channels are often called "interdependence" although not all of them are based on economic fundamentals. The non-crisis-contingent theories study the

[12]See Forbes and Rigobon (2000) for more detail.

[13]See Masson (1998). The basic idea of multiple equilibria is that the crisis in the first country affects investors' expectations in the second, changing the equilibrium of the latter economy and causing a crash. From the propagation point of view, then, during the period of crisis the transmission of the shock is governed by a change of investors' expectations rather than by real linkages or fundamentals.

[14]See Valdés (2000) and Calvo (1999).

[15]See Drazen (2000).

propagation of shocks independently from the existence of crises. These theories assume that transmission mechanisms after an initial shock are not significantly different from those operating before the crisis, because it is not assumed, for example, that trade will change during the period of the crisis in such a way that the propagation mechanism should be significantly affected.

Both the channels of contagion and the "shift-contagion" literatures have important policy implications.[16] The definition of contagion depending on channels of transmission guides policymakers to try to prevent the contagion, ex-ante policies, identifying which the channels of transmission of crisis among the markets and countries are. The "shift-contagion" definition of contagion guides policymakers to try to manage and mitigate contagion effects during the crisis. If crises are transmitted mainly through channels that exist only after a crisis, then specific short-run strategies – such as policies that provide liquidity, capital controls or financial assistance – could reduce the effects of a crisis started elsewhere in the world efficiently. On the other hand, if crises are transmitted mainly through permanent channels that exist not only during crisis but also in calm period, then these policies just delay the consequences of the crisis and cannot solve the necessary fundamental adjustment of the economy. Not only are the benefits of short-run isolation strategies limited, but an extensive literature documents that these strategies could be extremely costly. Thus, these policies will only have a limited effectiveness in reducing contagion. They will not prevent the country from being affected by the crisis. This last distinction is important so as to evaluate the effectiveness of ex-ante policies and short-run policies.

Empirical background on financial contagion

At an empirical level, there are different quantitative methodologies and measures to define interdependence and contagion. This measure could also be categorized by the different definitions of contagion and, therefore, they can help policymakers

[16] See Moser (2003) and Forbes and Rigobon (2000).

to create accurate and efficient policies. Each methodology has advantages and disadvantages depending on the specific definition of contagion. In brief, the main empirical literature has been surveyed by Pericoli and Sbracia (2003), Dungey, Fry, González-Hermosillo, and Martin (2005) or Dornbusch, Park, and Claessens (2000). The main methodological strategies used in the literature for measuring contagion are probability analysis,[17] cross-market correlations,[18] VAR models,[19] cointegration method,[20] Granger Causality,[21] latent factor,[22] GARCH models,[23] extreme value analysis,[24] and spatial models.[25]

However, all these methodologies face important econometric limitations when they try to answer the two main questions raised by Pericoli and Sbracia (2003). Rigobon (2002) shows that the financial data used in contagion literature is plagued with heteroskedasticity, endogeneity, and omitted variables and this requires that all methodologies take these features of the data into account. Unfortunately, various empirical papers that analyze contagion do not capture all the statistical and econometric features that mention the seminal paper of Rigobon (2002).

Main contributions to financial contagion

In this context, this thesis will try to give some methodological contribution to the literature of financial contagion. In Chapter 1, the first contribution is the implementation of spatial econometrics as a mechanism for assessing contagion. Various methodological approaches have been used to analyze the channels of transmission of crises, mainly in time series context. Unlike the other methodologies used, spa-

[17] See De Gregorio and Valdes (2001) or Eichengreen, Rose, and Wyplosz (1996), for example.
[18] See King, Sentana, and Wadhwani (1994) or Baig and Goldfajn (1998), for example.
[19] See Favero and Giavazzi (2002).
[20] See Reside and Gochoco-Bautista (1999).
[21] See Khalid and Kawai (2003) or Sander and Kleimeier (2003), for example.
[22] See Dungey, Martin, and Pagan (2000) or Bekaert, Harvey, and Ng (2005), for example.
[23] See again Dungey, Martin, and Pagan (2000) or Bekaert, Harvey, and Ng (2005) for example.
[24] See Bae, Karolyi, and Stulz (2003) or Longin and Solnik (2001). The first paper of this methodology could be Morgenstern (1959), although he does not use the term contagion.
[25] See Vayá-Valcarce and Villar Frexedas (2005), Kelejian, Tavlas, and Hondroyiannis (2006) or Novo et al. (2003).

tial econometrics allows for an expression of the transmission mechanisms of crisis under explicit dynamic-spatial assumptions. Surprisingly, this technique had not been previously used for the analysis of contagion, and indeed few authors had used it in the study of financial relations in general. The explicit spatial dependency among countries using this econometric technique opened up a new approach to financial contagion analysis.

In Chapter 2, we will cover some of the econometrics limitations pointed out by Rigobon (2002) for each univariate time series of stock returns. We will contribute with the implementation of Smeekes and Taylor (2012) unit root tests that are robust to unconditional heteroskedasticity. To the best of our knowledge, this is the first contribution in the financial literature that has used these unit root tests. Further, in an univariate time series context, we will introduce the Sansó, Aragó, and Carrion-i-Silvestre (2004) test that allows the endogenous determination of the structural breaks in the variance. Finally, we will compute the Breitung and Eickmeier (2011) test following a strategy based on the specification of an approximate factor model. This test accounts for the presence of structural breaks in the common factor and allows us to test for "shift-contagion".

Finally, in Chapter 3, we analyze the presence of "shift-contagion" using a new cointegration procedure that is robust to the main econometrics problems of the financial time series – i.e. the lack of accounting for heteroscedastic variance. One of the consequences of this contribution is that it solves the problem of determining the different regimes of volatility. Finally, we also introduce the indirect multi-step Granger causality analysis in Lütkepohl and Burda (1997) to test for the presence of "shift-contagion". To the best of our knowledge, there is no other contribution that analyzes financial contagion with multi-step causality test.

Chapter 1

Financial contagion between economies: an exploratory spatial analysis

1.1 Introduction

At present time, the importance of financial integration of markets and its possible consequences is still a controversial issue. The fact that the economy is more global implies that countries are more interdependent on each other. This brings new advantages, but also entails new dangers for countries. In this chapter we study one of these dangers: financial contagion in times of crisis. Generally speaking, this is understood as the transmission or propagation of disturbances among financial markets of different countries. However, this debate on the benefits and risks of economic interdependence also draws attention to problems that are both very old and very new.

The problems are new because of the impact of globalization, but old because they are based on economic and political visions and ideologies that always remain the same. It is possible to see the present international economic system based on neoliberal principles in which the supervisory role of the state has been forgotten and in which the market is considered the only efficient way to allocate resources, without state intervention.

In this chapter we present new ideas on the current debate on financial contagion. Specifically, we identify the economic variables that represented the crises in the Thai, Russian and Brazilian cases. We want to answer whether the cause of contagion between countries is due to the fact that their main macro economic magnitudes or economic fundamentals are at critical levels (commonly considered as the fundamentals of countries), or if, on the other hand, contagion between countries takes place because of trade, financial links, political or regional effects.

Various methodological approaches have been used to analyze the existence of contagion and the relative importance of the possible channels of transmission of crises (or channels of contagion). In recent years authors have sought to identify the econometric techniques that are better when conducting this kind of analysis. Indeed, one of the innovations of this chapter is the implementation of spatial econometrics as a mechanism for assessing contagion. Unlike the other methodologies used, spatial econometrics allows for an expression of international relations under explicit dynamic-spatial assumptions. Surprisingly, this technique has not been used previously for the analysis of contagion, and indeed few authors have used it in the study of financial relations in general. The study of an explicit dependency among the countries using this econometric technique may open up a new field of research in financial interdependence relations.

This chapter is structured as follows. After the introduction, Section 1.2 reviews the main channels of contagion. Section 1.3 analyses the econometric approach that has been used. Section 1.4 describes the variables of the study. Section 1.5 presents the result and, finally, Section 1.6 concludes.

1.2 The main channels of contagion

The literature establishes five possible channels for the transmission of crises from one country to another.[1,2]

The first possible channel of transmission of crisis is the existence of a common shock.[3] A classic example is the increase of the interest rate by the Federal Reserve before the Debt crisis. A more recent example is the appreciation of the dollar against the yen in 1995-96, which contributed to weaken the exports of the Asian Southeast and perhaps it also contributed to generate the Asian crisis.[4]

The second channel arises as a result of the similarity of economic fundamentals in different countries, understood as the macroeconomic (and sometimes also microeconomic) indicators that represent the state of health of an economy. This channel can be interpreted from two perspectives. In objective terms, the vulnerability of the countries is strongly related to the health of an economy. These indicators can also be understood in subjective terms: a country could be vulnerable to crisis depending on how markets perceive the broadcast in the mass media.[5]

The third contagion link derives from trade relationships. This channel can also be interpreted from two different points of view. Firstly, in mercantilist terms, the transmission channel begins with the devaluation of a trade competitor, which forces a country to devaluate its own currency so as to protect its export sector from losing competitiveness. The second one is the devaluation of the currency of *country* A due to the devaluation of the currency of *country* B, a trade partner: if *country* A does not devalue rapidly it may lose that market. A peculiarity about this link is that some authors consider that foreign direct investment is

[1] For a review of the methodological approaches, see Pericoli and Sbracia (2003) and Dungey, Fry, González-Hermosillo, and Martin (2005).

[2] There is no agreement on the question whether all the channels, which we will mention next, are channels of contagion. Masson (1999) explains this controversy in detail.

[3] Nevertheless, for some authors this may not be considered as a true channel of contagion since there is no transmission of a crisis from one country to another; rather the crisis occurs simultaneously in all countries.

[4] See Masson and Mussa (1995).

[5] See Baig and Goldfajn (1998).

a commercial channel, but other authors such as Hernández and Valdés (2001) consider it as a financial link.

The fourth channel derives from political links between countries, caused by integration processes or discretionary performances of the states. An explanation for contagion that focuses on the actions of policymakers. According to Drazen (2000), the political costs (in terms of loss of reputation) of the abandonment of an exchange rate commitment are lower when other countries are also devaluating their currency. In such a context, the loss of reputation associated to the devaluation will be lower for each country and the willingness to give up exchange rate parity higher. Hence, the probability of devaluation increases with other countries devaluing. Sometimes this channel is considered as a regional or neighbour channel.

The last channel arises from financial links among countries. In this case, the causes of contagion may be a common lender or direct investments across countries.[6] A set of effects may trigger contagion through financial links, such as risk effects, liquidity effects, spill effects, warning effects, call herding behaviour or financial panic. All these financial causes can be classified according to the rational or irrational behaviour of each investor or set of investors. Investors can also be classified as national or international investors. The rational changes made by investors (individuals, banks or funds) assume that the information is correct and that the problems are classic problems of portfolio: investors sell the assets of a country to maintain liquidity in their portfolio ("liquidity effect"), to cover an additional risk ("margin call"), or due to the minimum yield of the portfolio ("yield effect").

1.3 Methodological aspects

This chapter performs an exploratory spatial analysis which investigates the existence of dependency or spatial autocorrelation. Dependency or spatial autocor-

[6] This explanation can also be understood as a common shock according to certain authors.

relation, the main objective of spatial econometrics since its beginnings, appears as a result of the existence of a functional relation between what happens at a specific point in space and what happens in another place (Cliff and Ord (1973); Paelinck, Klaassen, Ancot, Verster, and Wagenaar (1979); Anselin (1988)): that is to say, when the value taken by a variable in a spatial location (x_i) is not explained solely by internal conditioners but also by the value of the same variable observed at another neighbouring points ($x_i, ..., x_N$):[7]

$$x_i = F(x_1, x_2, x_3, ..., x_N),$$

so we will not assume independence between the sample observations.[8] This spatial dependence, closely (though not solely) linked with the geographic proximity, according to Tobler (1979), can also be expressed in topological terms of contiguity. Let us suppose that a variable x is observed in N space units of a system, and also that the value of x in a spatial location i, a region for example, is influenced by its values in other neighbouring regions. Starting from here, we will be able to define the set of neighbours J of region i formed by all those regions in which:

$$Pr\left(x_i \mid x\right) = Pr\left(x_i \mid x_J\right),$$

that is, the probability that the variable x in region i has a certain value is the result of calculating its conditional probability to the value of variable x in its J neighbouring regions. The same idea can be expressed in terms of covariance:

$$Cov\left(x_i, x_j\right) = E\left(x_i, x_j\right) - E\left(x_i\right) * E\left(x_j\right) \qquad \forall i \neq j, \quad j \in J.$$

Consequently, the existence of spatial dependency does not allow for a change in the location of the values of a variable without affecting the information contained

[7] See Anselin (1988), Cliff and Ord (1973) and Paelinck, Klaassen, Ancot, Verster, and Wagenaar (1979).

[8] The existence of spatial autocorrelation implies that the sample contains less information than that present in another sample whose observations are independent (see Anselin and Rey (1997)).

in the sample.

Spatial autocorrelation can be positive or negative. If the presence of a particular phenomenon in a region causes the extension of this phenomenon to regions in the surroundings, thus favouring its concentration, this will be a case of positive autocorrelation. In contrast, negative autocorrelation will exist when the presence of a phenomenon in a region prevents or impedes its appearance in the surrounding or contiguous regions, that is to say, when nearby geographic units differ ones from other more than from regions far away in the space. Lastly, when the variable analysed is randomly distributed, spatial autocorrelation will not exist.

Spatial dependency is multidirectional (a region may be affected not only by another contiguous region, but by many others that surround it, just as this one region can influence them). As a result, the use of the lag operator L, $L^p x = x_{t-p}$, used in the time series context, which considers only a one-directional relationship, will not be useful here. The solution in the spatial context involves the definition of what is known as the spatial weights matrix W:

$$W = \begin{bmatrix} 0 & w_{1,2} & . & w_{1,N} \\ w_{2,1} & 0 & . & w_{2,N} \\ . & . & . & . \\ w_{N,1} & w_{N,2} & . & 0 \end{bmatrix},$$

a non-stochastic square matrix whose elements $w_{i,j}$ reflect the intensity of the interdependence between each pair of regions i and j. There is no one way to assign values to the weights of W, as the controversy on the issue in the literature demonstrates; there is no unanimously accepted definition of W.[9]

After analysing the concept of autocorrelation in the cross-section context, the following step is to study how to test the presence or absence of a dependency scheme in a certain variable. A set of spatial dependency statistics have been

[9] Anselin (1988) wrote that the definition of the W matrix must depend on the object of the study.

proposed in the literature, among which the Moran I is the most important.[10] It is computed as:

$$I = \frac{N}{S} * \frac{\sum_i \sum_h w_{ih} * z_i * z_h}{\sum_i z_i^2},$$

where N is the number of observations, $w_{i,j}$ is the element of the spatial weight matrix W that expresses the potential interaction between two regions i and h, S is the sum of all the weights (all the elements in the weights matrix) and z_i represents the normalised value of the variable analysed in region i. Although there is no agreement on the specification of W, the contiguity criterion is usually applied.

Once standardised, a significant and positive (negative) value of the Moran I statistic indicates the existence of positive (negative) spatial autocorrelation. On the other hand, non-significance of the Moran I test implies the null hypothesis is not rejected: the non-existence of spatial autocorrelation, that is, the prevalence of a random distribution of the variable throughout the space.

1.4 Variables and specifications

The present chapter analyses the Asian crisis in a wide sense. Three specific crises, or three stages of the same crisis, can be distinguished: the Thai crisis (beginning in July 1997 with the devaluation of the bath against the US dollar), the Russian crisis (beginning in August 1998 with the devaluation of the rouble and the restructuring of the debt) and finally, the Brazilian crisis (beginning in January 1999 with the end of the gradual adjustments to the exchange rate and a large-scale devaluation of the real).[11]

All the countries selected in the sample were affected by the Asian crisis in some of its forms, and have been analysed in most studies of financial contagion. The countries selected for this chapter are: Argentina, Bolivia, Brazil, Bulgaria, Chile, Hong Kong, Colombia, Czech Republic, Equator, Hungary, Indonesia, Ko-

[10] See Moran (1948).
[11] See Table 1.1 for more details.

rea, Malaysia, Mexico, Pakistan, Paraguay, Peru, Philippines, Poland, Russia, Singapore, South Africa, Thailand, Turkey, Ukraine, Uruguay, Venezuela, and Vietnam.

A vast amount of statistical information has been compiled to study the phenomenon of contagion and many indicators or variables have been used.[12] In this chapter we distinguish between objective variables which are believed to reflect or represent the crisis, and contagion channels, which consider possible ways in which crises are transmitted.

1.4.1 Objective variables

We assume that the crisis will be reflected by a change in the objective variables: a fall in the international reserves and the stock-exchange quotations, or the increase in the exchange and interest rates.[13] For this reason, we calculate the quarterly percentage variation of each variable during the period defined by the quarter prior to the beginning of the crisis and the first and second quarter of the crisis. The exception is the interest rate, for which is specified as the absolute quarterly change, dividing it by one plus the interest of the initial period. Thus, the quarterly variations reflect the short-term dynamics required to demonstrate contagion and to eliminate the effect of the variable in levels.[14]

1.4.2 The Channels of Contagion

We selected four possible channels of crisis transmission: trade, financial, economic fundamental similarities and regional.

TRADE CHANNELS There could be two ways for contagion in trade channels: those deriving from direct trade, and those deriving from trade competition

[12] These indicators describe certain behaviours of contagion but these do not account for the phenomenon in its entirety.

[13] The database used as a reference for obtaining objective variables has been the "International Financial Statistics (IFS)".

[14] The variables in levels do not allow the comparison between countries because of the different economic scale of the countries compared.

from third countries (indirect trade). The data are taken from the "Direction of Trade Statistics" of the International Monetary Fund (IMF).

Direct trade: trade exchanges The first type of trade-related contagion is caused by the mere fact of commercial exchange, that is, direct commerce, which can be induced by exports, imports or by the sum of both of them. These variables explain the contagion caused by dependency between a country and its trade partners. So trade, though it can contribute to growth and stability in times of "economic prosperity", it can also cause economic damage during times of crisis.

To define the weight matrices, we use information about the flow of imports and exports between the countries of the sample. Specifically, the weight $w_{i,j}$ is calculated as the ratio of the exports of country i with country j divided by the total of exports of i. This calculation is also used for the case of the imports and for the sum of exports and imports, with the difference that the latter is the ratio of the sum and not the sum of the ratios.

Indirect trade: competition from third countries To define the trade competition with third countries we only use exports. To value this channel accurately, we need to differentiate between commercial competition from the market comprised by the industrialized countries and competition from the market comprised by developing countries. In addition, it is worth distinguishing between competition by the total volume of exports (in absolute terms) and by the relative importance of the exports (in relative terms). The relative specification eliminates the possible effect of the size of the economy.[15]

The specification implemented for this channel has been used previously in the literature. The first authors to use this specification in the context of contagion were Glick and Rose (1999). They used a specification that does not allow the relationship among countries, and only with the country that was first affected by the crisis (called "zero country" in the literature). However, in our specification

[15] The distinctions (absolute or relative) provide us with the following specifications of the weights for W matrices. See Table 1.2.

we allow the relationship among countries, which is implicit in contagion.

FINANCIAL CHANNELS This transmission channel is understood in this chapter as the effect caused by a common banking moneylender, or the "common bank lender effect".

We used data from "the BIS consolidated international banking statistics" of the International Settlements Bank. These data include the loans given to banks outside the seventeen industrialized countries.[16]

The weight matrices were generated under the same specification as in the case of trade competition, since trade competition and competition in financial funds are equivalent. In this case, besides differentiating between competition of loans in absolute and relative terms, we assess the importance of the fact that the four or eight maximum moneylenders of all the countries chosen that provide more than ninety percent of all the loans to these countries.[17]

SIMILARITIES IN THE FUNDAMENTALS ACROSS COUNTRIES We specified six different weight matrices associated with six macro magnitudes: rate of unemployment, inflation, public deficit, domestic credit, expansion of credit and current account deficit. In all cases, the weights of the matrices were obtained as the reverse of the absolute distance of each variable between pairs of economies. In this way, two countries with similar values for the variables will have high $w_{i,j}$ weight, and two economies very different from each other (elevated economic distance) will have near zero $w_{i,j}$ weight. All these matrices will be symmetrical by construction.

The information required to generate these matrices was extracted from the IFS database of the IMF, although in some cases we have used the national statistics of the countries analysed to complete the existing information.

[16]The countries are Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, Holland, Norway, Spain, Sweden, United Kingdom and the US.

[17]The four first are: United Kingdom, Germany, US, Japan and the following ones are: Italy, France, Holland and Switzerland.

REGIONAL CHANNEL In addition to the above specifications, we also generate a weight matrix: the regional matrix. We consider those countries in the same continent as neighbours, and allocated to them a score of 1 (0 in opposite case).[18]

In this case, this matrix may reflect either a generic similarity in the macroeconomic fundamentals of countries i and j or a greater link of a commercial, financial or political nature between nearby countries.[19]

CRISIS CHANNEL Finally, we generate a last weight matrix: the crisis matrix. We consider those countries as neighbours if both do were affected or do not by the crisis, and allocated to them a score of 1 (0 if one is affected by crisis and other did not).[20]

After reviewing the different specifications of the weight matrices defined, two aspects stand out. Firstly, contagion may be simultaneous, which means that both the country affected and the country infected enter the crisis in the same time period (in our case, in a quarter) or, on the other hand, non- simultaneous, which means that the country affected and the country infected could receive the effects of the crisis in different periods (in our case the difference is a quarter, thus extending the period of possible contagion to a semester). This is why two structures of contagion are considered for the construction of the weight matrices. First, the matrix of simultaneous contagion, in which the weight matrix will be diagonal by blocks, and second, the non-simultaneous contagion matrix, which will be triangular inferior by blocks (allowing contact in the same quarter and with a delay or lag).

Secondly, the weights of the W matrices of commerce, finances and fundamental are calculated as the average of the value obtained by the variables in the two years before each crisis.[21] The only exception in the calculation of the weights of the

[18] South Africa is considered a country in the Asian region; placing it in another region does not affect the results.

[19] The market could consider them as equal and punish them in a similar way, causing the crisis to spread among them.

[20] Again, South Africa is also considered a country in the Asian region; placing it in another region does not affect the results.

[21] This has also been proved with the matrices of the year previous to the crisis, but the

first W is the expansion of credit, since, being an increase, we only use the data for the last year. Note that the matrices of finances are calculated from half year rather than annual data.

Finally we should note that other authors have used some of these specifications, although none of them considered this matrix from the perspective of spatial econometrics, with its consequences for the estimation of statistical inference.[22]

1.5 Results

In this section we report the results from the exploratory spatial analysis using the Moran I test statistic. The analysis addresses two main issues. First, we would like to analyse whether countries linked in some way (finance, trade, geographical proximity and/or economic policy) behave in similar ways in periods of crisis. Further, it would be interesting to analyse if there is a clear scheme of spatial autocorrelation in periods of crisis. Second, we would like to know which channels of contagion were the most important in each crisis and which objective variables were the best indicators of the crisis.

The results are displayed for each objective variable. The type of variable is shown in the upper left part of Tables 1.3 to 1.6. The results for each crisis (Thai, Russian and Brazilian) are shown in columns, and for each crisis the results are presented according to whether the matrix of contacts allows for non-contemporary dependency or only for contemporary dependency.

The main conclusions can be summarized as follows. Firstly, in periods of crisis there is a significant positive scheme of spatial autocorrelation in the objective variables analysed (the significant negative values at 5% do not persist in the two columns), or, in other words, in periods of crisis the similarity in the evolution of countries depends on previous economic patterns.

Secondly, there is a noticeably regional behaviour for all the crises, mainly in

variations in the results are relatively insignificant.

[22] De Gregorio and Valdes (2001) and Glick and Rose (1999), among others.

the contemporary analysis. However, the similarity in fundamentals does not seem to act as a significant channel of contagion.

Thirdly, in the Thai crisis, the best channels were geographic proximity and the competition of funds or common moneylender. In the Russian crisis, the best channels were direct commerce and, to a lesser extent, geographical proximity. In the Brazilian crisis, the only channel of contagion was geographical proximity (we think that the channels have a smaller explanatory capacity due to the proximity in time to other crises, which distorts the transmission channels; in addition, the crisis had been anticipated for some time, thus allowing the implementation of specific policies for each country).

Fourthly, the variables more controlled by the authorities of the countries (exchange and interest rates) behave similarly in periods of crisis, which stresses the importance of economic policy; the reserves and the quotations also have similar channels (these variables are more controlled by market forces). The memory of markets differs if the variable is controlled by market forces (in which case the memory is shorter and the rapidity greater) or by the authorities (more persistence).

Finally, it seems that in the variables that are more controlled by market forces (unlike those controlled by governments), trade and financial competition are the best channels; this competition is based on relative terms, and in relation to developed countries the result is in line with the findings of Van Rijckeghem and Weder (2001).

1.6 Conclusions

Controversy still surrounds the importance of the financial integration of markets and its possible consequences. The fact that the economy is more global means that countries are more interdependent on each other. This offers advantages, but also entails new dangers for countries. In this chapter we have studied one of these dangers: financial contagion in times of crisis. The crises analysed have been the

Thailand, Russia and Brazil crises.

The contributions of this chapter can be summarized as follows. First, we have used four objective variables, which characterize four markets, to represent the correct form of financial crises. Second, we have also regarded a wide number of contagion channels (trade links, financial links, regional effects and macroeconomic similarities) when conducting the analysis. Various definitions have been used trying to reflect different channels of crisis transmission from one country to another.

Third, the crises we have studied have a similar macroeconomic context, which ease the comparison of results. This feature has not been covered in other papers, where the analyses are conducted through different macroeconomic contexts since they use longer time series samples.

Fourth, we have used an extensive sample with twenty eight countries, all of them affected by the Asian crisis in some way or another.

Finally, in recent years several authors have discussed which econometric techniques are best suited for the analysis of financial contagion. The main innovation of this chapter is the implementation of spatial econometrics in this area. Unlike other methodologies used, spatial econometrics allows us to express the international relations under explicit dynamic-spatial multidirectional assumptions. We implement a valuable methodology based on an exploratory analysis, which represents an important step on the way towards a deeper analysis of financial contagion using spatial econometric techniques.

The investigation that has been conducted in this chapter indicates, first, in each crisis the markets more closely controlled by governments show similar channels of contagion; on the other hand, the markets more dependent on market forces also show a distinctive, characteristic trend. Second, we detect that contagion seems to have a clearly regional component. Finally, common moneylenders are among the main and most persistent channels of contagion in the three crises studied.

Table 1.1: Periods analysed according to crisis

Crises Analysed	Variation rates considered
Thailand Crisis	III quarter of 1997 versus II quarter of 1997
	IV quarter of 1997 versus III quarter of 1997
Russian Crisis	III quarter of 1998 versus II quarter of 1998
	IV quarter of 1998 versus III quarter of 1998
Brazilian Crisis	I quarter of 1999 versus IV quarter of 1998
	II quarter of 1999 versus I quarter of 1999

Note: The well-known database "International Financial Statistics (IFS)" was used as reference for obtaining the quantitative variables

Table 1.2: Weights of trade competition

ABSOLUTE COMPETITION	$w_{i,j} = \frac{X_{i,des}+X_{j,des}}{X_{i,.}+X_{j,.}} * \left(1 - \frac{\lvert X_{i,des}-X_{j,des}\rvert}{X_{i,des}+X_{j,des}}\right)$
RELATIVE COMPETITION	$w_{i,j} = \frac{X_{i,des}+X_{j,des}}{X_{i,.}+X_{j,.}} * \left(1 - \frac{\left\lvert \frac{X_{i,des}}{X_{i,.}} - \frac{X_{j,des}}{X_{j,.}} \right\rvert}{\frac{X_{i,des}}{X_{i,.}} + \frac{X_{j,des}}{X_{j,.}}}\right)$

Table 1.3: Moran I test of the percentage increase of the exchange rate. Period 1997-1999

	Thailand		Russia		Brazil	
	Simult	No Simult	Simult	No Simult	Simult	No Simult
Compet funds 4 main	2.70*	4.03*	0.10	-0.31	0.81	0.12
Compet funds 8 main	2.47**	3.79*	0.09	-0.38	0.85	0.10
Compet (relative country) funds 4 main	2.51**	4.69*	0.95	1.52	1.46	1.58
Compet (relative country) funds 8 main	1.88***	3.53*	0.77	1.25	1.45	1.46
Exports	2.41**	2.51**	4.80*	5.20*	0.40	0.76
Imports	2.93*	2.91*	5.78*	6.08*	0.51	0.72
Sum of exports and imports	2.76*	2.80*	5.48*	5.86*	0.45	0.76
Compet trade industralized	1.13	1.73***	-0.49	-1.27	1.32	0.36
Compet trade developing	0.66	0.84	-1.74***	-2.72*	0.78	-0.26
Compet (relative country) trade industralized	0.08	-0.11	-1.07	-2.36**	1.24	0.77
Compet (relative country) trade developing	-0.46	-1.39	-0.03	-0.44	1.36	0.76
Deficit by currency account	0.67	0.92	0.20	0.27	2.12**	1.67***
Deficit by currency account respect ppp	1.69**	2.32**	-0.16	-0.21	0.51	0.71
Deficit by currency account respect M2	-1.49	-1.84***	-0.11	-0.07	0.26	0.25
Domestic credit respect M2	0.53	0.69	0.06	-0.01	0.19	0.08
Public deficit respect GDP	0.94	1.25	0.41	0.51	-0.89	-1.25
Inflation	-0.69	-0.95	0.58	0.61	0.49	0.38
Unemployment	-1.25	-1.21	-0.18	-0.24	1.13	1.52
Crisis	0.85	0.92	-0.75	-0.99	7.62*	9.71*
Regional	4.65*	5.35*	1.81***	1.65	2.69*	3.44*

Note: superscripts $*$, $**$ and $***$ indicate rejection of the corresponding null hypothesis at 1, 5 and 10% level of significance, respectively

Table 1.4: Moran I test of the percentage increase of the international reserves. Period 1997-1999

	Thailand		Russia		Brazil	
	Simult	No Simult	Simult	No Simult	Simult	No Simult
Compet funds 4 main	2.83*	2.19**	4.43*	2.53**	-0.33	-0.23
Compet funds 8 main	2.85*	2.13**	4.73*	2.95*	-0.18	-0.01
Compet (relative country) funds 4 main	3.19*	1.87***	6.90*	6.04*	0.58	0.81
Compet (relative country) funds 8 main	3.56*	2.31**	6.94*	6.37*	0.81	1.27
Exports	1.14	0.11	3.06*	3.19*	2.98*	1.69***
Imports	0.58	-1.68***	3.80*	3.87*	4.20*	2.59*
Sum of exports and imports	0.91	-0.82	3.50*	3.63*	3.70*	2.21**
Compet trade industralized	3.73*	2.96*	3.72*	2.16**	-0.39	-0.23
Compet trade developing	3.74*	3.20*	4.33*	2.08**	0.40	0.49
Compet (relative country) trade industralized	4.18*	3.03*	5.67*	4.04*	0.95	0.86
Compet (relative country) trade developing	4.29*	3.26*	6.31*	5.79*	0.15	0.33
Deficit by currency account	1.04	1.42	0.30	-0.41	-0.42	-0.04
Deficit by currency account respect ppp	2.00**	1.72***	0.45	0.18	0.54	0.46
Deficit by currency account respect M2	-0.14	-0.73	0.37	-0.28	-0.23	-0.60
Domestic credit respect M2	1.29	0.80	1.26	1.13	0.20	0.25
Public deficit respect GDP	1.23	1.13	2.07**	1.38	1.16	1.02
Inflation	0.75	0.39	1.38	1.36	0.50	0.30
Unemployment	1.55	1.10	1.66***	1.52	0.07	-0.14
Crisis	2.51**	1.31	4.70*	2.23**	1.75	1.24
Regional	2.06*	1.30	4.34*	3.39*	4.09*	4.46*

Note: superscripts $*$, $**$ and $***$ indicate rejection of the corresponding null hypothesis at 1, 5 and 10% level of significance, respectively

Table 1.5: Moran I test of the increase of the interest rate. Period 1997-1999

	Thailand		Russia		Brazil	
	Simult	No Simult	Simult	No Simult	Simult	No Simult
Compet funds 4 main	2.07**	2.17**	0.99	1.02	-0.58	-1.06
Compet funds 8 main	2.03**	2.26**	1.06	1.11	-0.59	-1.07
Compet (relative country) funds 4 main	2.20**	2.06**	1.92***	2.36**	-0.08	-0.28
Compet (relative country) funds 8 main	1.93***	1.91***	2.14**	2.72*	-0.09	-0.33
Exports	1.57***	0.49	3.11*	1.74***	1.27	1.19
Imports	2.03**	0.36	4.92*	2.41**	1.90***	1.63
Sum of exports and imports	1.82***	0.43	4.18*	2.16**	1.66***	1.48
Compet trade industralized	0.90	1.56	0.87	0.73	-0.52	-0.70
Compet trade developing	1.55	1.92***	1.68***	1.07	-0.34	-0.63
Compet (relative country) trade industralized	1.06	0.85	1.92***	2.14**	-0.87	-2.31**
Compet (relative country) trade developing	0.21	0.16	1.53	1.98**	-0.43	-1.01
Deficit by currency account	0.48	0.25	0.51	0.31	-0.45	-0.15
Deficit by currency account respect ppp	1.41	0.97	0.35	0.33	-0.50	-0.66
Deficit by currency account respect M2	-0.02	-0.18	0.65	0.41	0.39	0.60
Domestic credit respect M2	0.00	-0.01	-0.19	-0.26	-0.24	-0.31
Public deficit respect GDP	-0.05	-0.02	-0.64	-0.21	0.28	0.41
Inflation	-0.20	-0.04	-0.16	0.38	0.30	0.22
Unemployment	-2.43**	-1.90***	0.13	-0.46	-0.42	-0.51
Crisis	2.04**	1.74***	2.23**	1.59	0.42	0.83
Regional	2.59*	1.60	1.09	1.20	-0.19	-0.40

Note: superscripts $*$, $**$ and $***$ indicate rejection of the corresponding null hypothesis at 1, 5 and 10% level of significance, respectively

Table 1.6: Moran I test of the percentage increase of the stock quotations. Period 1997-1999

	Thailand		Russia		Brazil	
	Simult	No Simult	Simult	No Simult	Simult	No Simult
Compet funds 4 main	3.55*	2.05**	11.53*	8.69*	9.55*	7.48*
Compet funds 8 main	3.62*	2.16**	11.78*	9.04*	9.76*	7.73*
Compet (relative country) funds 4 main	5.13*	4.41*	12.87*	11.54*	10.50*	9.41*
Compet (relative country) funds 8 main	5.10*	4.39*	13.28*	12.22*	10.73*	9.81*
Exports	1.75***	0.91	7.66*	4.16*	3.94*	1.99*
Imports	1.72***	0.55	7.69*	4.08*	4.27*	1.61
Sum of exports and imports	1.74***	0.74	7.71*	4.16*	4.12*	1.83***
Compet trade industralized	4.76*	3.48*	12.50*	9.42*	10.32*	8.57*
Compet trade developing	2.79*	1.96*	12.17*	9.08*	9.93*	7.72*
Compet (relative country) trade industralized	3.47*	2.95*	13.44*	12.21*	10.24*	9.29*
Compet (relative country) trade developing	5.58*	5.11*	12.99*	11.96*	10.27*	9.39*
Deficit by currency account	-1.04	-1.10	1.56	1.01	0.24	-0.10
Deficit by currency account respect ppp	1.41	0.58	0.89	0.49	1.45	0.65
Deficit by currency account respect M2	0.92	0.12	2.30**	1.05	3.85*	1.82***
Domestic credit respect M2	-0.63	-1.91**	1.37	0.70	1.02	0.34
Public deficit respect GDP	0.40	0.20	1.32	0.55	1.97**	0.66
Inflation	0.18	-0.06	1.61	1.01	2.56*	1.49
Unemployment	3.63*	2.60*	3.40*	1.78***	1.09	0.79
Crisis	2.93*	1.73	7.90*	4.72*	7.94¿	5.02*
Regional	2.26**	0.95	9.32*	5.75*	5.95*	3.35*

Note: superscripts $*$, $**$ and $***$ indicate rejection of the corresponding null hypothesis at 1, 5 and 10% level of significance, respectively

Chapter 2

Dependence and financial contagion in the stock market during the great recession

2.1 Introduction

The financial crisis that was originated in the US in 2007 developed into a global financial turmoil and a long lasting recession in many economies in the globe. The origin of the crisis can be traced back to the increase of unpaid mortgage loans, mostly extended to less creditworthy borrowers (sub-prime loans), that affected the stability of financial institutions exposed to them as well as to the tenants of financial products tied to these mortgages.[1] This all resulted in the collapse of large financial institutions, the bailout of affected banks and downturns in stock markets, which in turn, required political intervention.

The crisis affected other countries due to standard practices of the financial institutions such as securitization and off balance sheet financing. By the end of 2007, equity markets started falling from their recent peaks as a consequence of the sub-prime problem in the US and western countries such as Spain, UK, Ireland

[1] See Markose, Giansante, Gatkowski, and Shaghaghi (2010) for the analysis of too big to fail and the system risk.

or Greece, who suffered fast and sudden downturns in their financial markets. Some of them even required assistance from international institutions such as the International Monetary Fund (IMF) or the European Central Bank (ECB), which implemented measures to reestablish financial stability and the confidence in their banking and financial systems.

During the early months of the Global Financial Crisis (GFC), a large increase in the correlation between the stock returns of the largest OECD countries can be observed. Intuitively, this can be understood as evidence of contagion or financial shocks spillover effects among financial markets across different regions. It is important to differentiate between cross-country linkages that exist at all times – which in the literature is interpreted as interdependence – versus linkages that only exist briefly after shocks – which in the literature is interpreted as contagion. Therefore, as can be seen, there is a clear difference between contagion and interdependence, since contagion alters the correlations among financial markets, but not the interdependence that links these markets.

Monitoring the changes of the correlations is important in international investment for international portfolio management and risk assessment. Contagion might lead to situations in which risk cannot be mitigated by a smaller opportunity of diversification. Furthermore, the cross-border contagion may have significant consequences for financial stability. This instability has led us to analyze the main causes of co-variation of the stock markets in the most industrialized countries during the financial crisis.

Establishing a difference between contagion and interdependence is useful to understand the policy implications and the evaluation of policy responses. This distinction allows us better understanding on how crises are transmitted and what should be done in order to reduce their undesired effects. If the transmission of crises is propagated through interdependence – i.e., the cross-country linkages are the same in crises as in normal periods – policies that provide liquidity or financial assistance will be less effective in reducing the effects of the crises and contagion. In this case, these policies just delay a necessary adjustment. But if there is contagion, i.e., that cross-country linkages only exist briefly after the shocks occur – such as panic or a temporary liquidity risk – then policies to provide liquidity or financial assistance until economic relationships stabilize could potentially avoid an unnecessary and painful adjustment.[2] Therefore, it is important to distinguish between contagion and interdependence because policies that impose additional adjustment on countries can create additional risks by increasing their vulnerability to contagion.

Nevertheless, it is necessary to understand that the globalization and the different processes of economic integration have created a clear interrelationship among the financial variables. In particular, any analysis that pursues to investigate the presence of contagion has to take into account this relationship to guarantee that the conclusions of the study are not misleading.

In the present paper we analyze the presence of contagion in the financial crisis taking into account the strong dependence that exists among a set of developed economies. The main contributions of the article are the following ones. First, we carried out the study using unit root tests that are robust to potential features which are expected to be shown when analyzing financial variables – i.e., non-stationary volatility. To the best of our knowledge, this is the first contribution that has used these unit root tests in the financial literature. Second, we carry out the study using a flexible framework that defines the specification of common factor models. Factor models not only control for the strong dependence that exists among the financial variables, but also allow us take into account consideration any channel of transmission that is acting to spread the crisis among countries. The transmission mechanism can take many forms and most of them result from a healthy interdependence among countries in good times, as well as in bad times. Further, the use of common factor models allows us to draw conclusions that are robust to the omission of relevant variables and simultaneous equations bias problems.[3] From a policy point of view, it is essential to provide policymakers

[2]See Forbes (2012) for further details.

[3]See Forbes and Rigobon (2002) for the econometrics problems about contagion testing.

with timely and appropriate measures of correlation changes and contagion. This will certainly help to design appropriate policy responses and prepare contingency plans.

The GFC has expanded the definition of contagion. The fact that the GFC originated in the US has led us to consider a global shock or a shock to a large economy that is transmitted to others as a type of contagion. Thus, we can distinguish between two types of contagion: (i) "local contagion" and (ii) "global contagion". The local contagion might be bilateral or multilateral, depending on the linkages that can be established among the countries. The global contagion is the relationship between a country with the systemic risk or the global economy. The definition of these two types of contagion is useful in terms of the analysis of the causes, consequences and the corresponding policy implications of the financial shocks – i.e., global contagion affects the global regulation, whereas local contagion has implications at a regional or local regulation levels.

This chapter proceeds as follows. Section 2.2 briefly discusses the main contributions in the empirical literature that focus on contagion analysis. Section 2.3 discusses the data set that is used in the paper. Section 2.4 analyzes the empirical results focusing on, first, the order of integration of the time series and, second, on the analysis of parameter stability of the estimated common factors. Finally, Section 2.5 presents some concluding remarks.

2.2 Contagion literature: An overview

In this section, we present a short overview of the empirical approximations that have been followed in the literature to analyze the presence of contagion in periods of crisis. Although the focus of this section is based on the empirical approaches, it is worth introducing a brief comment on the theoretical contributions that have tackled the issue of financial crises and contagion. An extensive literature exists in the strictly theoretical field, which has given rise to generations of models that explain the transmission of financial crises among countries and financial markets.[4] For flexibility of our theoretical framework, we consider that the asset pricing models of the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) fit our empirical approach.[5] This specification allows us to have a better definition of the channels at an empirical level without the need to estimate them.[6]

Due to the evolution of the theoretical models, it is possible to find different definitions of contagion.[7] Basically, there are two ways to define financial contagion. The first approach defines contagion depending on the channels of transmission that are used to spread the effects of the crisis. The second approach defines "shift-contagion" or contagion depending on whether the transmission mechanisms are stable through time.[8] If the transmission among markets has been stable over time, then there is a relation of interdependence among markets. However, if the transmission changes through time, then, we will be facing a situation of contagion or "shift-contagion".[9]

The use of this definition of contagion allows us to assess the existence of contagion considering the presence of interdependence. This definition of contagion conveys the structural breaks in the transmission mechanism for the crisis owing to financial panics, herding or switching expectations across instantaneous equilibria. Specifically, we wish to focus on two types of contagion:[10] global contagion (or systemic risk), and local (or pure) contagion.

At a theoretical level, we find two theories to support these types of contagion. According to Masson (1998), the theory of "monsoonal effects" implies that conta-

[4] The development of the literature from the first through fourth-generation models, or the so-called "institutional" models, is reviewed by Breuer (2004). Other relevant surveys are Belke and Setzer (2004) and De Bandt and Hartmann (2000).

[5] See Ross (1976).

[6] Different papers of contagion using the CAPM model are King, Sentana, and Wadhwani (1994), Dungey, Martin, and Pagan (2000), Dungey, Fry, González-Hermosillo, and Martin (2005), Bekaert, Harvey, and Ng (2005) and Bekaert, Ehrmann, Fratzscher, and Mehl (2011).

[7] See Pericoli and Sbracia (2003) for the different definitions of contagion.

[8] This definition of contagion is related to the approach followed in Boyer, Gibson, and Loretan (1997), Forbes and Rigobon (2001) and Forbes and Rigobon (2002).

[9] Overviews of these issues are provided by Dornbusch, Park, and Claessens (2000), Pericoli and Sbracia (2003), Belke and Setzer (2004) and De Bandt and Hartmann (2000), among others.

[10] Bekaert, Harvey, and Ng (2005), Bekaert, Ehrmann, Fratzscher, and Mehl (2011) and Baur and Fry (2009) use these definitions.

gion during crises hits hardest those economies that are highly globally integrated – contagion operates through trade and financial linkages.[11] Second, Masson (1998) defines the theory of "spill-over effect" or "pure contagion", which implies that there is a significant change ("shift") in cross-market linkages after a shock to an individual country.

Among the econometric approaches that enable us to analyze contagion, the paper bases on the use of an approximate factor model.[12] The approximate factor model assumes that the observable variable $y_{i,t}$ can be decomposed as:

$$y_{i,t} = F_t' \pi_i + e_{i,t},$$

$i = 1, \ldots, N$, $t = 1, \ldots, T$, where F_t is a $(k \times 1)$-vector that accounts for the common factors, and $e_{i,t}$ is the idiosyncratic disturbance term, which is assumed to be time and weakly cross-section dependent and heteroscedastic. The $(k \times 1)$-vector of loading parameters π_i measures the effect that the common factors have on the i-th time series.

This approach does not impose a unique channel of contagion on the model, since it accounts for the combination of various mechanisms of transmission among countries – Bekaert, Ehrmann, Fratzscher, and Mehl (2011) shows that with this framework it is possible to cover the two main causes or channels of contagion that we mentioned above, and possible economic and financial policies that can be implemented. Further, the asset pricing models of the CAPM and APT fit within this framework.[13] Finally and as mentioned above, the factor model specification will allow us to eliminate problems associated with the omission of relevant variables and simultaneous equations estimation bias – see Forbes and Rigobon (2002) for further details.

One of the first studies that used factor models in this framework was Kamin-

[11] Bekaert, Harvey, and Ng (2005) use this definition. Other papers that study "global shocks" are Calomiris, Love, and Peria (2010), Fratzscher (2012) and Eichengreen, Mody, Nedeljkovic, and Sarno (2012).

[12] Bai (2003) for the inferential theory.

[13] See Ross (1976).

sky and Reinhart (2002), although the main aim of their study was the analysis of the interdependence among markets.[14] After this seminal work, a notable volume of literature has analyzed the presence of contagion using this methodology on different markets and financial crises. The approach that is followed in our paper is more related to the analyses in Dungey, Fry, González-Hermosillo, and Martin (2005), Bekaert, Ehrmann, Fratzscher, and Mehl (2011) and Eichengreen, Mody, Nedeljkovic, and Sarno (2012), who use a factor model to analyze the "shift contagion".[15] The main contribution of our article is the study of the presence of different contagions in the period of economic crisis taking into account the interdependence that exists among the financial markets of different developed economies. One measure to assess the degree of changes in co-movements among equity markets is to look at the common factors of the returns among financial markets over time, which is the avenue pursued in this paper.

2.3 Data and sample

The data source that is used in this paper is Thomson Financial Datastream database, from which we have selected a sample including the 22 OECD most industrialized economies: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Hungary, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and US. Specifically, the variable that we use is the one that Datastream list as DSGLOBAL. The continuously compounded return presents the theoretical growth in value of a notional stock holding without consideration to dividend, the price of which is that of the

[14] Another paper in which interdependence is also analyzed is King, Sentana, and Wadhwani (1994).

[15] See also Corsetti, Pericoli, and Sbracia (2005), Forbes and Rigobon (2002), Dungey, Martin, and Pagan (2000) and Bekaert, Harvey, and Ng (2005).

selected price index. The logarithmic return is used:

$$\begin{aligned} r_{i,t} &= \log(\frac{PI_{i,t}}{PI_{i,t-1}}) \\ PI_{i,t} &= PI_{i,t-1} + \frac{\sum_{j=1}^{n}(P_{i,j,t} * N_{i,t})}{\sum_{j=1}^{n}(P_{i,j,t-1} * N_{i,t} * f_{i,t})}, \end{aligned}$$

where $r_{i,t}$ is a logarithmic return on day t for the i-th country, $PI_{i,t}$ is the recalculated price index on day t for the i-th country, $P_{i,j,t}$ is the unadjusted price of j-th shares in issue for the i-th country, $N_{i,t}$ is a number of shares in issue for the i-th country on day t, $f_{i,t}$ is used to adjustment factor for a capital action occurring on day t, and n is the number of constituents in the i-th country index. We use the recalculated price index, based on the current constituents – i.e., historic data for the current constituents are used in the return index calculations to ensure data consistency.[16] The frequency of the data set is daily (Monday to Friday) and the period covers from January 1st, 2003 through April 30th, 2015. The daily returns are in national currencies.

2.4 Empirical analysis

2.4.1 Univariate analysis

In this section we assess the stochastic properties of the daily returns, focusing on the order of integration and the volatility of the time series. Financial time series such as stock returns are expected to show volatility. Further, the time series that we are analyzing are expected to be affected by the presence of structural breaks in the variance,[17] which can be reflecting, for instance, different relationships or correlations of financial markets. Non-stationary volatility is one of the most common econometric problems in the analysis of pure contagion. Pure contagion involves a change in the covariance matrix at a multivariate level, which in turn can

[16] See Datastream Global Equity Indices User Guide.

[17] See Forbes and Rigobon (2002) for the non-stationary volatility problems when dealing with contagion testing.

lead to non-stationary volatility at the univariate level. This feature is important since a structural change in volatility invalidates the inference drawn from the use of classical unit root test. The stationary time-varying conditional variance (GARCH structure) does not influence in the unit root test,[18] but non-stationary volatility can have a strong influence on the limiting distribution of the unit root tests.[19]

In this section, we first proceed testing for the existence of unconditional heteroskedasticity, a feature that is shown to be present in our data set. Then, and in order to accommodate this characteristic of the time series, we compute unit root tests that are robust to unconditional heteroskedasticity. To the best of our knowledge, there is no other contribution in the empirical literature that analyzes financial contagion following the strategy used in this paper. Further and as mentioned above, non-stationary volatility has a great influence on the stochastic properties of the processes, affecting the limiting distribution of the unit root tests. In order to overcome this drawback, in this paper we compute the bootstrap-based unit root test statistic proposed by Smeekes and Taylor (2012), a test statistic that is robust to non-stationary volatility,[20] trend uncertainty and uncertainty about the initial condition.

The test statistic in Smeekes and Taylor (2012) specifies the null hypothesis of unit root ($H_0 : c = 0$) against the alternative hypothesis ($H_0 : c > 0$) based on the specification of the following data-generating process (DGP):

$$\begin{aligned} y_t &= \mu + \beta_T t + x_t \\ x_t &= \rho_T x_{t-1} + u_t \\ u_t &= \sum_{j=0}^{\infty} \psi_j \epsilon_{t-j} =: \psi(L)\epsilon_t, \end{aligned}$$

[18] See Hansen and Rahbek (1998), Cavaliere (2003) or Ling, Li, and McAleer (2003).

[19] See Hamori and Tokihisa (1997), Kim, Leybourne, and Newbold (2002) and Cavaliere and Taylor (2008).

[20] The approach in Cavaliere and Taylor (2008) accounts for multiple forms non-stationarity: both single and multiple abrupt breaks in variance, polynomially trending volatility, piecewise trending volatility, and smooth transition variance breaks.

where $\rho_T = 1 - c/T$ and $\psi_0 = 1$, $t = 0, 1, \ldots, T$. The Smeekes and Taylor (2012) union test statistic is given by:

$$\begin{aligned} UR^*_{4,\tilde{\gamma}}(\pi) &= \min\Bigg\{ DF-QD^{\mu^*}_{\tilde{\gamma}}, (\frac{cv^{\mu^*}_{QD}(\pi)}{cv^{\tau^*}_{QD}(\pi)})DF-QD^{\tau^*}_{\tilde{\gamma}}, \\ &\qquad (\frac{cv^{\mu^*}_{QD}(\pi)}{cv^{\mu^*}_{OLS}(\pi)})DF-OLS^{\mu^*}_{\tilde{\gamma}}, (\frac{cv^{\mu^*}_{QD}(\pi)}{cv^{\tau^*}_{OLS}(\pi)})DF-OLS^{\tau^*}_{\tilde{\gamma}} \Bigg\}, \end{aligned}$$

where DF denotes the augmented Dickey-Fuller test statistic. The critical value that is used is defined so that:

$$cv^*_{UR,\tilde{\gamma}}(\pi) = \max\left\{ x : N^{-1} \sum_{b=1}^{N} I(UR^*_{4,\tilde{\gamma},b}(\pi) < x) \leq \pi \right\}.$$

Table 2.1 presents the results of the Smeekes and Taylor (2012) test statistic for the daily returns in levels. As can be seen, the null hypothesis of unit root is clearly rejected at the 5% level of significance. Therefore, we can conclude that the returns are I(0) stochastic processes. It is worth noticing the novel contribution to the empirical evidence that is made based on the use of robust unit root test since, as shown in Lansangan and Barrios (2009), incorrect estimation of the order of integration of the time series leads to an incorrect estimation of the common factor model using principal components.

Once the order of integration of the stock returns has been assessed, we proceed analyzing the volatility (conditional and unconditional heteroskedasticity) of these time series. The volatility analysis allows us to confirm the importance of using the Smeekes and Taylor (2012) unit root test statistic in the study of financial contagion.

Let us first focus on testing for the presence of unconditional heteroskedasticity in each time series, an expected phenomenon when dealing with financial variables, and whether such unconditional variance experiences changes throughout the period analyzed.[21,22] In order to address this issue, we proceed to compute

[21] See for example Cavaliere and Taylor (2008).

[22] See Wang and Nguyen Thi (2013). Lamoureux and Lastrapes (1990) point that the ignorance

the κ_2 statistic in Sansó, Aragó, and Carrion-i-Silvestre (2004).[23] However, some cautions should be taken before computing such test statistic, since the κ_2 statistic is not robust to conditional heteroskedasticity. Therefore, we need first to assess whether there is a GARCH structure in the variance and, if so, filtering out such structure for the whole time period.[24] It is worth mentioning that we focus on the whole time period when testing and estimate a GARCH model because the null hypothesis of the κ_2 statistic in Sansó, Aragó, and Carrion-i-Silvestre (2004) is that there is no structural change affecting the variance of the stochastic process. In order to select among the different model specifications and distributions, we focus on the largest log likelihood value and the smallest AIC and BIC information criterion. When there is no unanimous match, we select the model with the smallest information criterion, prioritizing the BIC information criterion. With the previous results, we find the best model between different ARMA-GARCH structures with different distributions. In the conditional mean we can select between a AR(1) and no ARMA structure. The order of the GARCH specification is always a $P = Q = 1$, but we select between GARCH and EGARCH specifications. The different distributions of the GARCH structure are Normal Gaussian Distribution, Student t-Distribution, Generalized Error Distribution and Hansen's Skew-t Distribution.[25]

Table 2.7 confirms the existence of unconditional heteroskedasticity in the GARCH-filtered returns. The test concludes that there are some structural breaks in the unconditional variance of 18 out of 22 returns.[26] Therefore, the main con-

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of structural breaks might cause over-estimation of heteroskedasticity and affect the reliability of its application to other analyses. Hansen (2001) maintains that structural breaks should be considered endogenous and determined by the data, since exogenous determination of the structural breaks would mislead the fitted model. See also Fang and Chang (2007).

[23] We also compute the test statistic in Inclan and Tiao (1994) and the κ_1 statistic Sansó, Aragó, and Carrion-i-Silvestre (2004) and reached the same conclusion.

[24] Table 2.2, Table 2.3, Table 2.4, Table 2.5 and Table 2.6 report the descriptive, the conditional mean and conditional variance tests for each first difference of the time series.

[25] We estimate an exponential GARCH(1,1,1) with Generalized Error Distribution during the whole period in all cases. In the conditional mean we select a AR(1) for Austria, Finland, Greece, Ireland, Portugal, Australia, US and Japan; and no ARMA structure in the other case.

[26] We also compute the test statistic without filtering the GARCH structure and arrived to the same conclusion, although up to eight structural breaks were detected in some cases.

clusion of our analysis so far is that the returns are I(0) stationary stochastic processes with non-stationary volatility.

Given that we have found evidence of structural breaks in the unconditional variance, we split the sample according to the regimes that define the structural breaks. In order to select among the different model specifications and distributions, we apply the same procedure that was used in the analysis of the whole time period.[27]

Finally, we analyze the presence of conditional heteroskedasticity on the returns computing the Engle (1982) and Broock, Scheinkman, Dechert, and LeBaron (1996) LM test statistics for each subperiod.[28] Both test statistics lead to the same conclusion, i.e., that the stock returns have a non-constant volatility in 51 out of 66 subperiods– these results are consistent with the correlograms of the time series and their squares. So, we select the best GARCH model for each subperiod according to the criteria of the largest log likelihood value and the smallest AIC and BIC information criterion.[29] Consequently, the univariate analysis that has been conducted in this section leads us to conclude that the returns are I(0) stationary processes with non-stationary volatility and non-constant conditional volatility. So, we filter out the estimated subperiod-specific GARCH structure, dividing the returns by the estimated conditional standard deviation if this subsample has a GARCH structure.

2.4.2 The global and US contagion effects during the great recession

In this section we will analyze the global contagion among the stock return of our sample. In order to analyze the global contagion we follow a strategy that bases on the specification of an approximate factor model. Specifically, we test the

[27] Details on the results are available from the authors upon request.

[28] Details on the results of conditional heteroskedasticity for all countries and subperiods are available from the authors upon request.

[29] See Eichengreen, Mody, Nedeljkovic, and Sarno (2012) for the problems that can appear when working with multivariate GARCH models.

global contagion with the Breitung and Eickmeier (2011) and the Chen, Dolado, and Gonzalo (2014) test statistics.[30]

The adequacy of the use of factor model is assessed through the computation of two test statistics. First, the Kayser-Meyer-Olkin measure of sampling adequacy reaches a value that is close to 100%, which indicates that factor model is adequate. Second, the Bartlett's test of sphericity also leads to the same conclusion.[31] Therefore, common factor model can be applied to our data.

It is worth mentioning that the approximation that is implemented in this paper improves the strategy followed in Bekaert, Ehrmann, Fratzscher, and Mehl (2011).[32] Thus, our strategy simplifies the reduction of the necessary factors and avoids the potential econometric problems associated with the estimation of the common factors. As in Bekaert, Ehrmann, Fratzscher, and Mehl (2011), we analyze the time-varying loadings, but we also consider the possibility that there may be a structural break in the common factor structure following the proposals in Breitung and Eickmeier (2011) and Chen, Dolado, and Gonzalo (2014).

The estimation of the common factor model considers the panel data set that is defined by $T \times N$ matrix of GARCH-filtered of stock returns, taking into account the presence of serial dependence, heteroskedasticity in the idiosyncratic component, and weak dependence across the idiosyncratic component.[33] We consider this model because Breitung and Eickmeier (2011) argue that the dynamic factor model is not an accurate specification in the presence of structural breaks.[34]

In order to analyze the global contagion, we have to define two periods, the calm period after the crisis and crisis period. We define the tranquil (calm) and turbulent (crisis) periods as stretching from January 1st, 2003 through August 8th,

[30] We would like to thank Breitung and Eickmeier for providing us the MATLAB code to carrying out the computations.

[31] Table 2.8 reports the tests.

[32] See Eichengreen, Mody, Nedeljkovic, and Sarno (2012) for a similar approach.

[33] See Bai (2003) and Bai and Ng (2002) for a detailed description of the assumptions.

[34] Despite of the criticism in Breitung and Eickmeier (2011) we observe that some authors use the dynamic factor model specification for their analyses. See, for example, Cipollini and Kapetanios (2009).

2007 and from August 9th, 2007 through April 30th, 2015, respectively.[35] The common factor model is estimated on the GARCH-filtered of the stock returns panel data set for the whole time period, but also for the tranquil and turbulent subperiods.

A crucial step in the statistical analysis of common factor models is the preliminary identification of the number of static common factors (r). This number is indeed needed in the implementation of the various estimation and forecasting algorithms.[36]

The selection of the number of common factors that is required for the computation of the Breitung and Eickmeier (2011) test statistic is carried out using the Onatski (2010) information criterion and the Onatski (2009) test statistic considering the whole time period, which point to the presence of one common factor.[37]

After selecting the number of factors, we use the Breitung and Eickmeier (2011) test statistic to analyze the global contagion. We use the "dynamic" test with an unknown break date, allowing for an AR(p) model for the idiosyncratic component. Table 2.10 reports the test statistic in Breitung and Eickmeier (2011) that, regardless of the lag length that is used, detects the presence of one structural break in June 27th, 2007, a date that is consistent with the turnaround in the financial markets.[38] As it can be seen, the test statistic in Breitung and Eickmeier (2011) concludes that there is global contagion affecting the stock returns. Table 2.10 also presents the computation of the test statistics in Chen, Dolado, and Gonzalo (2014), which limits the presence of a structural break. We believe that this last result is more difficult to interpret because the Chen, Dolado, and Gonzalo (2014) suggest that a factor dependent on others and in our case there is only one factor. The individual test statistics in Breitung and Eickmeier (2011) indicate

[35] This date is the ECB interventions by opening lines of €96.8 billion in low-interest credit when the Bear-Stearns hedge funds suspended payments.

[36] See Hallin and Liška (2007).

[37] We set the level of significance at the 10% when performing the statistical inference using the Onatski (2009) test. For robustness check we have also used the Alessi, Barigozzi, and Capasso (2010) information criterion, which detects two common factors.

[38] Note that the estimated break date is close to the one found in Alessi, Barigozzi, and Capasso (2010): July 27th, 2007.

that the global contagion has affected all OECD countries that we have analyzed.

Chen, Dolado, and Gonzalo (2014) approach can also be used to try to distinguish between structural breaks that affect the loadings and structural breaks that affect the common factors.[39] We split the sample with starting point of crisis on August 9th, 2007. The number of static common factors that is selected is one for both the calm and crisis periods.[40] Provided that the number of common factors are the same in both periods, we conclude that the structural break is affecting in the factor not the loadings – see Chen, Dolado, and Gonzalo (2014) for further details. Therefore, in our sample, the distinction between structural breaks affecting the loadings and the common factor component is conclusive.

It is worth noticing that the explanatory power of the common factors is different for each subperiod. The common factor during the crisis explains 51.2% of the variability of the stock returns, while the factor that has been selected on the previous period only explains 42.1% of such variability. Therefore, this feature adds to the evidence of the presence of structural change, which has implied that the behavior of the markets and the interrelations among the analyzed countries change during the great recession. These changes of the variability of the stock returns are important in terms of international investment for international portfolio management and risk assessment.

Finally, Table 2.11 reports the component matrix and communalities of the estimated common factors. As can be seen, the common factor has a CAPM interpretation in the tranquil period. This common factor increase in the crisis period which more influence in most of all countries. This feature leads us to conclude that the systemic risk has changed and increased in the crisis period. The changes of the correlations and communalities are also important in international investment for international portfolio management and risk assessment.

[39] Regarding Eichengreen, Mody, Nedeljkovic, and Sarno (2012), the main contribution is the use of the Breitung and Eickmeier (2011) test statistic and the subsequent estimation of the common factors for each subperiod.

[40] The number of common factors for the static common factor model is obtained using the information criterion in Onatski (2010) and the test statistic in Onatski (2009). Details on the results of the selection of factors in each subperiod are available from the authors upon request.

These results make us doubt about whether it actually exists the same gains of international portfolio diversification in crisis period than in other periods. Taking into account with these results, it seems that there exists less gains of international portfolio diversification in crisis periods.

2.4.3 Analysis of pure contagion

This section focuses on the local contagion and its shifting behavior following the proposal in Dungey, Fry, González-Hermosillo, and Martin (2005) – we implement the panel, multivariate and bivariate test statistics. All these tests specify the null hypothesis of no pure contagion, only interdependence, against the alternative hypothesis of pure contagion. We select these alternative formulation because they are computationally faster than the multivariate extension formulation based on the Determinant of the Change in Covariance (DCC) matrix test proposed by Rigobon (2003) but they have similar statistical behavior.

The analysis of pure contagion is carried out through the estimation of the following regression equation:

$$\begin{aligned}\left(\frac{Z_{i,t}}{\sigma_{z,i}}\right) &= \alpha_{i,0} + \alpha_{i,1} d_t + \sum_{k=1}^{r} \lambda_{i,k}^{r} w_{k,t} \\ &+ \sum_{j=1, j\neq i}^{N} \delta_{i,j} \left(\frac{Z_{i,t}}{\sigma_{z,i}}\right) + \sum_{j=1, j\neq i}^{N} \gamma_{i,j} \left(\frac{Z_{i,t}}{\sigma_{z,i}}\right) d_t + \eta_{i,t},\end{aligned} \tag{2.1}$$

where $Z_i = (x_{i,1}, x_{i,2}, ..., x_{i,T_X}, y_{i,1}, y_{i,2}, ..., y_{i,T_y})'$, $i = 1, ..., 21$, and

$$d_t = \begin{cases} 1 & \text{for } t > T_x \\ 0 & \text{otherwise} \end{cases},$$

being T_x and T_y the sample sizes of the calm and crisis periods, respectively. The $Z_{i,t}$ vector is the stock return on both periods and represents the $T = T_x + T_y$ observations set by stacking the non-crisis ($x_{i,t}$) and crisis ($y_{i,t}$) observation of the time series. In our case $T_x = 1201$ and represents August 8th, 2007, whereas $T_y = 2015$ and represents April 30th, 2015. The variable $w_{k,t}$ represents a common shock that impacts upon all returns on both subperiods with loadings $\lambda^{r}_{i,k}$. The $\sigma_{z,i}$ is the estimated GARCH conditional standard deviation. As mentioned above, the number of common factors that is estimated for both the non-crisis and crisis periods is $r = 1$. The inclusion of $w_{k,t}$ in (2.1) allows us to take into account the global contagion in the analysis of pure contagion. Finally, $\eta_{i,t}$ denotes the disturbance term.

The panel test proposed in Dungey, Fry, González-Hermosillo, and Martin (2005) bases on testing the following null hypothesis:

$$H_0 : \gamma_{i,j} = 0, \qquad \forall j \neq i,$$

their multivariate test specifies the following null hypothesis:

$$H_0 : \gamma_{i,j} = 0, \qquad i \ fixed, \quad \forall j \neq i,$$

and, finally, the bivariate test statistic focuses on the null hypothesis:

$$H_0 : \gamma_{i,j} = 0, \qquad i \ fixed, \quad j \neq i,$$

$i, j = 1, \ldots, N$.

Table 2.12 shows the results of the panel test statistic, which indicates that pure contagion has taken place. Since this statistic pools the evidence of all countries together, we cannot be sure about whether the result is driven just by few countries. In order to have a better insight about whether pure contagion affects all countries in our sample, we proceed carrying out the analysis country-by-country. As it can be seen from Table 2.12, the multivariate test corroborates the previous result, showing that 19 countries out of 22 – the exceptions are for Netherlands, Sweden and Hungary – experienced pure contagion in the great recession.

Finally, and to offer a complete picture of the contagion phenomenon, we focus on testing for the presence of bivariate contagion, performing a total of 463 bivariate tests. In 444 out of 463 cases, we found local contagion. There are only 19 test statistics for which the null hypothesis of interdependence cannot be rejected.[41] The most interesting conclusion of this interdependence analysis is that bidirectional interdependence was not detected in any of the 19 test statistics, thereby all of 19 tests statistics have a unidirectional interdependence relationship.

2.5 Conclusions

This paper contributes to the analysis of the current economic situation of the financial markets by stating that the market behavior in such a turbulent period is marked by a strong transversal dependence that differs from the one in the tranquil situation. We focus on a panel data set defined with the most industrialized OECD countries, which has led us to conclude that, under the current economic conditions, the dependence that links the financial markets of these countries has a unique character that can be associated to a financial contagion. The paper has found that the stock returns of the most industrialized OECD countries are I(0) stationary processes with non-stationary volatility. The assessment of the stochastic properties of the stock returns is crucial in order to proceed with the analysis of the financial contagion.

The analysis that has been carried out in this paper focuses on the structural stability of the approximate common factor model that aims to test the presence of global contagion (shift in the systemic risk). The application of test statistics to assess the structural stability of the common factor has revealed the presence of structural instabilities. The applied techniques allowed us to detect that just one common factor explains most of the stock market variability during both the crisis and calm period. Furthermore, the common factors behave differently in times of financial turmoil than in more tranquil periods, i.e., the systemic risk changes and increases in the crisis period. These changes of the correlations and communalities are also important in international investment for international portfolio management and risk assessment. These results cast some doubts about whether portfolio

[41] Details on these results are available from the authors upon request.

diversification allows great benefits in reducing the risk of investments.

Finally, the paper has also focused on the presence of local contagion, finding that this feature is also present in the data set that we have analyzed and that it constitutes a network contagion among these markets.

Table 2.1: Bootstrap union unit root tests of Smeekes and Taylor (2012) for the level of stock returns

		Level			
		UR-A		UR-B	
	Statistic	Value	p-val	Value	p-val
Austria	-8.814	-2.559	0.000	-2.550	0.000
Belgium	-8.718	-2.452	0.000	-2.452	0.000
Finland	-9.531	-2.425	0.000	-2.425	0.000
France	-57.304	-2.313	0.000	-2.313	0.000
Germany	-56.865	-2.272	0.000	-2.272	0.000
Greece	-10.357	-2.610	0.000	-2.610	0.000
Ireland	-8.399	-2.250	0.000	-2.245	0.000
Italy	-12.624	-2.279	0.000	-2.279	0.000
Netherlands	-10.256	-2.576	0.000	-2.576	0.000
Portugal	-9.243	-2.331	0.000	-2.338	0.000
Spain	-55.618	-2.326	0.000	-2.326	0.000
Denmark	-8.939	-2.398	0.000	-2.398	0.000
Norway	-9.471	-2.435	0.000	-2.429	0.000
Sweden	-57.771	-2.247	0.000	-2.247	0.000
United Kingdom	-58.767	-2.355	0.000	-2.355	0.000
Hungary	-9.481	-2.388	0.000	-2.388	0.000
Switzerland	-53.768	-2.334	0.000	-2.334	0.000
Australia	-58.370	-2.416	0.000	-2.416	0.000
New Zealand	-10.274	-2.367	0.000	-2.369	0.000
Canada	-16.219	-2.435	0.000	-2.435	0.000
United States	-62.809	-2.382	0.000	-2.381	0.000
Japan	-9.466	-2.328	0.000	-2.331	0.000

Note: Value indicates the critical value at 5 % level of significance

Table 2.2: Descriptive statistics of first difference of the stock

	Mean	Median	Stand. dev.	Skewness	Kurtosis
Austria	0.00	0.00	0.01	-0.37	10.25
Belgium	0.00	0.00	0.01	-0.16	9.68
Finland	0.00	0.00	0.01	-0.22	7.82
France	0.00	0.00	0.01	0.00	9.59
Germany	0.00	0.00	0.01	0.51	18.57
Greece	-0.00	0.00	0.02	-0.13	8.78
Ireland	0.00	0.00	0.01	-0.52	9.48
Italy	0.00	0.00	0.01	-0.11	8.92
Netherlands	0.00	0.00	0.01	-0.26	10.57
Portugal	0.00	0.00	0.01	-0.15	11.98
Spain	0.00	0.00	0.01	0.04	9.50
Denmark	0.00	0.00	0.01	-0.36	9.96
Norway	0.00	0.00	0.02	-0.55	9.84
Sweden	0.00	0.00	0.01	-0.01	7.77
United Kingdom	0.00	0.00	0.01	-0.16	10.99
Hungary	0.00	0.00	0.02	-0.07	10.10
Switzerland	0.00	0.00	0.01	-0.29	11.46
Australia	0.00	0.00	0.01	-0.43	9.19
New Zealand	0.00	0.00	0.01	-0.38	7.68
Canada	0.00	0.00	0.01	-0.71	15.89
United States	0.00	0.00	0.01	-0.33	14.26
Japan	0.00	0.00	0.01	-0.48	10.80

Table 2.3: Ljung-Box Q test on the residuals regressed on q lags and a constant for the whole period

	Statistic	P-value
Austria	30.14	0.00
Belgium	22.78	0.01
Finland	24.08	0.01
France	32.80	0.00
Germany	16.35	0.09
Greece	43.30	0.00
Ireland	30.90	0.00
Italy	30.06	0.00
Netherlands	33.13	0.00
Portugal	35.48	0.00
Spain	16.55	0.08
Denmark	31.26	0.00
Norway	21.47	0.02
Sweden	22.92	0.01
United Kingdom	48.43	0.00
Hungary	58.70	0.00
Switzerland	52.30	0.00
Australia	16.45	0.09
New Zealand	52.29	0.00
Canada	77.13	0.00
United States	63.57	0.00
Japan	13.43	0.20

Note: We select $q = 10$ lags maximun

Table 2.4: LM test of the residuals regressed on q lags and a constant for the whole period

	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$	$q=6$	$q=7$	$q=8$	$q=9$	$q=10$
Austria	22.83^a	26.49^a	26.60^a	26.87^a	26.86^a	26.91^a	30.65^a	31.53^a	31.70^a	32.07^a
Belgium	8.51^a	9.14^a	11.76^a	11.79^b	11.72^b	14.07^b	14.46^a	19.21^a	20.36^b	23.02^a
Finland	0.76	1.15	5.35	7.32	16.35^a	17.84^a	18.82^a	20.55^a	20.99^a	25.08^a
France	0.36	4.90^c	15.08^a	17.98^a	27.03^a	27.40^a	27.76^a	27.98^a	31.58^a	33.35^a
Germany	0.04	0.37	2.69	2.83	6.05	6.08	12.84^c	12.88	13.35	16.26^c
Greece	17.87^a	20.17^a	20.17^a	26.11^a	26.52^a	27.59^a	36.99^a	41.84^a	42.36^a	43.43^a
Ireland	10.02^a	12.26^a	12.46^a	12.54^a	12.75^a	22.23^a	22.24^a	26.40^a	29.46^a	29.51^a
Italy	0.39	0.56	4.76	10.49^b	23.95^a	24.63^a	25.40^a	26.63^a	27.61^a	28.90^a
Neth.	1.66	1.75	9.18^b	14.10^a	26.04^a	26.33^a	27.30^a	32.89^a	32.81^a	33.12^a
Portugal	13.49^a	13.79^a	14.29^a	14.28^a	20.42^a	23.22^a	30.97^a	31.24^a	35.38^a	35.29^a
Spain	1.18	3.77	7.31^c	7.90^c	13.72^b	13.69^b	13.90^b	13.97^c	15.50^c	17.42^c
Denmark	10.10^a	10.71^a	11.96^a	18.33^a	29.08^a	30.99^a	31.29^a	32.27^a	32.40^a	33.33^a
Norway	1.23	6.07^b	6.10	6.26	14.28^a	16.23^a	19.29^a	19.34^a	19.35^b	20.31^b
Sweden	1.22	6.97^b	10.58^a	10.77^b	22.71^a	23.55^a	24.39^a	25.16^a	25.35^a	26.64^a
UK	4.16^a	7.68^a	21.80^a	35.78^a	43.26^a	45.96^a	46.01^a	45.97^a	46.57^a	46.57^a
Hungary	10.24^a	27.79^a	27.70^a	44.67^a	44.79^a	49.07^a	49.09^a	49.14^a	50.40^a	52.96^a
Switz.	8.98^a	17.82^a	23.37^a	29.93^a	46.54^a	48.60^a	52.67^a	52.84^a	53.19^a	54.19^a
Australia	2.81^c	3.14	10.58^a	10.61^b	11.00^b	11.02^c	12.10^c	12.73	16.21^b	16.31^c
N. Zealand	13.34^a	22.34^a	25.61^a	25.60^a	28.11^a	30.90^a	34.04^a	49.35^a	51.43^a	51.61^a
Canada	4.78^a	13.26^a	13.52^a	23.28^a	45.60^a	53.91^a	53.94^a	59.49^a	62.33^a	68.70^a
US	33.95^a	40.89^a	41.08^a	41.47^a	46.57^a	47.09^a	52.40^a	58.32^a	61.17^a	62.90^a
Japan	0.55	3.65	6.79^c	7.28	7.31	11.15^c	11.17	12.17	13.46	13.74

Note: Supscripts a, b and c denote rejection of the null hypothesis at the 1, 5 and 10 % level of significance, respectively

Table 2.5: Engle LM test of the squared residuals regressed on q lags and a constant for the whole period

	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$	$q=6$	$q=7$	$q=8$	$q=9$	$q=10$
Austria	363.90^a	564.83^a	714.92^a	754.09^a	784.83^a	833.86^a	847.97^a	848.79^a	854.32^a	882.86^a
Belgium	276.03^a	397.12^a	425.90^a	483.98^a	553.31^a	638.80^a	652.80^a	653.12^a	656.26^a	663.20^a
Finland	38.84^a	101.15^a	146.02^a	159.65^a	236.66^a	257.26^a	263.15^a	283.75^a	288.94^a	306.25^a
France	157.21^a	311.81^a	393.68^a	429.28^a	550.44^a	551.19^a	552.79^a	552.75^a	566.11^a	585.72^a
Germany	161.29^a	183.79^a	197.01^a	206.15^a	241.38^a	242.89^a	271.30^a	272.28^a	289.40^a	291.46^a
Greece	66.55^a	166.60^a	226.64^a	301.81^a	311.62^a	316.08^a	345.72^a	352.28^a	364.29^a	364.67^a
Ireland	115.03^a	250.14^a	264.81^a	358.51^a	438.84^a	633.89^a	668.78^a	671.32^a	674.30^a	674.21^a
Italy	120.30^a	248.65^a	354.66^a	435.25^a	535.81^a	545.50^a	546.42^a	548.20^a	581.95^a	591.01^a
Neth.	189.41^a	472.29^a	589.08^a	602.43^a	814.70^a	821.86^a	825.52^a	827.79^a	828.80^a	860.29^a
Portugal	143.65^a	240.78^a	298.73^a	352.18^a	476.86^a	482.50^a	489.28^a	489.91^a	509.80^a	509.81^a
Spain	115.67^a	195.13^a	252.29^a	377.78^a	419.82^a	421.69^a	428.19^a	429.65^a	446.13^a	454.59^a
Denmark	157.19^a	399.99^a	456.32^a	518.63^a	797.23^a	797.51^a	809.43^a	809.26^a	822.32^a	822.76^a
Norway	256.36^a	382.02^a	582.47^a	752.18^a	911.54^a	929.36^a	931.95^a	939.02^a	984.19^a	989.67^a
Sweden	120.68^a	242.71^a	392.03^a	427.11^a	524.88^a	541.35^a	545.09^a	545.27^a	581.52^a	619.28^a
UK	187.44^a	362.60^a	523.18^a	588.78^a	704.63^a	705.87^a	705.83^a	711.13^a	738.87^a	772.02^a
Hungary	403.18^a	448.14^a	465.88^a	481.39^a	499.02^a	537.47^a	543.20^a	577.41^a	646.67^a	686.48^a
Switz.	408.24^a	525.83^a	566.03^a	602.53^a	689.80^a	690.39^a	690.98^a	693.69^a	705.24^a	729.53^a
Australia	233.46^a	459.11^a	599.78^a	659.35^a	676.24^a	700.16^a	702.77^a	792.78^a	793.50^a	793.92^a
N. Zealand	138.25^a	753.08^a	764.30^a	798.15^a	805.84^a	809.23^a	841.85^a	863.32^a	880.65^a	899.87^a
Canada	413.70^a	440.54^a	564.95^a	600.91^a	784.03^a	1020.14^a	1032.28^a	1057.43^a	1078.27^a	1081.65^a
US	157.30^a	568.35^a	590.25^a	631.24^a	800.68^a	857.02^a	896.28^a	905.79^a	927.18^a	932.97^a
Japan	186.99^a	740.91^a	744.89^a	844.24^a	843.95^a	905.30^a	908.68^a	909.52^a	922.33^a	926.08^a

Note: Supscripts a, b and c denote rejection of the null hypothesis at the 1, 5 and 10 % level of significance, respectively

Table 2.6: Sign Size Bias Test

	SB test	p-val	NSB test	p-val	PSB test	p-val	General	p-val
Austria	2.387	0.008	-38.651	0.000	51.460	0.000	2397.114	0.000
Belgium	1.447	0.074	-35.022	0.000	55.445	0.000	2414.518	0.000
Finland	1.984	0.024	-39.183	0.000	44.122	0.000	2460.378	0.000
France	2.337	0.010	-35.235	0.000	55.166	0.000	2415.182	0.000
Germany	1.182	0.119	-20.636	0.000	107.548	0.000	1925.704	0.000
Greece	1.759	0.039	-35.379	0.000	50.013	0.000	2378.646	0.000
Ireland	2.382	0.009	-43.042	0.000	38.850	0.000	2366.686	0.000
Italy	3.134	0.001	-36.206	0.000	55.185	0.000	2421.324	0.000
Netherlands	2.235	0.013	-39.836	0.000	44.544	0.000	2388.023	0.000
Portugal	1.350	0.088	-31.259	0.000	60.129	0.000	2171.966	0.000
Spain	2.114	0.017	-31.624	0.000	63.057	0.000	2322.025	0.000
Denmark	1.777	0.038	-39.006	0.000	39.864	0.000	2239.991	0.000
Norway	2.851	0.002	-47.356	0.000	36.762	0.000	2469.380	0.000
Sweden	1.961	0.025	-36.151	0.000	54.182	0.000	2525.841	0.000
UK	2.029	0.021	-38.965	0.000	46.578	0.000	2373.646	0.000
Hungary	0.310	0.378	-31.738	0.000	54.719	0.000	2277.252	0.000
Switzerland	2.586	0.005	-39.227	0.000	47.877	0.000	2332.894	0.000
Australia	2.408	0.008	-43.948	0.000	35.001	0.000	2395.938	0.000
New Zealand	2.632	0.004	-39.308	0.000	43.049	0.000	2347.400	0.000
Canada	3.403	0.000	-45.426	0.000	38.982	0.000	2328.760	0.000
US	3.032	0.001	-41.962	0.000	44.938	0.000	2343.334	0.000
Japan	2.386	0.009	-41.340	0.000	42.435	0.000	2240.787	0.000

Note: Sign Bias (SB), Negative Size Bias (NSB), Positive Size Bias (PSB) tests and general test for asymmetric volatility. The test are applied to the residuals from an $AR(p)$ model, with p determined by the AIC

Table 2.7: Sansó et al. (2004) κ_2 test statistic

Country	Number of breaks	Break positions					
Austria	5	31/07/2007	19/09/2008	01/01/2009	01/01/2010	01/01/2013	
Belgium	3	21/02/2003	28/02/2007	14/04/2009			
Finland	5	06/01/2004	16/08/2007	01/01/2010	11/02/2011	01/01/2013	
France	4	28/01/2005	07/06/2007	06/06/2008	26/12/2012		
Germany	0						
Greece	1	24/01/2008					
Ireland	3	29/09/2008	01/01/2010	28/06/2012			
Italy	5	03/02/2003	16/09/2004	18/04/2005	18/06/2007	01/01/2013	
Netherlands	5	20/08/2003	26/07/2007	01/01/2009	10/08/2009	05/09/2012	
Portugal	2	16/08/2007	22/08/2012				
Spain	2	06/06/2007	05/09/2012				
Denmark	0						
Norway	5	09/08/2007	09/09/2008	30/01/2009	14/08/2009	13/09/2012	
Sweden	5	03/02/2003	28/09/2004	07/06/2007	29/05/2009	01/01/2013	
United Kingdom	4	18/06/2003	26/07/2007	01/01/2009	31/08/2012		
Hungary	0						
Switzerland	4	31/12/2004	27/02/2007	22/07/2009	02/01/2013		
Australia	4	06/03/2007	22/01/2008	27/02/2009	09/04/2012		
New Zealand	0						
Canada	6	24/07/2007	19/09/2008	12/06/2009	08/04/2010	08/08/2011	09/02/2012
United States	3	17/09/2008	01/05/2009	28/02/2012			
Japan	0						

Note: The long-run variance is estimated using the quadratic spectral window with automatic bandwidth selection

Table 2.8: KMO and Bartlett's Tests

		Test
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.95
Bartlett's Test of Sphericity	Approx. Chi-Squared	42592.37
	d.f.	210
	p-value	0.000

Table 2.9: Individual Sup-LM Breitung and Eickmeier (2011) Test

	Lag length	Stat	P-Value	Break date
Austria	1	29.27	0	01/02/2013
	2	190.71	0	06/08/2010
	3	1650.4	0	16/08/2007
Belgium	1	2205.6	0	13/06/2007
	2	93.43	0	22/02/2007
	3	176.28	0	26/08/2010
Finland	1	11.15	0.02	04/02/2014
	2	940.97	0	21/02/2011
	3	58.09	0	14/09/2012
France	1	31	0	02/11/2010
	2	120.04	0	20/01/2010
	3	52.91	0	17/05/2007
Germany	1	127.47	0	14/08/2009
	2	58.44	0	21/02/2013
	3	49.05	0	26/07/2007
Greece	1	32.72	0	12/05/2006
	2	159.37	0	19/11/2012
	3	18.5	0	10/10/2005
Ireland	1	13.43	0.01	27/02/2007

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Table 2.9 – continued from previous page

	Lag length	Stat	P-Value	Break date
	2	45.34	0	27/02/2012
	3	20.54	0	16/05/2006
Italy	1	5.83	0.21	18/10/2012
	2	29.09	0	01/02/2013
	3	189.76	0	06/08/2010
Netherlands	1	1649.3	0	16/08/2007
	2	2203.31	0	13/06/2007
	3	93.4	0	22/02/2007
Portugal	1	174.71	0	26/08/2010
	2	9.93	0.12	04/02/2014
	3	943.37	0	21/02/2011
Spain	1	57.58	0	14/09/2012
	2	31.34	0	01/11/2010
	3	120.48	0	20/01/2010
Denmark	1	52.72	0	17/05/2007
	2	128.11	0	14/08/2009
	3	59.59	0	21/02/2013
Norway	1	49.33	0	26/07/2007
	2	32.73	0	12/05/2006
	3	158.58	0	19/11/2012
Sweden	1	18.21	0	10/10/2005

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Table 2.9 – continued from previous page

	Lag length	Stat	P-Value	Break date
	2	13.43	0.03	27/02/2007
	3	45.41	0	27/02/2012
United Kingdom	1	19.98	0	16/05/2006
	2	5.84	0.5	18/10/2012
	3	28.87	0	01/02/2013
Hungary	1	188.69	0	06/08/2010
	2	1646.96	0	16/08/2007
	3	2201.72	0	13/06/2007
Switzerland	1	93.45	0	22/02/2007
	2	174.44	0	26/08/2010
	3	9.85	0.27	04/02/2014
Australia	1	942.73	0	21/02/2011
	2	55.75	0	14/09/2012
	3	31.17	0	01/11/2010
New Zealand	1	120.74	0	20/01/2010
	2	52.67	0	17/05/2007
	3	128.34	0	14/08/2009
Canada	1	59.47	0	21/02/2013
	2	49.72	0	26/07/2007
	3	32.47	0	12/05/2006
United States	1	158.41	0	19/11/2012

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Table 2.9 – continued from previous page

	Lag length	Stat	P-Value	Break date
	2	18.09	0.01	10/10/2005
	3	13.26	0.08	27/02/2007
Japan	1	45.42	0	27/02/2012
	2	19.8	0.01	16/05/2006
	3	5.74	0.77	18/10/2012

Table 2.10: Breitung and Eickmeier (2011) and Chen et al. (2013) test

	Lag length	Stat	p-value	Break date
Breitung and Eickmeier LM* test	1	4982.60	0.00	27/06/2007
	2	4980.77	0.00	27/06/2007
	3	4975.81	0.00	27/06/2007
		Stat	p-value	
Chen et al. (2014) test	Sup-LM	3.61	0.44	
	Exp-LM	0.51	0.43	
	Ave-LM	0.80	0.44	

Table 2.11: Component matrix of the estimation common factor

	Crisis		Non-Crisis	
	Component 1	Communalities Extraction	Component 1	Communalities Extraction
Austria	0.793	0.629	0.65	0.629
Belgium	0.801	0.641	0.811	0.641
Finland	0.83	0.689	0.66	0.689
France	0.933	0.87	0.176	0.87
Germany	0.897	0.804	0.866	0.804
Greece	0.462	0.213	0.507	0.213
Ireland	0.713	0.508	0.611	0.508
Italy	0.675	0.456	0.829	0.456
Netherlands	0.89	0.792	0.855	0.792
Portugal	0.709	0.503	0.52	0.503
Spain	0.807	0.652	0.847	0.652
Denmark	0.747	0.557	0.657	0.557
Norway	0.716	0.513	0.606	0.513
Sweden	0.844	0.713	0.811	0.713
United Kingdom	0.873	0.762	0.858	0.762
Hungary	0.542	0.294	0.437	0.294
Switzerland	0.832	0.693	0.818	0.693
Australia	0.371	0.137	0.384	0.137
New Zealand	0.206	0.042	0.124	0.042
Canada	0.516	0.266	0.467	0.266
United States	0.653	0.426	0.56	0.426
Japan	0.328	0.107	0.402	0.107

Note: The extraction method that is used is principal component analysis

Table 2.12: Panel and multivarite Dungey et al. (2005) test statistics

	Statistic	p-value
Panel	2478.140	0.00

Multivariate analysis

	Statistic	p-value
Austria	164.019	0.000
Belgium	16961.054	0.000
Finland	9478.145	0.000
France	8681.365	0.000
Germany	208.967	0.000
Greece	5691.577	0.000
Ireland	286.619	0.000
Italy	29970.750	0.000
Netherlands	18.561	0.613
Portugal	9881.403	0.000
Spain	4518.218	0.000
Denmark	83.850	0.000
Norway	3969.855	0.000
Sweden	5.060	1.000
United Kingdom	1995.178	0.000
Hungary	11.707	0.947
Switzerland	7088.142	0.000
Australia	6762.866	0.000
New Zealand	641.794	0.000
Canada	4020.345	0.000
United States	347.294	0.000
Japan	1830.136	0.000

Table 2.13: Bivarite Dungey et al. (2005) test statistics

Affected Country	Origin Country	P-Value
Austria	Netherlands	0.613
Austria	Hungary	0.578
Germany	Greece	0.602
Germany	New Zealand	0.945
Ireland	Greece	0.631
Ireland	New Zealand	0.44
Denmark	Germany	0.338
Denmark	Greece	0.106
Denmark	Ireland	0.544
United Kingdom	Greece	0.068
Hungary	Germany	0.615
Hungary	Ireland	0.151
Hungary	Denmark	0.18
Switzerland	Spain	0.282
Australia	Spain	0.104
New Zealand	Greece	0.812
United States	Netherlands	0.126
Japan	Spain	0.772
Japan	Switzerland	0.206

Note: The null hypothesis of interdependence or no pure contagion

Chapter 3

Contagion in public debt markets: A cointegration approach with non-stationary volatility

3.1 Introduction

The European debt crisis was originated in the US in 2007 developed into a global financial turmoil and a long lasting recession in many economies of the globe. By the end of 2007, equity markets started falling from their peaks as a consequence of the sub-prime problem in the US and western countries such as Spain, UK, Ireland or Greece, who suffered fast and sudden downturns in their financial markets. The collapse of large financial institutions, the bailout of affected banks and downturns in stock markets, which, in turn, required political intervention. In this context, many states all over the world, especially in Europe, saved their institutions by absorbing most of the financial industry risk.[1] Thus, the risk of the industry was passed to excessive sovereign debt. Therefore, the global financial crisis has evolved into a sovereign debt crisis. Some of them even required assistance from international institutions such as the International Monetary Fund (IMF) or the

[1] See Markose, Giansante, Gatkowski, and Shaghaghi (2010) for the analysis of too big to fail and the system risk.

European Central Bank (ECB) who implemented measures to reestablish financial stability and the confidence in their banking and financial systems. For this reason, in this Chapter we focus on the debt market.

During the Global Financial Crisis (GFC) and the European debt crisis, a large increase in the correlation between the stock returns of the largest OECD countries can be observed. Intuitively, this can be understood as evidence of contagion or financial shock spillover among financial markets across different regions. However, it is important to differentiate between cross-country linkages that exist at all times – what is often called interdependence – versus linkages that only exist briefly after shocks – what is called contagion. Specifically, we define interdependence when we confirm that similar cointegration relationships or Granger causality relationships among bonds between pre-crisis and crisis periods exist. If we do not find similar relationships, we could consider that contagion exists. Contagion could modify the long-run and/or short-run links among financial markets, but not the interdependence that links these markets. Monitoring the stability of these relationships is important in international investment for international portfolio management and risk assessment. In this way, there is a literature of portfolio management that uses cointegration at the high frequency by motivated by arbitrage arguments.[2]

The definition of contagion versus interdependence is also useful in order to understand the policy implications and its evaluating policy responses. This restrictive definition allows us better understand how crises are transmitted and what should be done. If the transmission of crises is among interdependence, i.e., the cross-country linkages are the same in all states of the world, policies that provide liquidity or financial assistance will be less effective in reducing contagion. In this case, these policies just delay a necessary adjustment. But, if there is contagion, i.e. that cross-country linkages only exist briefly after shocks – such as panic or a temporary liquidity risk – then policies to provide liquidity or financial assistance until economic relationships stabilize could potentially avoid an unnecessary and

[2]See Caldeira and Moura (2013) for a brief survey.

painful adjustment.[3]

In the European bond markets context, the bond contagion is important for the transmission of the European Central Bank policy among European countries. The greater integration or contagion of European bond markets may reduce the efficiency of the common monetary policy to maintain price stability among long-term interest rates.[4] Also, differentiating between contagion and interdependence is important because policies which impose additional adjustment on a country can create additional risks by increasing their vulnerability to contagion on the international financial system. Furthermore, the cross-border contagion may also have significant consequences for international financial stability. Contagion might lead to the fact that systemic risk cannot be mitigated by an opportunity of diversification in international investment for international portfolio management. The cross-border shocks in one country are transmitted to other countries and this interdependence or contagion may have adverse consequences for the stability. This instability has led us to analyze the main causes of co-variation of the debt markets in the most industrialized countries during the financial crisis.

Nevertheless, it is necessary to understand that the globalization and the different processes of financial integration/convergence have created a greater interrelationship among the markets. For this reason, we also consider necessary to survey the literature of markets integration and its results. In particular, we have thought that any analysis that pursues to investigate the presence of contagion is better if we take into account this financial integration or interdependence relationship to guarantee that the conclusions of the study are not misleading. Related to this markets integration literature, another way of understanding the contagion could be as a change of cointegration relationship when we move from quiet period to crisis period.[5]

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[3] See Forbes (2012) for further details.

[4] See Clare, Maras, and Thomas (1995).

[5] The existence of cointegration, that implies markets integration, would contradict this financial theory about Efficient Market Hypothesis because the returns of one market can be predictable in the long-run from the returns of the other. Granger (1986) concludes that silver and gold prices are not cointegrated so that these markets are weak efficient markets. Other au-

From a policy point of view, it is essential to provide policymakers with timely and appropriate measures of correlation changes and contagion. This will certainly help to design appropriate policy responses and prepare contingency plans. Lastly, the GFC has expanded the definition of contagion. The fact that the GFC originated in the US has led us to consider a global shock or a shock to a large economy that is transmitted to others as a type of contagion. Thus, one now needs to distinguish among two types of contagion: (i) "local contagion" and (ii) "global contagion". The local contagion might be due to the existence of bilateral linkages between countries. The global contagion focuses on the multilateral relationship among countries and it is the relationship of a country with the systemic risk or global economy. This definition of contagion allows us to analyze in more detail the possible causes and consequences of the transmission of the shock. These two types of contagion are useful in terms of policy implications. Each contagion has different policy implications. The global contagion has a consequence in the global regulation and local contagion has implications in regional or local regulation. The latter concept that is introduced in this paper is the distinction between strong and fast contagion. We investigate whether the dependence or cointegration of the variables in levels among the markets is a long-run dependence which is persistent in the long term and, therefore, strong. Instead, the short-run dependence that can be found among the first difference of the variables is one more ephemeral or the so-called "fast dependence". The long contagion is related to financial integration and is tested using cointegration analysis. The short-run contagion is analyzed with Granger causality. These last two types of dependence are also useful in terms of policy implications.

The main contributions of the article are the following ones. First, we analyze the current crisis using up to date data, which allows us to give possible solutions to the present situation. Second, we carry out the study using flexible unit root test robust to non-stationary volatility, trend uncertainty and uncertainty about

thors pointed out that cointegration and efficiency would not be incompatible. See, for example, Dwyer and Wallace (1992) or Darrat and Zhong (2002).

initial condition. We only find Carrion-i-Silvestre and Villar Frexedas (2014) in the contagion literature that has used this test. We choose this test because it captures all the properties of the financial time series.[6] Third, we also analyze the presence of cointegration using a new procedure that is robust to main econometrics problems of the financial time series when analyzing the presence of contagion. We did not find any paper in the contagion literature that has used this cointegration test. Fourth, we do not need to determine endogenously or exogenously the different regimes of volatility (non-stationary volatility) so that the cointegration test assumes that the univariate process can have these characteristics. Fifth, cointegration analysis allows us take into account any channel of transmission that is acting to spread the crisis among different countries. The transmission mechanisms can take many forms and most of them result from a healthy interdependence between countries in good times, as well as in bad times.[7] This technique also identifies and quantifies the effects of the crisis transmission without resorting to ad hoc identification of the fundamentals. Besides, this procedure allows us to draw conclusions that are robust to the omission of relevant variables and simultaneous equations bias problems.[8] Last, we also analyze local short-run contagion using Granger causality following the definition of classical Granger causality concept in Granger (1969) and indirect Granger causality in Lütkepohl and Burda (1997), which is based on the concept of multi-step causality. To the best of our knowledge, we do not know other contribution that analyzes financial contagion with multi-step causality test. Finally, we introduce the determination of the beginning of the crisis endogenously. This contribution allows us to fix the crisis period for each country, instead the exogenous pull determination of all countries. We do not also know other contribution that analyzes financial contagion with unknown break of the crisis and cointegration robust to Forbes and Rigobon (2002) econometric problems.

[6] See Forbes and Rigobon (2002) for the econometrics problems about contagion testing.

[7] In addition to this important feature for the contrast of "shift contagion". We see that the cointegration is also been used for the analysis channel of transmission. See Giordano, Pericoli, and Tommasino (2013), De Santis (2012) or Gómez-Puig and Sosvilla Rivero (2014).

[8] See Forbes and Rigobon (2002) for the econometrics problems about contagion testing.

This chapter proceeds as follows. Section 3.2 briefly discusses the main contagion empirical literature. Section 3.3 discusses data that is used in this chapter. Section 3.4 analyzes the empirical results focusing on, first, the order of integration and non-stationary volatility of the time series, second, on the analysis of parameter stability of the cointegration relationships and, third, on the analysis of Granger causality. Section 3.5 analyzes the both fast and strong contagion with the endogenous determination of the starting of crisis. Finally, Section 3.6 presents some concluding remarks.

3.2 Contagion literature: An overview

In this section, we give a short overview of the empirical approximations that have been followed in the literature to analyze the presence of contagion in periods of crisis. Although the focus of this section is based on the empirical approaches, it is worth introducing a brief comment on the theoretical contributions that have tackled the issue of financial crises and contagion. An extensive literature exists in the strictly theoretical field, which has given rise to diverse models or generations of models that explain the transmission of financial crises among countries and financial markets.[9]

Due to the evolution of theoretical models, it is possible to find different definitions of contagion.[10] Basically, there are two ways to define financial contagion. The first approach defines contagion depending on the channels of transmission that are used to spread the effects of the crisis. The second concept defines "shift-contagion" or contagion depending on whether the transmission mechanisms are stable through time.[11] In the last definition, if the transmission among markets has been stable in different moments of time, we could conclude that there is a relation

[9] The development of the literature from the first through fourth-generation models, or the so-called "institutional" models, is reviewed by Breuer (2004). Other relevant surveys are Belke and Setzer (2004) and De Bandt and Hartmann (2000).

[10] See Pericoli and Sbracia (2003) for the different definitions of contagion.

[11] This definition of contagion is related to the approach of Boyer, Gibson, and Loretan (1997), Forbes and Rigobon (2001) and Forbes and Rigobon (2002).

of interdependence among markets, whereas if this transmission changes through time, then, we will be facing a situation of contagion or “shift-contagion”.[12]

The definition that we rely on throughout this paper is the one that allows us to confirm the existence of contagion with regard to the situation of interdependence. This definition of contagion conveys the break or breaks in the transmission mechanism for the crisis owing to financial panics, herding or switching expectations across instantaneous equilibria.[13] Specifically, we wish to focus on two types of contagion: (i) global contagion and (ii) local contagion.[14] At a theoretical level, we note the Masson (1998) theory supports our definition. Masson (1998) found these two types of contagion or interdependence. First, the theory of “monsoonal effects” or systemic risk and, second, the theory of “spill-over effect”. The first one implies that contagion during crises hits hardest those economies that are highly globally integrated, where integration can be due to the existence of trade and financial linkages.[15] The second one is “pure contagion”, which implies that there is a significant increase or “shift” in cross-market linkages after a shock to an individual country.

Among the econometric approaches that enable us to study contagion, we have selected the methodology that is based on cointegration and Granger causality analyses. We consider that this approach is the best specification that reflects and catches up our definitions of contagion for several reasons. First, we believe that is the best way to discern between a stable long-term relationship and a relationship that acts in the short term. Cointegration really allows us to find whether this relationship (strong interdependence or strong contagion) exists in the long-run and Granger causality allows us to find the short-run interdependence or conta-

[12] Overviews of the issues are provided by Dornbusch, Park, and Claessens (2000), Pericoli and Sbracia (2003), Belke and Setzer (2004) and De Bandt and Hartmann (2000), among others.

[13] The change of the channels and intensity of shocks propagation in crisis periods could be explained by the role of multiple equilibria.

[14] Bekaert, Harvey, and Ng (2005), Bekaert, Ehrmann, Fratzscher, and Mehl (2011) and Baur and Fry (2009) use these definitions.

[15] Bekaert, Harvey, and Ng (2005) use this definition. Others paper that studies “global shocks” are Calomiris, Love, and Peria (2010), Fratzscher (2012) and Eichengreen, Mody, Nedeljkovic, and Sarno (2012).

gion and the direction of causality. Second, these approaches do not impose a unique channel of contagion on the model, but it allows us to fit the combinations of various mechanisms of transmission among countries. The cointegration approach also allows us to identify the main causes or channels of global and local contagions.[16] In addition, the use of a multivariate cointegration approach will allow us to eliminate problems associated with the omission of relevant variables and simultaneous equations estimation bias.[17]

If we centre on the literature that is closely related to our analysis, the contributions can be broadly divided in two groups. The first one, the markets integration or markets convergence, computes the number of common stochastic trends using cointegration analysis, mainly focusing on time-varying cointegration relationships (recursive and rolling cointegration). One of the first approximations that used cointegration in this framework was Kasa (1992).[18] After this seminal work, a notable volume of literature has analyzed the presence of contagion using time-varying cointegration.[19] At this point, we wish to emphasize the abundant cointegration literature that analyzes the convergence or markets integration but without taking into account the periods of crisis or/and unconditional volatility. Crises entail a change in the unconditional volatility and classical cointegration analysis are not robust to non unconditional volatility. Some papers take into account structural breaks in the mean but we have found none that accounts for the presence of structural breaks in variance when carrying out the cointegration analysis. We contribute with a new cointegration tests robust to unconditional volatility to analyze markets integration and strong contagion.

The second strand of the literature focuses on financial contagion.[20] One of

[16] See Bekaert, Ehrmann, Fratzscher, and Mehl (2011).

[17] See Forbes and Rigobon (2002) for the econometrics problems about contagion testing.

[18] Other papers in which cointegration is also analyzed are Corhay, Rad, and Urbain (1993) or Richards (1995).

[19] Other papers in which cointegration is also analyzed are Rangvid (2001a), Pascual (2003), Voronkova (2004), or Basse (2014).

[20] For survey of cointegration in contagion see Mollah and Hartman (2012). In the introduction of AuYong, Gan, and Treepongkaruna (2004) can also see a brief summary of the contagion test using cointegration and Granger causality.

the first approximations that used cointegration in this framework was Cashin and McDermott (1995).[21] After this seminal work, a notable volume of literature has analyzed the presence of contagion using cointegration and Granger causality on different markets and financial crises, but mainly focusing on Granger causality.[22] In this article we relate the fast contagion definition with the literature of Granger causality. Our approach is then more related to the contributions of Yunus (2013), Fofana and Seyte (2012) and Gentile and Giordano (2012), who use a cointegration test to analyze the "shift contagion".[23] In Granger causality context, our approach is then more related to the papers of AuYong, Gan, and Treepongkaruna (2004), Khalid and Kawai (2003) or Sander and Kleimeier (2003).

Considering the different approaches and definitions that have been proposed in the literature, we aim at focusing on the following situations, depending on the framework or scope in which the analysis is carried out:

1. Long-run framework
   (a) Strong interdependence. Requires the existence of stable cointegration relationships across subperiods
      i. Local strong interdependence, which focuses on bivariate systems ($m = 2$)
      ii. Global strong interdependence, which focuses on multivariate systems ($m > 2$)
   (b) Strong contagion. Requires the existence of unstable cointegration relationships
      i. Local strong contagion, which centres on bivariate systems ($m = 2$)
      ii. Global strong contagion, which centres on multivariate systems ($m > 2$)

[21] Other papers in which cointegration is also analyzed are Longin and Solnik (1995) or Malliaris and Urrutia (1992).
[22] See Khalid and Kawai (2003), Sander and Kleimeier (2003), Gómez-Puig and Sosvilla-Rivero (2014) or Lee, Tucker, Wang, and Pao (2014).
[23] See also Corsetti, Pericoli, and Sbracia (2005), Forbes and Rigobon (2002), Dungey, Martin, and Pagan (2000) and Bekaert, Harvey, and Ng (2005).

(c) Disconnection. Cointegration relationships are switched off in some of the periods, but not on the others

    i. Local disconnection, which centres on bivariate systems ($m = 2$)

    ii. Global disconnection, which centres on multivariate systems ($m > 2$)

2. Short-run framework

   (a) Fast interdependence: requires Granger causality to be stable across subperiods

      i. Local fast interdependence, which analyses bivariate systems ($m = 2$)

      ii. Global fast interdependence, which analyses multivariate systems ($m > 2$)

   (b) Fast contagion: requires Granger causality to change across subperiods

      i. Local fast contagion, which studies bivariate systems ($m = 2$)

      ii. Global fast contagion, which studies multivariate systems ($m > 2$)

   (c) Fast disconnection. Granger causality is switched off in some of the periods, but not on the others

      i. Local fast disconnection, which studies bivariate systems ($m = 2$)

      ii. Global fast disconnection, which studies multivariate systems ($m > 2$)

The three situations that are considered cover different degrees of dependence, going from the case in which the relationships do not change across subperiods (interdependence) to the case in which the relationships disappear in some of the subperiods (disconnection). Disconnection possibility is interesting, since it covers the case in which markets protect themselves preventing the contagion just by switching off the relationships that exists among them.

3.3 Data and sample

The data source is Thomson Reuters Financial Datastream database, from which we have selected a sample including 22 (OECD industrialized) economies: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States. The data that we use in this paper is the daily average redemption yield, annualized and in local currency, of benchmark 10 year maturity government bond market indices (10-year sovereign bond yields). We select the long-term government bonds instead of shorter-term ones because the monetary policy operations are more likely to have a clearer influence on long-term government bonds than on the short-term ones[24] and the long-term government bonds can be used as closer maturity substitutes to stocks.

We choose the benchmark indices because they are based on single bonds. The bond selected for each economy is the most representative bond available for the given maturity band at each point in time. Benchmarks are selected according to the accepted conventions within each market. Generally, the benchmark bond is the latest issue within the given maturity band; consideration is also given to yield, liquidity, issue size and coupon. The constituents are reviewed at the beginning of each month, and any changes are made at that time. Constituents are then fixed until the start of the following month.[25]

The Average Redemption Yield - Annualized (RA) presents the return on a bond if it is bought today at the market price and is held to its maturity date. This yield does not only reflect the gain or loss held when it matures, but also the future and present interest payments. The redemption yield is the discount rate at which the sum of coupons and principal from the bond, all future cash flows, is equal to the price of the bond. The Average Redemption Yield - Annualized is calculated as:

$$RA_{i,t} = \frac{\sum_{j=1}^{n} Y_{i,j,t} * D_{i,j,t} * (P_{i,j,t} + A_{i,j,t}) * N_{i,j,t}}{\sum_{j=1}^{n} D_{i,j,t} * (P_{i,j,t} + A_{i,j,t}) * N_{i,j,t}},$$

where $RA_{i,t}$ is a Average Redemption Yield - Annualized on day t for the i-th time

[24] See Urich and Wachtel (2001).
[25] See Datastream Government Bond Indices.

series index, $Y_{i,j,t}$ is the redemption yield to assumed maturity on day t for the j-th bond in the i-th time series index, $D_{i,j,t}$ is the duration of the j-th bond in the i-th time series index on day t, $P_{i,j,t}$ is the clean price on day t for the j-th bond in the i-th time series index, $A_{i,j,t}$ is the accrued interest to the "normal" settlement date for the j-th bond in the i-th time series index on day t, $N_{i,j,t}$ is the nominal value of amount outstanding when is known, otherwise the issued amount, on day t for the j-th bond in the i-th time series index.[26]

The frequency of the data set is daily (Monday to Friday) and the period covers from April 1st, 1999 through November 17th, 2014 – see Figure 3-1 for the level of the bond yields and Figure 3-2 for its first difference. This period is selected so that it enables us to analyse both the tranquil and crisis periods and it avoid possible problems due to the introduction of the Euro currency. We choose daily data because we thought that lower frequency series may lose part of the information on financial interdependence and contagion.

3.4 Empirical Analysis. Known break date

3.4.1 Univariate analysis

In this section we will analyze each 10-year sovereign bond yields. The sovereign bond series, as other financial time series, are expected to show conditional and unconditional volatility in their variance. In the period of time that we are analyzing, we expect that some bonds are affected by the presence of structural breaks in variance (unconditional heteroskedasticity),[27] which can be due, for instance, to different intensities of each financial markets in crisis periods. We address the issue of the non-stationary volatility (unconditional heteroskedasticity), one of the most common econometric problems in the analysis of "shift-contagion". First, the non-stationary volatility at the univariate level can involve a change in the un-

[26] See Datastream Global Equity indices User Guide.

[27] See Forbes and Rigobon (2002) for the non-stationary volatility problems about contagion testing.

conditional variance-covariance matrix at a multivariate level, which in turn can mislead the interpretation of financial contagion.

In econometric terms, a structural change in volatility invalidates the classical unit root and cointegration tests. The stationary time-varying conditional variance (conditional heteroskedasticity) does not influence in the unit root and cointegration tests[28] but non-stationary volatility can have a strong influence in the limiting distribution of these tests under their respective null hypotheses.[29] Unfortunately, the unconditional heteroskedasticity is a common feature in financial time series.[30]

In this section, we proceed testing for the existence of unconditional heteroskedasticity (Sansó, Aragó, and Carrion-i-Silvestre (2004)), a feature that, if present in the dataset, has to be accounted for to get meaningful conclusions from the order of integration analysis. We show that, in fact, this is the case so that unit root tests that the bootstrap-based unit root test statistic proposed by Smeekes and Taylor (2012) is computed – this statistic is robust to non-stationary volatility,[31] trend uncertainty[32] and uncertainty about the initial condition.

The Smeekes and Taylor (2012) test specifies the null hypothesis of unit root ($H_0 : c = 0$) against the alternative hypothesis of I(0) ($H_0 : c > 0$) based on the specification of the following data-generating process (DGP) – in order to simplify the exposition we delete the i subscript from the notation:

$$\begin{aligned} y_t &= \mu + \beta_T t + x_t \\ x_t &= \rho_T x_{t-1} + u_t \\ u_t &= \sum_{j=0}^{\infty} \psi_j \epsilon_{t-j} =: \psi(L)\epsilon_t; \qquad (\psi_0 = 1), \end{aligned}$$

[28] See Hansen and Rahbek (1998), Cavaliere (2003) or Ling, Li, and McAleer (2003).

[29] See Hamori and Tokihisa (1997), Kim, Leybourne, and Newbold (2002) or Cavaliere and Taylor (2008).

[30] See, for example, Cavaliere and Taylor (2008).

[31] Cavaliere and Taylor (2008) includes in non-stationary: both single and multiple abrupt breaks in variance, polynomially trending volatility, piecewise trending volatility, and smooth transition variance breaks.

[32] Robust to with and without a deterministic linear trend.

where $\rho_T = 1 - c/T$, $t = 0, 1, \ldots, T$.[33] The Smeekes and Taylor (2012) union test statistic at the π level of significance is given by:

$$\begin{aligned} UR^*_{4,\widetilde{\gamma}}(\pi) &= \min(DF - QD^{\mu^*}_{\widetilde{\gamma}}, (\frac{cv^{\mu^*}_{QD}(\pi)}{cv^{\tau^*}_{QD}(\pi)})DF - QD^{\tau^*}_{\widetilde{\gamma}}, \\ &\quad (\frac{cv^{\mu^*}_{QD}(\pi)}{cv^{\mu^*}_{OLS}(\pi)})DF - OLS^{\mu^*}_{\widetilde{\gamma}}, (\frac{cv^{\mu^*}_{QD}(\pi)}{cv^{\tau^*}_{OLS}(\pi)})DF - OLS^{\tau^*}_{\widetilde{\gamma}}), \end{aligned}$$

where DF denotes the augmented Dickey-Fuller test. The critical value that is used to perform the statistical inference is obtained as:

$$cv^*_{UR,\widetilde{\gamma}}(\pi) = \max\{x : N^{-1} \sum_{b=1}^{N} I(UR^*_{4,\widetilde{\gamma},b}(\pi) < x) \leq \pi).$$

The results of the Smeekes and Taylor (2012) test statistic are presented in Table 3.1 for both the bonds yields and first difference of the bonds yields time series. As can be seen, the null hypothesis of unit root is clearly rejected at the 1% level of significance when applied on the first difference of the bonds yields, whereas it is not rejected when computed for the level of the bonds yields. Therefore, we conclude that the bonds yields are I(1) non-stationary stochastic processes.

Let us now focus on the analysis of the unconditional volatility of the different series. The unconditional volatility analysis allows us to confirm the importance of Smeekes and Taylor (2012) test in the study of financial contagion. The analysis of the unconditional volatility is a key aspect of the financial contagion literature as evidenced by Rigobon (2003). Table 3.2 provides the descriptive analysis of the first difference of the bound yields for each country, which reveals that unconditional volatility might be present in the dataset that is studied.

To test whether the unconditional variance of the first difference of the bonds experiences changes throughout the period analyzed, we compute the κ_2 statistic

[33] With the assumption 1' (Non-stationary volatility), 2 (Trend uncertainty), 3 (Uncertainty about the initial condition), 4 and 5 of the Smeekes and Taylor (2012).

in Sansó, Aragó, and Carrion-i-Silvestre (2004).[34,35] Unfortunately, the κ_2 test is not robust to conditional mean and conditional heteroskedasticity. To tackle with these issues we first to test for the presence of an ARMA-GARCH structure and, in case that evidence in favour of an ARMA-GARCH structure is found, estimate the ARMA-GARCH model and filter out the stochastic process before computing the κ_2 test.[36]

First, we test each first difference of the time series for conditional mean and conditional variances with the ARMA-GARCH structure. The first test that has been used is the conditional mean because the misspecification of the conditional mean provokes poor properties of GARCH test.[37] The results of this test are showed in Table 3.3, which reveal the presence of autocorrelation, at least at the 10% level of significance, in 18 out of 22 cases.

Tables 3.5 and 3.4 report the Engle (1982) and Broock, Scheinkman, Dechert, and LeBaron (1996) LM tests to study the volatility of the first difference of the bonds yields. The computation of both tests statistics leads to the same conclusion, i.e., the first difference of bonds yields has a non-constant conditional volatility. These results are consistent with the correlograms of the series and their squares, and indicate that the ARMA-GARCH specification is plausible. Finally, we analyze for non-linear GARCH structure or leverage effect, using the Sign Bias (SB), Negative Size Bias (NSB), and Positive Size Bias (PSB) tests and the general test for asymmetric volatility effects.[38] The results of these statistics are reported in Table 3.6, which point to the presence of non-constant conditional volatility in our data.[39]

Since evidence in favour of a GARCH structure has been found, we proceed

[34] Lamoureux and Lastrapes (1990) bring out that the ignorance of structural breaks might provoke over-estimation of heteroskedasticity.

[35] We also performance the test in Inclan and Tiao (1994) and κ_1 statistic Sansó, Aragó, and Carrion-i-Silvestre (2004) and obtained the same conclusions.

[36] Details on the results are available from the authors upon request.

[37] See Lumsdaine and Ng (1999).

[38] See Engle and Ng (1993).

[39] See Eichengreen, Mody, Nedeljkovic, and Sarno (2012) for the problems that can appear when working with multivariate GARCH model.

with the estimation of a GARCH model specification to model the volatility of the first difference of the bonds yields. The ARMA-GARCH model specification and the distribution that is used are selected on the basis of the log-likelihood and the AIC and BIC information criteria, giving more weight to the BIC information criterion in case of discrepancies. For the conditional mean we select between an AR(1) model and a non-ARMA structure. The order of the GARCH(P, Q) specification is set at $P = Q = 1$, but we allow selecting among different GARCH and EGARCH specifications. Finally, the different distributions for the GARCH structure are the Normal Gaussian Distribution, Student t-Distribution, Generalized Error Distribution and Hansen's Skew-t Distribution.[40] Once the best ARMA-GARCH specification is selected for the first difference of each bonds yields, we proceed to filter out the time series and compute the κ_2 statistic in Sansó, Aragó, and Carrion-i-Silvestre (2004). Table 3.7 reports the κ_2 statistic, which confirms the existence unconditional heteroskedasticity in the (GARCH-filtered) first difference of the bonds yields.[41] As can be seen, the κ_2 test concludes that there is at least one structural break in the unconditional variance for 15 out of 22 cases, where at least one of the estimated structural breaks lies within the period of crisis.[42]

To sum up, the analysis that has been conducted in this section reveals the presence of unconditional heteroskedasticity in the bonds yields. Forbes and Rigobon (2002) points out that this feature has to be considered when studying financial contagion. This requires the use of the unit root statistic in Smeekes and Taylor (2012) if meaningful conclusions about the order of integration of the time series are to be obtained. The overall conclusion that is drawn from the analysis that

[40] The ARMA(1,0)-GARCH(1,1)-GED distribution estimation are for Australia, Austria, Belgium, Denmark, Finland, France, Ireland, Italy, Netherlands, Norway, Spain and Sweden. The ARMA(0,0)-GARCH(1,1)-GED distribution estimation are for Germany, Switzerland, United Kingdom, United States, New Zealand, Canada and Japan. The ARMA(1,0)-EGARCH(1,1)-GED distribution estimation is for Greece. The ARMA(0,0)-EGARCH(1,1)-GED distribution estimation is for Portugal. Finally, The ARMA(1,0)-EGARCH(1,1)-Hansen distribution estimation is for Hungary.

[41] Hansen (2001) points out that the exogenous determination of the structural break would mislead the model fitted.

[42] We also performance the test without GARCH structure and achieved the same conclusions, although up to eight structural breaks have been detected, depending on the case.

has been carried out in this section is that bonds yields can be characterized as I(1) non-stationary processes with non-stationary volatility.

3.4.2 Long-run analysis of bonds yields

This section analyzes the presence of strong contagion (markets integration or convergence) using cointegration analysis, but establishing the distinction between local and global strong contagion. In this regard, local strong contagion is related to bilateral linkages between countries,[43] whereas global strong contagion allows us to relate a country with the systemic risk – i.e., the global economy. The characterization of these types of contagion is done depending on the dimension of the system for which cointegration analysis is carried out. In practice, this implies studying different sub-sets of countries.

Local strong contagion focuses on cointegrated bivariate systems, in which the cointegration relationship changes when we move, for instance, from the quiet to the crisis period. Besides, local strong interdependence appears when the bivariate system defines a cointegration relationship that remains stable across periods. Similarly, local global contagion – unstable cointegration relationships – and local global interdependence – stable cointegration relationships – extend these definitions considering multivariate cointegrated systems. It is worth noticing that this will require dealing with, at least, trivariate cointegrated systems.

The analysis that is conducted in this chapter can be grouped in two blocks. First, we assume that the starting point of the crisis period is exogenous and common to all countries. Second, we will relax this assumption considering model specifications that allow for the estimation of the break point in an endogenous way for each system of variables that is considered. As for the block of the analysis that considers the date of the break as known, the starting point of the crisis period has been exogenously set on August 9th, 2007, a decision that is based on two facts. First, this is the date in which worldwide liquidity shortages began and

[43] A significant part of the literature only analyzes the two-dimensional cointegration.

the central banks – mainly the Federal Reserve and the European Central Bank – coordinated efforts to increase the liquidity of the markets. Second, it defines two subsamples that allow the comparison between periods without worrying about the finite sample performance of the different statistics since each period has a similar number of observations. Consequently, we define the tranquil period as the one going from April 1st, 1999 through August 8th, 2007, and the crisis period the one covering from August 9th, 2007 till November 17th, 2014.

As stated in the previous section, the bonds yields time series suffer from unconditional volatility. This feature does not allow us to apply the classical cointegration analysis, since the sequential procedure based on the asymptotic (pseudo-) likelihood ratio tests of Johansen (1995) can be significantly upward size distorted in the presence of non-stationary heteroskedasticity. In fact, Cavaliere, Rahbek, and Taylor (2010) show that the sequential (pseudo-) likelihood ratio test of Johansen (1995) is no longer valid, even asymptotically, in the presence of non-stationary heteroskedasticity. To overcome this drawback, we instead apply the estimation procedure in Cavaliere, Angelis, Rahbek, and Taylor (2015), which provides the joint estimation of the lag order of the vector error correction model (VECM) and the cointegration rank using the BIC information criterion – the BIC statistic is shown to have better performance in finite samples among the statistics that Cavaliere, Angelis, Rahbek, and Taylor (2015) essayed.[44,45] Cavaliere, Angelis, Rahbek, and Taylor (2015) shows that their proposal delivers consistent estimates of both the cointegration rank and the lag length of the VECM model when unconditional heteroskedasticity is present.[46] To the best of our knowledge, there is no other contribution in the empirical literature that analyzes financial contagion using this robust cointegration analysis.

[44] As a robustness check, we have also perfomanced the wild bootstrap implementation of the Johansen (1995) test procedure proposed by Cavaliere, Rahbek, and Taylor (2014).

[45] Both tests are robust of the form of unconditional heteroskedasticity considered in Cavaliere, Rahbek, and Taylor (2010).

[46] The incorrect selection of the lag length has a strong consequence in the finite performance of the cointegration test. See Cheung and Lai (1993), Yap and Reinsel (1995), Saikkonen and Luukkonen (1997) or Kascha and Trenkler (2011).

The approach in Cavaliere, Angelis, Rahbek, and Taylor (2015) is based on a m-dimensional process $\{X_t\}$ with a DGP that satisfies a vector autoregressive model (VAR) of unknown order k written in a VECM representation:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \alpha\rho' D_t + \phi d_t + \epsilon_{t,} \qquad t = 1, ..., T, \tag{3.1}$$

where α and β are $(m \times r)$-matrices, with r denoting the unknown cointegration rank. The error term ϵ_t is assumed to satisfy the assumptions outlined in Cavaliere, Rahbek, and Taylor (2014). The deterministic component in equation (3.1) is defined according to one of the following cases: (i) $D_t = 0$, $d_t = 0$ (no deterministic component); (ii) $D_t = 1$, $d_t = 0$ (restricted constant); or (iii) $D_t = 1$, $d_t = 1$ (restricted linear trend).[47] The autoregressive lag order k and cointegration rank r can be jointly determined by (jointly) minimising the BIC information criterion:

$$BIC(k, r) = T \log |S_{00}^{(k)}| + T \sum_{i=1}^{r} \log(1 - \widehat{\lambda}_i^{(k)}) + (\log T)\pi(k, r), \tag{3.2}$$

where $\widehat{\lambda}_1^{(k)} > ... > \widehat{\lambda}_p^{(k)}$ are the p largest solutions to the eigenvalue problem:

$$|\lambda S_{11}^{(k)} - S_{10}^{(k)} S_{00}^{(k)-1} S_{01}^{(k)}| = 0,$$

where $S_{ij}^{(k)} := T^{-1} \sum_{t=1}^{T} R_{it}^{(k)} R_{jt}^{(k)\prime}$, i, $j = \{0, 1\}$, with $R_{0t}^{(k)}$ and $R_{1t}^{(k)}$ denoting the orthogonal projections of ΔX_t and $(X_{t-1}', D_t)'$ on ΔX_{t-1},..., ΔX_{t-k-1} and d_t, respectively. The authors consider three different deterministic specifications: (i) in the case of no deterministic component ($D_t = 0$, $d_t = 0$ in (3.1)), $\pi(k, r) = r(2p - r) + p(p + 1) + p^2(k - 1)$; (ii) for the restricted constant case ($D_t = 1$, $d_t = 0$ in (3.1)), $\pi(k, r) = r(2p - r + 1) + p(p + 1) + p^2(k - 1)$, and (iii) for the case of a restricted trend ($D_t = 1$, $d_t = 1$ in (3.1)), $\pi(k, r) = r(2p - r + 1) + p(p + 2) + p^2(k - 1)$.

The joint estimation of the lag order and the cointegration rank – denoted by $\widetilde{k}_{BIC}$ and $\widetilde{r}_{BIC}$, respectively – is obtained as:

[47] See, e.g. Johansen (1995).

$$(\widetilde{k}_{BIC}, \widetilde{r}_{BIC}) = \underset{k=1,\ldots,K;\; r=0,\ldots,m}{\arg\min} \; BIC(k,r). \tag{3.3}$$

Table 3.8 presents the results of the statistics in Cavaliere, Angelis, Rahbek, and Taylor (2015) for the calm and crisis periods. If we focus on the results for the bivariate case ($m = 2$), we can see that there is little evidence of cointegration. In the calm period, only 3.9% of all possible combinations of bonds yields pairs define a cointegration relationship. The percentage decreases considerably during the crisis, since only 0.4% of the pairwise relationships – i.e., just 1 out of 231 combinations – define a cointegration relationship. In general, these results indicate that there is scarce evidence of local long-run interdependence, since cointegration only holds just in few cases during the calm period, but almost disappear in the crisis period.[48] Further, it is worth mentioning that none of the cointegration relationships that have been found during the calm period remain during the crisis period. The evidence that has been found points to the inexistence of local strong contagion, with limited evidence of local strong interdependence that only holds during the calm period. Consequently, this situation is more in accordance with the case of disconnection, in which cointegration is present in the calm period and disappears during the crisis.

Table 3.8 shows that there is a significant increase of strong global interdependence during the calm period when the dimension of the system increases. The percentage of detecting at least one cointegration relationship ($r \geq 1$) goes from 3.9% ($m = 2$) to 30.79% ($m = 7$), which indicates that the international portfolio diversification implies great benefits in long term investments in the calm period.[49] As can be seen, the increase in m does not lead to detect more common stochastic trends, since the cointegration rank is, in general, at most $r = 2$ – there are three exceptions in which $r = 3$.

[48] We have performed the analysis considering the whole time period, and the conclusions are similar.

[49] We performed the BIC-based joint cointegration test in full period to analyze the robustness of our results. We found similar conclusion in full period. It allows us to have a more robust finding.

During the crisis period the number of cointegration relationships decreases significantly as m increases – see Table 3.8. These results reinforce the previous conclusion and indicate the (almost) inexistent strong global interdependence during the crisis period. For instance for $m = 3$, the procedure detects 11 cointegration relationships during the crisis period, all of them being different from the ones detected during the calm period. When $m = 4$, only 5 out of 15 cointegration relationships are detected in the calm period, and for $m = 5$ only 1 out of 5 cointegration relationships is found in the calm period. Therefore, these results point to the prevalence of a disconnection situation, since cointegration is only found during the calm period, but not during the crisis period.

Table 3.9 details the countries that are involved in the estimated cointegration relationships. If we focus on the calm period, we can see that the countries involved in the cointegration relationships are France, Portugal, Italy, Germany and Austria. From them, the most relevant country is France since France is involved in the majority of the cointegrated systems and its position in the majority of the cointegrated systems is the first. As for the crisis period, the relevant countries are Greece, Portugal, Italy and Germany, three of them involved in the recent debt crisis, being now Greece the most relevant country.

Finally, we find the main countries that were directly involved in the crisis when we choose the only one cointegration relationship in the pull of six countries in the crisis period. Therefore, the overall conclusion is that the OECD debt markets have the presence of strong global contagion given that there has been a significant change in the interdependence with both the new cointegration relationships and the countries. However, we do find neither significance local long-run interdependence nor significance local long-run contagion.

3.4.3 Short-run analysis of bonds yields

Since scarce evidence in favour of cointegration has been found for the whole time period, here we study the short-run relationships that might be present among the bonds yields of different countries. We focus on those combinations for which no cointegration has been found throughout the whole period, and use the concept of Granger causality advocated in Granger (1969) working with bivariate ($m = 2$) and trivariate ($m = 3$) systems.[50] The goal of the analysis is to investigate whether causality between pairs of countries remain stable across subperiods (fast interdependence), changes across subperiods (fast contagion) or disappears in some subperiods (fast disconnection). The implementation of Granger causality in bivariate systems is straightforwards, since there is no possibility of having indirect channels of causality between two variables. Things are more complicated when dealing with systems of higher dimensions – i.e., when $m = 3$ in our case – since causality between a given pair of variables can be due to the existence of either a direct and/or an indirect relationship. To overcome this issue, we apply the multi-step Granger causality approach suggested in Lütkepohl and Burda (1997) – see further details below. The discussion that follows is structured attending to the dimension of the system.

Granger causality analysis for bivariate systems

The concept of Granger causality implies that the cause cannot come after the effect. In a bivariate system, if X_t causes Y_t, then X_t should help to improve the predictions of Y_t. In addition, if Y_t also causes X_t, $(X_t, Y_t)'$ defines a so-called "feedback bivariate system". The specification of the classical Granger causality test when $(X_t, Y_t)'$ define a system of I(1) non-cointegrated variables is a Wald test that specifies the null hypothesis that $H_0 : \beta_{y,i} = 0 \; \forall i$ – i.e., X_t does not Granger cause Y_t – against the alternative hypothesis that $H_1 : \beta_{y,i} \neq 0$ for some i – i.e.,

[50] Other papers in which approach is also used are Khalid and Kawai (2003) or AuYong, Gan, and Treepongkaruna (2004). The AuYong, Gan, and Treepongkaruna (2004) proposal distinguishes between short run causality and long run causality.

X_t Granger causes Y_t – in (3.5):

$$\Delta X_t = \alpha_x + \sum_{i=1}^{k-1} \beta_{x,i} \Delta X_{t-i} + \sum_{i=1}^{k-1} \gamma_{x,i} \Delta Y_{t-i} + \epsilon_{1,t} \quad (3.4)$$

$$\Delta Y_t = \alpha_y + \sum_{i=1}^{k-1} \beta_{y,i} \Delta X_{t-i} + \sum_{i=1}^{k-1} \gamma_{y,i} \Delta Y_{t-i} + \epsilon_{2,t}. \quad (3.5)$$

The statistical inference is performed computing a Wald test statistic. Note that it is possible to test also the other direction of causality specifying the null hypothesis that $H_0 : \gamma_{x,i} = 0 \ \forall i$ – i.e., Y_t does not Granger cause X_t – against the alternative hypothesis that $H_1 : \gamma_{x,i} \neq 0$ for some i – i.e., Y_t Granger causes X_t – in (3.4).

The lag length k in (3.4) and (3.5) is the one estimated in the previous section using the BIC information criterion as suggested in Cavaliere, Angelis, Rahbek, and Taylor (2015), since this is the best and robust way to estimate k given the characteristics of our dataset. Note that Granger causality tests are sensible to the selection of k and the proposal in Cavaliere, Angelis, Rahbek, and Taylor (2015) is robust to non-stationary volatility, a feature that is present in the data that is analyzed.[51] It is worth emphasizing thus that this strategy of estimating k should outperform other approaches in the literature that analyse financial contagion using Granger causality tests.

The results for the direct bivariate causality tests – i.e., when $m = 2$ – are reported in Table 3.10, for the tranquil period, and in Table 3.11, for the crisis period. Some remarks are in order. First, for the calm period, 66% of all possible combinations show some form of bivariate Granger causality – 62% of all possible combinations represent bidirectional causality (feedback causality systems). On the contrary, for the crisis period the percentage of bivariate Granger causality relationships reduces to 51% of all possible combinations – 50% defining feedback causality systems. As can be seen, important evidence of short-run interdependence has been found since some direction of Granger causality is detected in 66% (calm period) and 51% (crisis period) of cases. The second conclusion that can

[51] See Thornton and Batten (1985) and Cavaliere, Angelis, Rahbek, and Taylor (2015).

be drawn from these results is that the OECD debt market has experienced a weak local short-run contagion since the short-run dynamics causality is significantly different between the calm and crisis periods – 66% (calm period) against 51% (crisis period) – although 75% of all Granger causality relationships that are estimated in the crisis period are also found during the calm period.

Granger causality analysis for trivariate systems

Contrary to bivariate setups analysis, Granger causality for higher dimensional systems should take into account the possibility of indirect causality. For instance, if we define a system with three stochastic processes, $(X_t, Y_t, Z_t)'$, the analysis of causality between X_t and Y_t should consider Z_t as an indirect channel of causality since, although X_t might not Granger cause Y_t directly, it would be the case that X_t Granger causes Z_t , and in turn Z_t Granger causes Y_t. This defines a indirect channel of causality that should be accounted for. In this paper we address this issue through the computation of the multi-step Granger causality test designed in Lütkepohl and Burda (1997). Multi-step Granger causality analyzes causality between two variables for systems of dimension $m > 2$. To the best of our knowledge, there is no other contribution in the empirical literature that analyzes financial contagion that bases the study in the computation of multi-step Granger causality tests. Therefore, another important contribution of this paper is the generalization of financial contagion analysis using Granger causality tests that control for potential channels of indirect causality.

The analysis that is conducted in this section assumes that the DGP for a three-dimensional vector of I(1) non-cointegrated stochastic processes $(X_t, Y_t, Z_t)'$

admits the following VAR(k) model representation:

$$\Delta X_t = \alpha_x + \sum_{i=1}^{k-1} \beta_{x,i} \Delta X_{t-i} + \sum_{i=1}^{k-1} \gamma_{x,i} \Delta Y_{t-i} + \sum_{i=1}^{k-1} \delta_{x,i} \Delta Z_{t-i} + \epsilon_{1,t} \quad (3.6)$$

$$\Delta Y_t = \alpha_y + \sum_{i=1}^{k-1} \beta_{y,i} \Delta X_{t-i} + \sum_{i=1}^{k-1} \gamma_{y,i} \Delta Y_{t-i} + \sum_{i=1}^{k-1} \delta_{y,i} \Delta Z_{t-i} + \epsilon_{2,t} \quad (3.7)$$

$$\Delta Z_t = \alpha_z + \sum_{i=1}^{k-1} \beta_{z,i} \Delta X_{t-i} + \sum_{i=1}^{k-1} \gamma_{z,i} \Delta Y_{t-i} + \sum_{i=1}^{k-1} \delta_{z,i} \Delta Z_{t-i} + \epsilon_{3,t}. \quad (3.8)$$

The multi-step causality test of Lütkepohl and Burda (1997) specifies the null hypothesis that the m_y-dimensional vector Y_t is not h-step causal for the m_z-dimensional process Z_t $\left(Y_t \nrightarrow_{(h)} Z_t\right)$ considering that there are m_x additional variables X_t in the system – note that in our setup $m_x = m_y = m_z = 1$, although the framework is general enough to allow for block multi-step Granger causality testing. The null and alternative hypotheses can be written as:

$$\begin{cases} H_0 : & (I_h \otimes R)\, a^{(h)} = 0 \\ H_1 : & (I_h \otimes R)\, a^{(h)} \neq 0 \end{cases},$$

where R is the $(km_z m_y \times km^2)$ matrix that defines the parametric restrictions, and

$$a^{(h)} = \begin{bmatrix} \alpha \\ \alpha^2 \\ \vdots \\ \alpha^h \end{bmatrix},$$

is the vector of parameters that are involved in the definition of the non-linear parametric restrictions – see Lütkepohl and Burda (1997) for further details. The modified Wald test statistic proposed in Lütkepohl and Burda (1997) is given by:

$$
\begin{aligned}
\lambda_w^{\text{mod}} &= T\left((I_h \otimes R)\,\hat{a}^{(h)} + \frac{w_\lambda^{(h)}}{\sqrt{T}} \right)' \\
&\quad \left[(I_h \otimes R)\,\widehat{\Sigma}_{\hat{a}}\,(h)\,(I_h \otimes R') + \lambda \widehat{\Sigma}_w\,(h) \right]^{-1} \\
&\quad \left((I_h \otimes R)\,\hat{a}^{(h)} + \frac{w_\lambda^{(h)}}{\sqrt{T}} \right),
\end{aligned}
$$

with $w_\lambda^{(h)} \sim N(0, \lambda \widehat{\Sigma}_w\,(h))$ being a vector of random variables that are drawn independently of $\widehat{\alpha}$, $\lambda > 0$ is some fixed real number – Lütkepohl and Burda (1997) suggest setting $\lambda = 0.1$ – $\widehat{\Sigma}_{\hat{a}}\,(h)$ is a consistent estimator of the asymptotic covariance matrix of $\sqrt{T}\left(\hat{a}^{(h)} - a^{(h)}\right)$, and where

$$
\widehat{\Sigma}_w\,(h) = \begin{bmatrix} 0 & 0 \\ 0 & I_{h-1} \otimes diag\left(R \widehat{\Sigma}_{\hat{a}} R' \right) \end{bmatrix},
$$

with $\hat{a}^{(h)}$ the estimator of $a^{(h)}$ that can be computed based on the multivariate OLS estimator $\widehat{\alpha}$ of α. Under the null hypothesis that, for instance, Y_t does not Granger cause Z_t – i.e., $Y_t \nrightarrow_{(h)} Z_t$ – the λ_w^{mod} statistic converges in the limit to:

$$
\lambda_w^{\text{mod}} \xrightarrow{d} \chi^2_{hkm_z m_y}.
$$

The main results of multi-step causality and trivariate causality are showed in Table 3.12. The main conclusions of the multi-step causality analysis are two. First, we have found that the indirect causality between the calm and crisis periods was not significant. In the crisis period, we only found 81 relationships (0.001%) show causality. In the calm period, we found that 96 relationships (0.001%) show multi-step causality. Therefore, we find that the causality between countries is direct and fast. Second, we have found that the multi-step causality did not change significantly. Accordingly, we conclude that the bivariate causality is of a direct type and it has not changed significantly across periods, since weak evidence of significant shifts has been found in the crisis period.

Finally, the second approach split the three-dimensional vector $(X_t, Y_t, Z_t)'$ into two subvectors.[52] Then the three-dimensional process $(X_t, Y_t, Z_t)'$ can be formulated as in equations (3.4) and (3.5) and the statistic become the classical Granger causality.

The results of the trivariate causality are quite similar to the ones obtained by the direct bivariate Granger causality analysis. We find that the short-run causality is different in the tranquil (70%) and crisis (57%) periods. The feedback of all causality relationships in the calm period (73%) is also higher than in the crisis period (58%). However, 74% of the new causality relationships that are estimated in the crisis period were not present in the calm period. These results point to the presence of higher fast contagion than the previous results. The overall conclusion is that a significant local short-run interdependence exists, and that this interdependence is direct and the local short-run contagion is weak.

3.5 Empirical Analysis. Unknown break date

The analysis that has been conducted so far assumes that the date of the break that defines the calm and the crisis periods is known a priori. This implies that the conclusions that have been obtained are conditional on the exogenous selection of the date of the break that has been chosen. In order to overcome this limitation, this section relaxes this assumption endogenizing the selection of the break point. The analysis is carried out in two steps, depending on the way that the structural break affects the different parts of the VECM model. First, we assume that the structural break only changes the dynamics of the system, so that it is possible to have different orders of the VECM specification for the different subperiods. However, we will assume that the cointegration space remains stable across subperiods – i.e., the cointegration rank , cointegration vectors and loading parameters are constant throughout the period analyzed. Second, we will proceed to estimate a VECM specification where both the short-run and the long-run components of the

[52] A further detailed discussion may be found in Lütkepohl (2005).

model are affected by the structural break. Consequently, not only the dynamics of the system are affected by the presence of a structural break, but also the cointegration space. The analysis is presented according to this distinction.

3.5.1 Structural break and the dynamics

One of the characteristics of the previous analysis is the assumption of a common and known date of the for all systems. Although the selection of the break point is in accordance with the consensus in the literature, the exogenous selection of the date of the break might be seen as a potential limitation of the study. To get rid of this drawback, we proceed with the estimation of bivariate and trivariate VECM models with short-run dynamics that is allowed to change across subperiods, and where the date of the break is heterogeneous and endogenously selected for each system.

Let us define the vector of variables $X_t = (x_t, y_t)'$ for which the following model specification has been proposed:

$$\Delta X_t = \alpha \rho' D_t + \phi d_t + \alpha \beta' X_{t-1} + \Gamma_{0,k-1}(L) \Delta X_t + \Gamma_{1,k-1}(L) 1(t > T_1) \Delta X_t + \epsilon_t, \tag{3.9}$$

$t = 1, ..., T$, with $\Gamma_{0,k-1}(L) = \sum_{i=1}^{k-1} \Gamma_{0,i} L^i$ and $\Gamma_{1,k-1}(L) = \sum_{i=1}^{k-1} \Gamma_{1,i} L^i$ being lag polynomials, and $1(t > T_1)$ is the indicator function with T_1 denoting the unknown break date. The specification given in (3.9) accounts for the presence of one structural break located at T_1, which changes the dynamics of the system, but where both the deterministic component and the error correction term remain stable. The estimation of the cointegration rank , the lag order (k) and the date of the break (T_1) is done using the BIC information criterion as in Cavaliere, Angelis, Rahbek, and Taylor (2015).

Once the date of the break has been estimated for each bivariate and trivariate systems, we proceed with the analysis of (strong and fast) contagion – due to the large number of combinations, we do not report detailed results about the estimated break dates for each system, although they are available upon request.

The results show that only 26% of the estimated structural breaks for the bivariate systems are placed before the official start of the crisis, which is set on August 9st, 2007. When focusing on the trivariate systems, this percentage decreases to the 23%. It is worth noticing that, in both cases, the country for which the estimated date of the break is placed more frequently after the official date is Greece.

Table 3.13 presents the results for the long-run contagion. As can be seen, the endogenous determination of the beginning of the crisis implies a clear increase of the estimated number of cointegration relationships during the calm period, but not during the crisis period. Note that this feature is found for both the bivariate and trivariate systems. For the bivariate systems, the percentage of detection of one cointegration relationship during the calm period with exogenous date of the break is 3.9% – see Table 3.8 – whereas it rises to 15.2% when the date of the break is estimated – see Table 3.13. The percentages during the crisis period are 0.4% and 1.7%, respectively. For the trivariate systems, these percentages change clearly during the calm period – 11.1% for the exogenous break date and 23.3% for the endogenous break date-based results – but not during the crisis period – 0.7% when using the exogenous break date and 0.6% when using the estimated break date. These robust results point to the prevalence of a disconnection situation.

Table 3.14 reports the results for the short-run contagion analysis. The results are similar to the ones obtained using the exogenous determination of the beginning of the crisis and, consequently, the estimation of the date of the break does not change the main conclusions of the chapter.

3.5.2 Structural break and the cointegration space

Following Andrade, Bruneau, and Gregoir (2005), we generalize the specification given in (3.9) considering that both the short-run and the long-run components of the VECM model are affected by the presence of a structural break. In this case, we only focus on bivariate VECM models for which the short and the long-run relationships is allowed to change, where the break date is heterogeneous across systems and endogenously selected. The model specification is written as:

$$\Delta X_t = \alpha_0 \rho_0' D_t + \phi_0 d_t + \alpha_0 \beta_0' X_{t-1} + \Gamma_{0,k_0-1}(L)\,\Delta X_t + \epsilon_t; \quad t \leq T_1 \tag{3.10}$$

$$\Delta X_t = \alpha_1 \rho_1' D_t + \phi_1 d_t + \alpha_1 \beta_1' X_{t-1} + \Gamma_{1,k_1-1}(L)\,\Delta X_t + \epsilon_t; \quad t > T_1, \tag{3.11}$$

where T_1 denotes the unknown break date. As above, the estimation of the cointegration rank (for each subperiod), the lag order (for each subperiod), and the date of the break are selected using the BIC information criterion. As mentioned above, it is worth mentioning that we restrain the analysis to bivariate systems, although the extension of this methodology to trivariate systems will be addressed in future research.

The results for the long-run and short-run contagion analysis for bivariate systems are reported in Tables 3.15 and 3.16. The general picture that is obtained is similar to the one that is drawn using the date of the break that is chosen following the consensus in the literature. However, we can see some subtile differences when we analyse the cointegration relationships. First, we find that only 2 of the 10 of the breaks that have been estimated in the calm and crisis periods are placed after the consensus date defined in the literature. Second, only two of the cointegration relationships – France versus Ireland and Austria versus Portugal – are detected regardless of the assumption about the determination of the date of the break. Apart from these, we can see that the results that are drawn under the assumption of known common date of the break for all systems are robust to the generalization that uses estimated dates of the break.

3.6 Conclusions

This chapter contributes to the analysis of the European debt crisis and the great recession by stating that the market behavior – measured in terms of the short-run and long-run dependence – during the crisis period differs from the one observed during the tranquil period. The analysis is performed using the sample of the most industrialized OECD countries, and has led us to conclude that, under the current economic conditions, the strong and fast dependence that link the debt markets of these countries have a unique character that can be associated to financial contagion.

The analysis that has been conducted reveals that the returns of the sovereign debt of the most industrialized OECD countries can be characterized as non-stationary processes with non-stationary volatility, features that should be accounted for when estimating models that try to analyse the presence of contagion.

The strategy that has been followed in this chapter to test the presence of contagion is based on cointegration and Granger causality analyses. This framework is general enough to cover the situations of global and local contagions, on the one hand, and strong and fast contagions, on the other hand, accounting for all possible channels of transmission. In this regard, our approach mitigates the potential drawbacks caused by misspecification errors. However, we cannot ascertain which specific contagion channel is more prevalent in the present study, a question that is out of the scope of our research.

The cointegration analysis that has been carried out reveals that the strong dependence (cointegration relationships) that exists during the tranquil period disappears in the crisis period. Further, the short-run Granger causality analysis indicates that the short-run dependence experiences a weak decrease during the crisis period. Note that these results might be useful for international portfolio management, financial stability and risk assessment. Finally, it should be stressed that these conclusions are based on robust cointegration and Granger causality analyses that account for the presence of non-stationary volatility, an feature that allows us to overcome the criticism pointed out in Forbes and Rigobon (2002).

Table 3.1: Bootstrap union unit root tests of Smeekes and Taylor (2012)

	Levels					First differenced				
		UR-A		UR-B			UR-A		UR-B	
	Statistic	c.v.	p-val	c.v.	p-val	Statistic	c.v.	p-val	c.v.	p-val
Austria	-1.607	-2.264	0.356	-2.197	0.330	-23.036	-2.261	0.000	-2.261	0.000
Belgium	-1.433	-2.265	0.516	-2.258	0.506	-27.681	-2.246	0.000	-2.246	0.000
Finland	-1.564	-2.230	0.382	-2.154	0.352	-10.640	-2.327	0.000	-2.327	0.000
France	-1.706	-2.306	0.308	-2.230	0.282	-10.766	-2.289	0.000	-2.289	0.000
Germany	-1.782	-2.268	0.230	-2.184	0.199	-10.795	-2.339	0.000	-2.340	0.000
Greece	-2.026	-3.439	0.246	-3.227	0.256	-58.522	-3.374	0.000	-3.374	0.000
Ireland	-1.416	-2.584	0.558	-2.586	0.558	-30.973	-2.566	0.000	-2.566	0.000
Italy	-1.683	-2.457	0.334	-2.461	0.334	-41.262	-2.458	0.000	-2.458	0.000
Neth.	-1.662	-2.254	0.314	-2.181	0.278	-32.789	-2.272	0.000	-2.272	0.000
Portugal	-1.143	-2.721	0.705	-2.653	0.713	-38.244	-2.713	0.000	-2.714	0.000
Spain	-1.634	-2.464	0.390	-2.458	0.390	-51.671	-2.423	0.000	-2.423	0.000
Denmark	-1.563	-2.281	0.391	-2.170	0.352	-10.276	-2.307	0.000	-2.308	0.000
Norway	-1.774	-2.269	0.238	-2.178	0.199	-11.536	-2.315	0.000	-2.314	0.000
Sweden	-1.924	-2.221	0.146	-2.154	0.119	-10.966	-2.316	0.000	-2.316	0.000
UK	-1.742	-2.281	0.268	-2.219	0.248	-61.349	-2.307	0.000	-2.307	0.000
Hungary	-1.906	-2.276	0.156	-2.264	0.159	-44.566	-2.296	0.000	-2.296	0.000
Switz.	-1.786	-2.286	0.254	-2.227	0.224	-30.465	-2.274	0.000	-2.274	0.000
Australia	-1.697	-2.290	0.307	-2.259	0.296	-69.810	-2.290	0.000	-2.290	0.000
N. Zealand	-1.816	-2.279	0.224	-2.223	0.202	-10.791	-2.345	0.000	-2.345	0.000
Canada	-2.476	-2.230	0.019	-2.146	0.012	-63.771	-2.270	0.000	-2.270	0.000
US	-1.977	-2.299	0.146	-2.257	0.129	-12.993	-2.327	0.000	-2.328	0.000
Japan	-1.879	-2.296	0.194	-2.295	0.189	-9.675	-2.288	0.000	-2.288	0.000

Note: Value indicatesthe critical value at 5 % level of significance

Table 3.2: Descriptive statistics of first difference of the bonds

	Mean	Median	Stand. dev.	Skewness	Kurtosis
Austria	0.00	0.00	0.04	0.38	5.36
Belgium	0.00	0.00	0.05	0.20	7.82
Finland	0.00	0.00	0.04	0.22	4.79
France	0.00	0.00	0.04	0.16	5.99
Germany	0.00	0.00	0.04	0.12	4.57
Greece	0.00	0.00	0.50	-40.98	2323.88
Ireland	0.00	0.00	0.07	-0.14	34.31
Italy	0.00	0.00	0.06	-0.83	25.44
Netherlands	0.00	0.00	0.04	0.20	4.29
Portugal	0.00	0.00	0.10	1.30	58.27
Spain	0.00	0.00	0.06	-1.09	22.18
Denmark	0.00	0.00	0.04	0.15	6.47
Norway	0.00	0.00	0.05	0.16	6.53
Sweden	0.00	0.00	0.04	0.10	5.43
United Kingdom	0.00	0.00	0.05	0.09	4.95
Hungary	0.00	0.00	0.12	3.55	97.09
Switzerland	0.00	0.00	0.04	0.04	9.27
Australia	0.00	0.00	0.07	0.05	5.58
New Zealand	0.00	0.00	0.05	0.31	7.02
Canada	0.00	0.00	0.05	0.17	4.26
United States	0.00	0.00	0.06	0.06	5.36
Japan	0.00	0.00	0.03	0.42	7.42

Table 3.3: Ljung-Box Q test on the residuals regressed on q lags and a constant for the whole period

	Statistic	P-value
Austria	53.54	0.00
Belgium	127.91	0.00
Finland	19.79	0.03
France	16.88	0.08
Germany	26.66	0.00
Greece	209.63	0.00
Ireland	277.22	0.00
Italy	87.55	0.00
Netherlands	28.40	0.00
Portugal	296.19	0.00
Spain	257.29	0.00
Denmark	44.83	0.00
Norway	70.86	0.00
Sweden	50.40	0.00
United Kingdom	26.74	0.00
Hungary	11.57	0.31
Switzerland	17.78	0.06
Australia	39.57	0.00
New Zealand	6.39	0.78
Canada	10.62	0.39
United States	15.13	0.13
Japan	23.45	0.01

Note: We select $q = 10$ lags maximun

Table 3.4: LM test of the residuals regressed on q lags and a constant for the whole period

	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$	$q=6$	$q=7$	$q=8$	$q=9$	$q=10$
Austria	24.60^a	25.11^a	26.96^a	26.96^a	37.10^a	37.35^a	38.99^a	39.34^a	46.73^a	48.98^a
Belgium	96.32^a	96.98^a	104.74^a	104.77^a	116.34^a	116.79^a	117.05^a	117.39^a	117.47^a	117.59^a
Finland	9.68^a	10.42^b	16.61^a	17.95^a	19.17^a	19.30^a	19.35^b	19.44^b	19.86^b	19.92^b
France	3.42^c	6.29^b	6.75^c	7.26	11.59^b	12.19^c	13.64^c	13.66^c	17.55^b	18.19^b
Germany	17.64^a	18.56^a	20.60^a	22.18^a	22.50^a	23.07^a	25.14^a	25.65^a	26.06^a	26.35^a
Greece	29.65^a	41.62^a	165.15^a	194.82^a	199.99^a	204.58^a	230.44^a	232.18^a	244.75^a	247.79^a
Ireland	180.06^a	198.48^a	205.31^a	211.38^a	215.81^a	217.49^a	217.42^a	221.94^a	228.40^a	228.67^a
Italy	50.68^a	60.34^a	67.95^a	70.70^a	81.03^a	81.19^a	83.56^a	84.64^a	84.79^a	84.94^a
Neth.	20.79^a	20.95^a	24.25^a	25.98^a	26.94^a	27.25^a	28.59^a	28.75^a	29.04^a	29.16^a
Portugal	209.95^a	215.22^a	215.73^a	250.87^a	251.65^a	258.86^a	262.45^a	263.44^a	277.29^a	278.18^a
Spain	174.74^a	180.44	202.06	214.52^a	221.54^a	223.18^a	225.08^a	225.02^a	226.02^a	227.07^a
Denmark	34.93^a	36.88^a	37.62^a	37.51^a	38.33^a	38.38^a	38.51^a	41.32^a	43.58^a	45.71^a
Norway	36.35^a	41.69^a	43.87^a	46.73^a	50.17^a	55.54^a	57.19^a	57.63^a	62.05^a	67.20^a
Sweden	42.32^a	42.35^a	43.71^a	43.48^a	45.70^a	46.82^a	49.96^a	50.50^a	50.48^a	50.49^a
UK	6.42^a	8.17^b	13.44^a	14.96^a	16.45^a	17.49^a	21.22^a	21.47^a	24.33^a	25.81^a
Hungary	2.70^c	2.70	2.73	5.72	9.25^c	11.36^c	12.21^c	12.18	12.24	12.40
Switz.	1.49	2.94	5.33	6.08	9.53^c	10.64^c	15.92^b	15.98^b	16.26^c	16.69^c
Australia	32.45^a	37.21^a	39.31^a	39.53^a	39.57^a	40.33^a	40.48^a	40.19^a	42.14^a	42.48^a
N. Zealand	1.33	4.16	4.16	4.12	4.38	4.51	4.93	5.13	5.30	6.40
Canada	0.00	7.48^b	7.51^c	7.43	8.73	8.81	9.97	10.19	10.24	10.84
US	0.00	8.92^b	9.26^b	9.39^b	10.56^c	11.00^c	13.12^c	13.82^c	13.87	15.06
Japan	0.05	1.54	3.73	8.68^c	10.48^c	10.75^c	11.16	13.52^c	16.98^b	22.64^a

Note: Supscripts a, b and c denote rejection of the null hypothesis at the 1, 5 and 10 % level of significance, respectively

Table 3.5: Engle LM test of the squared residuals regressed on q lags and a constant for the whole period

	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$	$q=6$	$q=7$	$q=8$	$q=9$	$q=10$
Austria	36.31^a	54.36^a	171.16^a	184.36^a	208.26^a	261.57^a	268.29^a	274.73^a	288.98^a	289.75^a
Belgium	637.62^a	723.87^a	799.14^a	849.15^a	969.92^a	1007.11^a	1007.32^a	1021.55^a	1034.96^a	1037.58^a
Finland	26.52^a	47.33^a	66.04^a	83.61^a	101.63^a	118.29^a	127.99^a	135.51^a	139.01^a	148.37^a
France	70.13^a	113.52^a	243.33^a	247.68^a	275.42^a	305.93^a	319.08^a	321.04^a	326.81^a	330.25^a
Germany	40.15^a	56.60^a	88.61^a	103.33^a	140.52^a	172.21^a	179.00^a	199.16^a	205.71^a	224.88^a
Greece	0.35	0.51	17.66^a	17.76^a	17.76^a	17.81^a	17.80^a	17.80^b	17.85^b	17.84^c
Ireland	266.19^a	409.93^a	432.49^a	451.71^a	516.12^a	534.66^a	536.88^a	544.18^a	568.11^a	601.32^a
Italy	48.95^a	224.48^a	285.54^a	295.89^a	298.05^a	300.77^a	303.01^a	309.29^a	310.02^a	322.99^a
Nether.	39.31^a	56.40^a	77.41^a	98.46^a	107.58^a	126.99^a	134.24^a	145.99^a	161.14^a	182.86^a
Portugal	87.37^a	146.60^a	157.04^a	210.20^a	214.45^a	220.16^a	224.05^a	230.88^a	241.85^a	330.06^a
Spain	63.46^a	104.83^a	127.82^a	173.96^a	181.68^a	183.34^a	191.25^a	194.83^a	202.48^a	217.12^a
Denmark	52.09^a	56.40^a	99.72^a	101.41^a	104.13^a	108.20^a	121.38^a	141.09^a	148.35^a	152.43^a
Norway	64.62^a	88.37^a	105.88^a	132.87^a	150.49^a	193.22^a	200.43^a	200.39^a	204.62^a	207.26^a
Sweden	106.23^a	114.13^a	130.65^a	163.36^a	168.64^a	181.53^a	181.50^a	185.05^a	188.41^a	193.73^a
UK	110.68^a	115.05^a	120.16^a	136.12^a	170.27^a	183.02^b	192.97^a	193.59^a	198.43^a	224.02^a
Hungary	0.19	0.21	1.05	1.05	1.57	1.53	1.55	2.43	2.44	2.49
Switz.	15.78^a	24.66^a	27.83^a	31.46^a	34.95^a	40.25^a	46.56^a	53.05^a	61.04^a	88.76^a
Australia	114.62^a	129.65^a	148.04^a	155.33^a	159.43^a	164.12^a	167.58^a	169.61^a	187.22^a	189.02^a
N. Zealand	73.71^a	80.54^a	92.13^a	93.18^a	96.74^a	98.57^a	99.01^a	99.34^a	102.41^a	106.39^a
Canada	41.99^a	65.52^a	73.81^a	129.75^a	138.21^a	141.06^a	152.84^a	156.42^a	156.57^a	174.29^a
US	25.45^a	51.29^a	68.98^a	128.03^a	156.69^a	168.90^a	179.10^a	179.33^a	199.04^a	208.14^a
Japan	119.08^a	154.72^a	271.22^a	284.89^a	309.63^a	315.92^a	338.99^a	344.05^a	362.11^a	418.71^a

Note: Supscripts a, b and c denote rejection of the null hypothesis at the 1, 5 and 10 % level of significance, respectively

Table 3.6: Sign Size Bias Test

	SB test	p-val	NSB test	p-val	PSB test	p-val	General	p-val
Austria	-3.100	0.001	-25.376	0.000	84.123	0.000	3280.253	0.000
Belgium	-1.625	0.052	-30.056	0.000	71.577	0.000	3098.919	0.000
Finland	-2.196	0.014	-29.428	0.000	69.130	0.000	3309.027	0.000
France	-1.194	0.116	-32.493	0.000	64.679	0.000	3168.612	0.000
Germany	-1.933	0.027	-32.619	0.000	59.646	0.000	3324.589	0.000
Greece	0.864	0.194	-169.306	0.000	5.835	0.000	3621.422	0.000
Ireland	-0.369	0.356	-42.667	0.000	49.963	0.000	2701.670	0.000
Italy	0.096	0.462	-46.562	0.000	34.535	0.000	2587.971	0.000
Netherlands	-2.148	0.016	-29.967	0.000	65.995	0.000	3400.647	0.000
Portugal	-0.713	0.238	-27.757	0.000	93.396	0.000	2685.158	0.000
Spain	0.423	0.336	-48.803	0.000	25.294	0.000	2521.390	0.000
Denmark	-1.115	0.132	-32.522	0.000	64.669	0.000	3069.229	0.000
Norway	-1.449	0.074	-33.609	0.000	67.781	0.000	3180.289	0.000
Sweden	-1.340	0.090	-31.772	0.000	63.566	0.000	3095.359	0.000
UK	-1.392	0.082	-33.448	0.000	58.857	0.000	3240.707	0.000
Hungary	2.902	0.002	-15.913	0.000	204.256	0.000	2332.288	0.000
Switzerland	-0.850	0.198	-34.261	0.000	50.383	0.000	2692.456	0.000
Australia	0.011	0.496	-32.225	0.000	66.056	0.000	3123.760	0.000
N. Zealand	-0.865	0.194	-28.162	0.000	79.016	0.000	3038.556	0.000
Canada	-1.722	0.043	-31.117	0.000	66.511	0.000	3402.927	0.000
US	-1.557	0.060	-34.255	0.000	54.090	0.000	3117.325	0.000
Japan	-2.701	0.003	-26.119	0.000	87.708	0.000	3090.553	0.000

Note: Sign Bias (SB), Negative Size Bias (NSB), Positive Size Bias (PSB) tests and general test for asymmetric volatility. The test are applied to the residuals from an $AR(p)$ model, with p determined by the AIC

Table 3.7: Sansó et al. (2004) test statistic

	Number of breaks	Break date positions
Austria	0	
Belgium	0	
Finland	0	
France	3	02/03/2004; 06/10/2008; 08/10/2009
Germany	5	02/03/2004; 24/01/2008; 29/09/2008; 22/07/2009; 26/12/2012
Greece	5	24/01/2008; 19/11/2009; 18/04/2011; 30/11/2012; 18/09/2013
Ireland	2	10/05/2010; 13/04/2012
Italy	2	11/07/2011; 27/11/2012
Netherlands	0	
Portugal	2	10/05/2010; 29/10/2013
Spain	6	30/06/1999; 24/03/2000; 24/01/2008; 08/08/2011; 20/11/2012; 13/08/2013
Denmark	3	22/10/2004; 30/01/2008; 31/12/2012
Norway	0	
Sweden	3	25/06/2004; 23/01/2008; 17/12/2012
United Kingdom	7	04/11/1999; 21/11/2000; 07/12/2001; 28/12/2004; 12/12/2007; 13/10/2008; 09/12/2009
Hungary	0	
Switzerland	0	
Australia	6	16/07/2004; 14/11/2007; 13/10/2008; 05/03/2010; 08/08/2011; 01/01/2013
New Zealand	3	24/11/2004; 17/07/2008; 31/12/2009
Canada	3	08/11/2004; 13/12/2007; 12/03/2012
United States	4	03/02/2005; 13/12/2007; 26/11/2009; 16/05/2012
Japan	4	06/11/2001; 19/06/2003; 18/03/2009; 06/09/2010

Note: we use the κ_2 test (corrects for non-mesokurtosis and persistence in conditional variance), using the spectral quadratic window and automatic bandwidth selection

Table 3.8: Estimation of cointegration rank using the procedure in Cavaliere, Angelis, Rahbek, and Taylor (2015)

			$r \geq 1$	Break down of the results							
				$r = 0$		$r = 1$		$r = 2$		$r = 3$	
Dimension (m)	Combinations	Period	%	%	Number	%	Number	%	Number	%	Number
2	231	Calm	3.9	96.1	222	3.9	9	0	0	-	-
		Crisis	0.4	99.6	230	0.4	1	0	0	-	-
3	1540	Calm	11.2	88.8	1367	11.1	171	0.1	2	0	0
		Crisis	0.7	99.3	1529	0.7	11	0	0	0	0
4	7315	Calm	16.0	83.3	6092	15.2	1107	0.8	56	0.01	1
		Crisis	0.2	99.8	7310	0.2	15	0	0	0	0
5	26334	Calm	21.5	78.3	20616	19.8	5217	1.7	456	0.1	2
		Crisis	0	100	26330	0.0	4	0	0	0	0
6	74613	Calm	25.8	74.2	55358	25.2	18748	0.6	469	0	0
		Crisis	0	100	74612	0.0	1	0	0	0	0
7	170544	Calm	30.9	69.1	117862	29.6	50480	1.3	2202	0	0
		Crisis	0	100	170544	0	0	0	0	0	0

Table 3.9: Countries of cointegration vector $\{r \geq 1\}$ using the joint procedure

	Bivariate		Trivariate				4th						5th						6th				7th			
Rank	r=1	%	r=1	%	r=2	%	r=1	%	r=2	%	r=3	%	r=1	%	r=2	%	r=3	%	r=1	%	r=2	%	r=1	%	r=2	%
Calm period	FR	31%	FR	30%	ES	33%	FR	27%	FR	28%	AT	25%	FR	26%	FR	25%	FR	20%	FR	23%	FR	23%	FR	13%	FR	17%
	PT	13%	PT	13%	BE	33%	PT	14%	NZ	26%	BE	25%	IT	11%	PT	24%	PT	20%	PT	11%	PT	20%	IT	6%	PT	10%
	AT	13%	AT	9%	FR	16%	IT	10%	AT	12%	FR	25%	NO	11%	IT	12%	AT	20%	IT	10%	IT	15%	PT	6%	DE	9%
	BE	6%	IT	9%	AT	16%	AT	10%	IR	10%	ES	25%	AT	9%	AU	11%	BE	13%	DE	9%	DE	9%	DE	6%	IT	7%
	FI	6%	BE	8%			DE	8%	BE	8%			DE	8%	DE	6%	IT	13%	NL	9%	HU	7%	NL	6%	NL	7%
	DE	6%	ES	5%			NL	7%	NO	4%			JP	8%	NL	5%	CA	7%	AT	9%	AT	7%	AT	5%	JP	5%
Crisis period			GR	27%	GR	23%							GR	20%					GR	17%						
			DK	27%	DK	20%							IR	15%					DE	17%						
			BE	15%	BE	10%							IT	15%					IR	17%						
			FI	15%	FI	7%							SP	15%					IT	17%						
			NL	12%	FR	7%							AT	10%					NL	17%						
			FR	8%	PT	7%							DK	10%					ES	17%						

Note: The rejection of the corresponding null hypothesis is at 5 % level of significance

Table 3.10: Granger causality tranquil period

	AT	BE	FI	FR	DE	GR	IR	IT	NL	PT	ES	DK	NO	SE	UK	HU	CH	AU	NZ	CA	US	JP
Austria		NaN	-	NaN	0.01	0.03	0.00	0.00	-	NaN	0.03	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.01	-	0.00
Belgium	NaN		-	0.00	0.00	0.00	0.00	0.00	-	0.00	NaN	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.00	0.03	0.00
Finland	0.00	0.02		NaN	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.00	0.02	0.00
France	NaN	0.00	NaN		NaN	0.00	NaN	0.00	NaN	0.00	0.00	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.00	0.03	0.00
Germany	0.00	-	-	NaN		-	0.01	0.00	-	0.00	0.01	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.01	-	0.00
Greece	-	-	-	0.00	-		-	-	0.01	0.00	-	0.00	0.00	0.01	-	-	0.00	0.00	0.00	-	-	0.00
Ireland	0.00	0.00	0.00	NaN	0.00	0.00		0.00	-	0.00	0.00	0.00	0.00	0.00	-	0.04	0.00	0.00	0.00	0.00	0.04	0.00
Italy	0.00	-	-	0.00	0.00	0.00	0.02		-	NaN	0.00	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.02	-	0.00
Netherlands	0.00	0.00	0.00	NaN	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00
Portugal	NaN	0.00	0.01	0.00	0.00	0.00	0.00	NaN	-		0.00	0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.04	-	0.00
Spain	0.00	NaN	-	0.00	0.00	0.00	0.00	0.00	-	0.00		0.00	0.00	0.00	-	-	0.00	0.00	0.00	0.00	0.05	0.00
Denmark	0.01	-	-	0.00	0.00	0.01	-	0.01	-	0.00	0.01		0.00	0.02	-	-	0.00	0.00	0.00	0.01	-	0.00
Norway	0.00	-	-	0.00	0.00	0.03	-	0.00	-	0.00	0.00	0.00		-	-	-	0.00	0.00	0.00	0.00	-	0.01
Sweden	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00		-	-	0.00	0.00	0.00	0.00	-	0.00
United Kingdom	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	-	0.00	0.00	0.00	0.00	0.00		0.04	0.00	0.00	0.00	0.00	0.01	0.00
Hungary	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		-	-	-	-	-	-
Switzerland	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	-	0.00	0.00	0.00	0.00	0.01	-	-		0.00	0.00	-	-	0.00
Australia	-	-	-	0.01	-	-	-	-	-	0.01	-	0.00	-	-	-	-	-		0.00	0.05	-	-
New Zealand	-	-	-	-	-	-	-	-	-	0.03	-	0.00	-	-	-	0.01	-	-		-	-	0.05
Canada	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00		0.00	0.00
United States	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	-		0.00
Japan	-	-	-	-	-	-	-	-	-	0.03	-	-	-	-	-	-	-	-	-	0.02	-	

Note: - indicates rejection of the corresponding null hypothesis at 5 % level of significance. NaN is for long-term relationships

Table 3.11: Granger causality crisis period

	AT	BE	FI	FR	DE	GR	IR	IT	NL	PT	ES	DK	NO	SE	UK	HU	CH	AU	NZ	CA	US	JP
Austria		0.00	0.00	-	0.00	-	0.01	-	-	0.04	0.00	0.00	0.00	0.00	-	0.01	0.00	0.00	0.00	-	-	0.00
Belgium	0.00		0.00	0.00	0.00	-	-	-	0.00	-	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.03	-	0.00
Finland	0.01	0.00		-	0.00	-	0.00	-	-	0.00	0.00	0.00	0.00	0.00	-	0.02	0.00	0.00	0.00	-	-	0.00
France	-	0.00	-		0.01	-	-	0.00	-	-	0.00	0.00	0.00	0.00	-	0.02	0.00	0.00	0.00	-	-	0.00
Germany	0.00	0.00	0.00	0.00		0.03	0.00	-	0.01	0.00	0.00	0.00	0.00	0.00	-	0.01	0.00	0.00	0.00	-	-	0.00
Greece	-	-	-	-	-		-	-	-	-	-	-	-	-	0.03	-	-	0.00	0.01	-	-	-
Ireland	-	-	-	-	-	-		0.01	-	0.00	0.02	0.00	-	-	-	0.03	0.03	0.02	0.03	-	-	-
Italy	-	-	-	-	-	0.00	0.00		-	0.00	0.00	0.02	-	-	-	0.00	-	-	0.00	-	-	-
Netherlands	-	0.00	-	-	0.00	-	0.00	-		0.00	0.00	0.00	0.00	0.00	-	0.03	0.00	0.00	0.00	-	-	0.00
Portugal	-	-	-	-	-	0.00	-	0.00	-		0.00	0.00	0.02	-	-	-	-	0.03	0.03	-	-	-
Spain	-	-	-	-	-	0.00	0.00	0.02	-	0.00		0.00	-	-	-	0.03	-	0.02	-	-	-	-
Denmark	-	0.00	-	-	0.00	-	0.01	-	0.02	0.01	-		0.00	0.01	-	-	0.00	0.00	0.00	0.05	-	0.00
Norway	-	0.00	-	-	-	-	0.00	-	-	0.02	-	0.04		-	0.02	0.02	0.04	0.00	0.00	0.01	-	0.00
Sweden	-	0.00	-	-	0.00	0.02	0.00	-	-	0.02	-	0.00	0.00		0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00
United Kingdom	0.01	0.00	-	-	0.01	0.03	0.00	-	-	0.00	0.01	0.00	0.00	0.00		-	0.00	0.00	0.00	0.00	0.01	0.00
Hungary	0.00	0.01	-	0.01	-	-	-	-	-	-	-	-	-	-	-		-	-	-	-	-	-
Switzerland	0.00	0.00	0.01	0.01	-	-	-	-	0.01	-	-	0.00	0.00	-	0.01	0.05		0.00	0.00	-	-	0.00
Australia	-	-	-	-	-	-	-	0.04	-	-	-	-	0.01	-	-	-	-		0.00	-	-	0.00
New Zealand	-	-	-	-	-	-	-	0.00	-	-	0.03	-	0.00	-	-	-	0.02	0.00		0.01	NaN	0.00
Canada	0.00	-	0.00	0.00	0.00	-	0.02	-	0.00	0.04	-	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00		0.00	0.00
United States	0.00	-	0.00	0.00	0.00	-	-	-	0.00	-	-	0.00	0.00	0.00	0.00	-	0.00	0.00	NaN	-		0.00
Japan	0.01	0.03	-	0.00	-	-	-	0.00	-	-	0.01	-	-	-	-	0.01	0.00	-	0.00	-	-	

Note: - indicates rejection of the corresponding null hypothesis at 5 % level of significance. NaN is for long-term relationships

Table 3.12: Granger causality analysis for trivariate systems

			Granger causality relationships		Feedback	
	Permutations	Period	%	Number	%	Number
2 - multi-step	8202	Calm	0.0	81	-	-
	9174	Crisis	0.0	96	-	-
3 - Direct trivariate	8202	Calm	70	5712	73	4148
	9174	Crisis	57	5229	58	3084

Table 3.13: Estimation of cointegration rank using the procedure in Cavaliere, Angelis, Rahbek, and Taylor (2015). Unknown break affecting the short-run component

				Break down of the results					
			$r \geq 1$	$r = 0$		$r = 1$		$r = 2$	
Dimension (m)	Combinations	Period	%	%	Number	%	Number	%	Number
2	231	Calm	15.2	84.8	196	15.2	35	-	-
		Crisis	1.7	98.3	227	1.7	4	-	-
3	1540	Calm	26.7	73.4	1129	23.3	359	3.4	52
		Crisis	0.6	99.4	1530	0.6	10	0	0

Table 3.14: Granger causality analysis for bivariate and trivariate systems. Unknown break affecting the short-run component

			Granger causality relationships		Feedback	
Dimension (m)	Permutations	Period	%	Number	%	Number
2 - Direct bivariate	392	Calm	65	253	64	162
	454	Crisis	54	246	49	120
2 - multi-step	6930	Calm	0	22	-	-
	9180	Crisis	1	117	-	-
3 - Direct trivariate	6930	Calm	68	4717	72	3412
	9180	Crisis	58	5308	58	3046

Table 3.15: Estimation of cointegration rank using the procedure in Cavaliere, Angelis, Rahbek, and Taylor (2015). Unknown structural break affecting the short-run and long-run components

			Break down of the results			
			$r = 0$		$r = 1$	
Dimension (m)	Combinations	Period	%	Number	%	Number
2	231	Calm	95.7	221	4.3	10
		Crisis	99.9	230	0.04	1

Table 3.16: Granger causality analysis for bivariate systems. Unknow structural break affecting both the short-run and long-run components

			Granger causality relationships		Feedback	
	Permutations	Period	%	Number	%	Number
2 - Direct bivariate	442	Calm	64	288	59	170
	460	Crisis	45	209	33	70

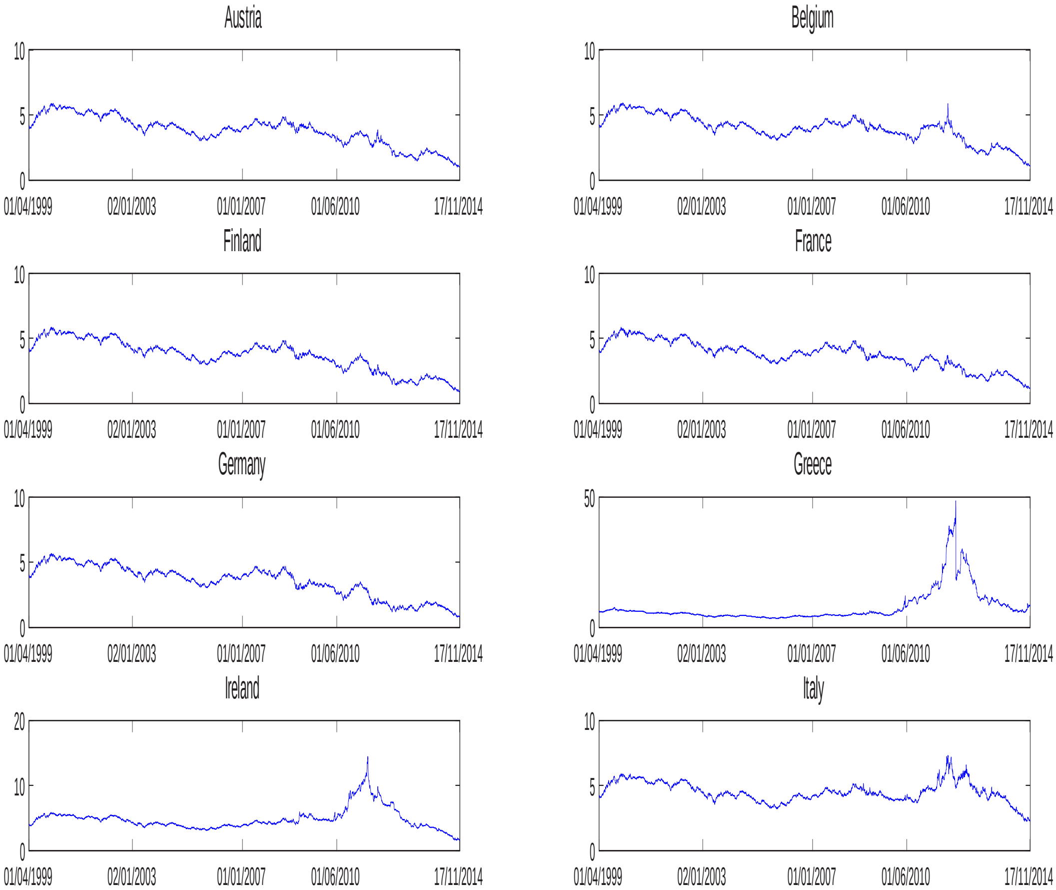

Figure 3-1: Bond yields

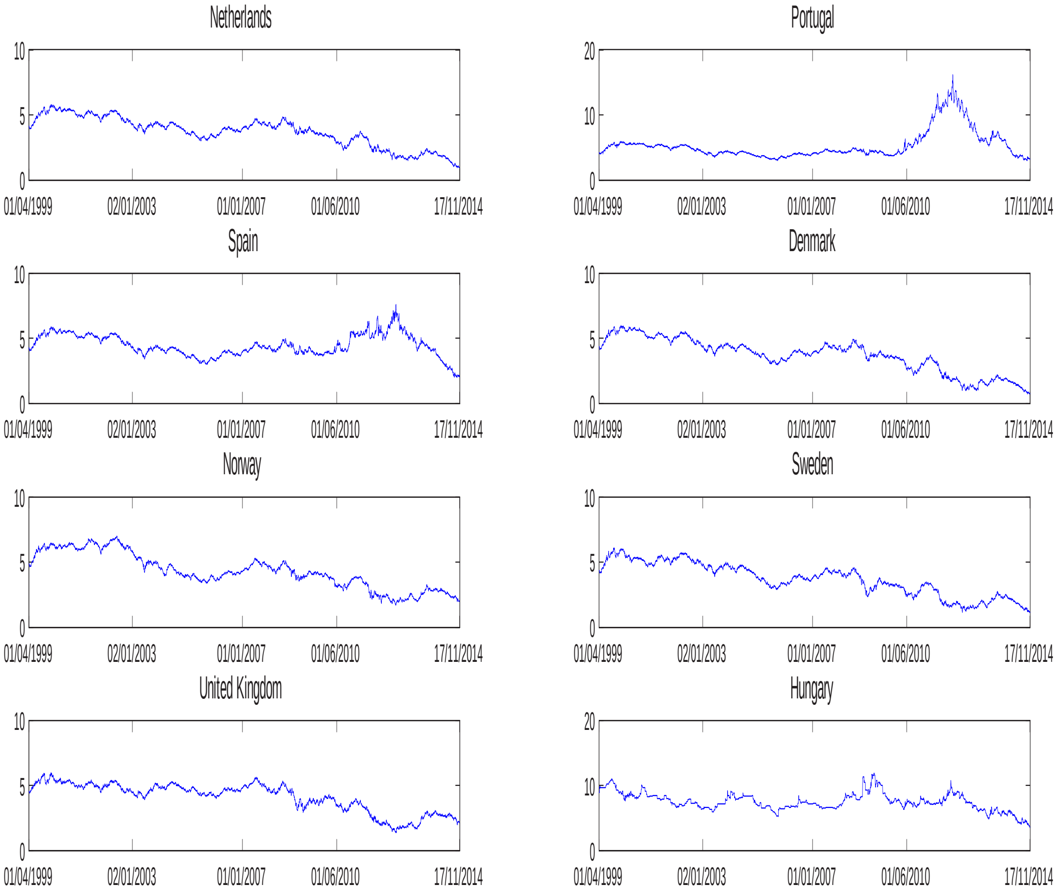

Figure 3-1: Bond yields

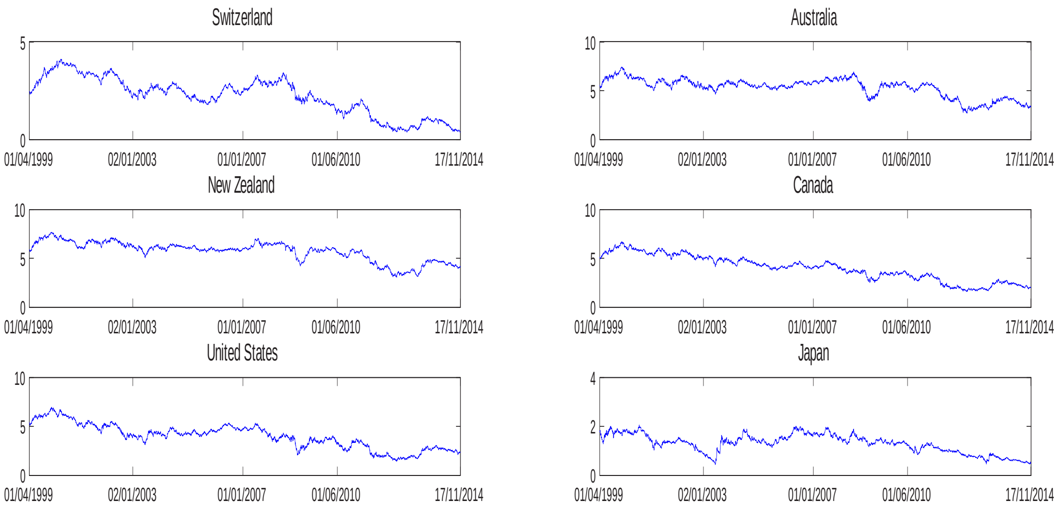

Figure 3-1: Bond yields

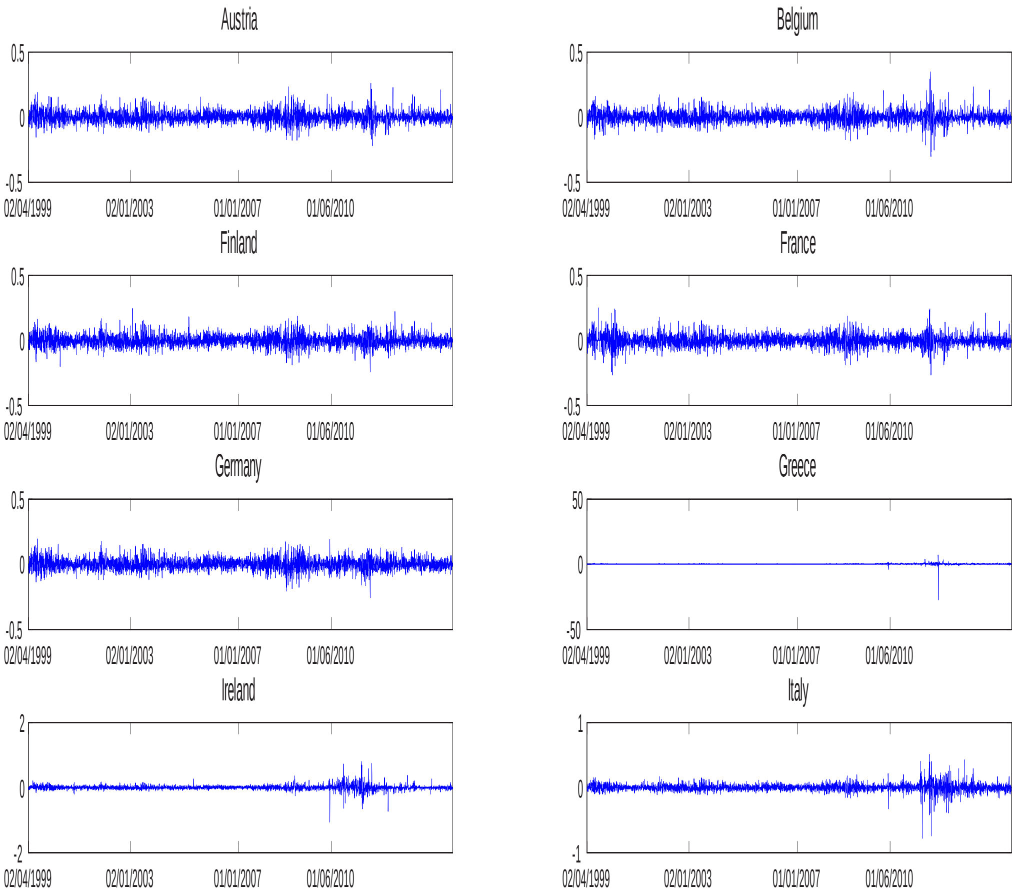

Figure 3-2: First difference of bond yields

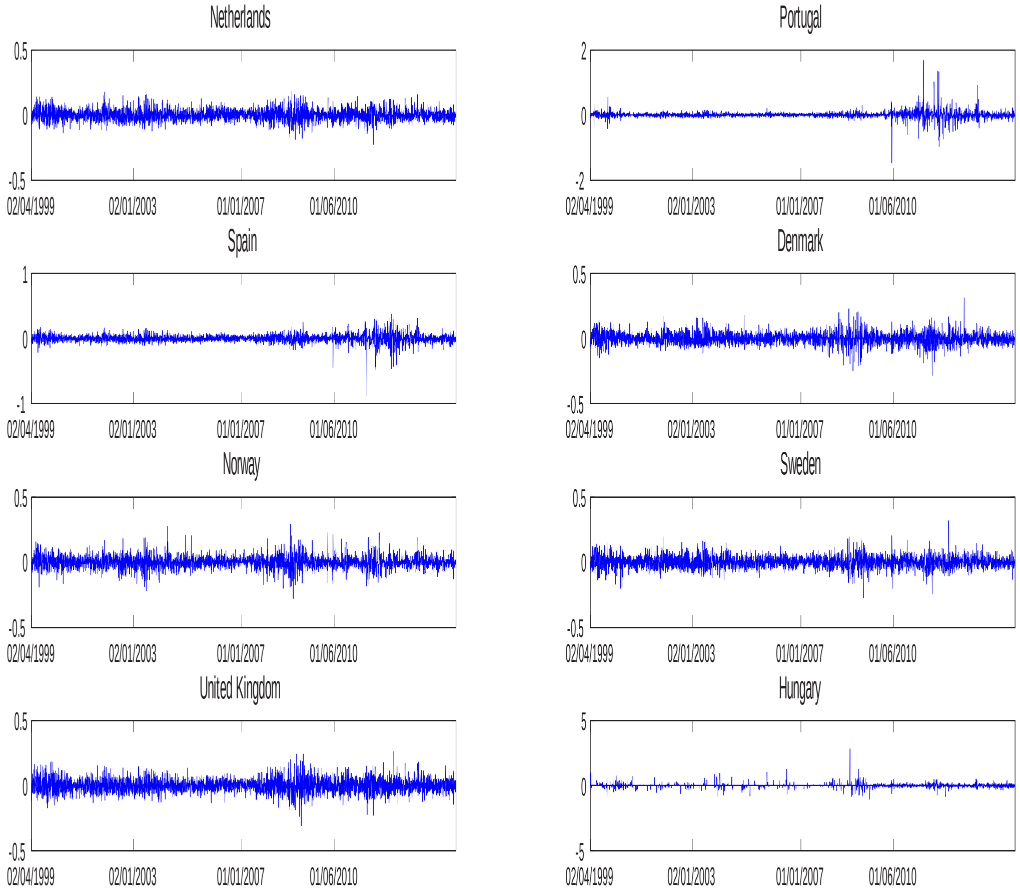

Figure 3-2: First difference of bond yields

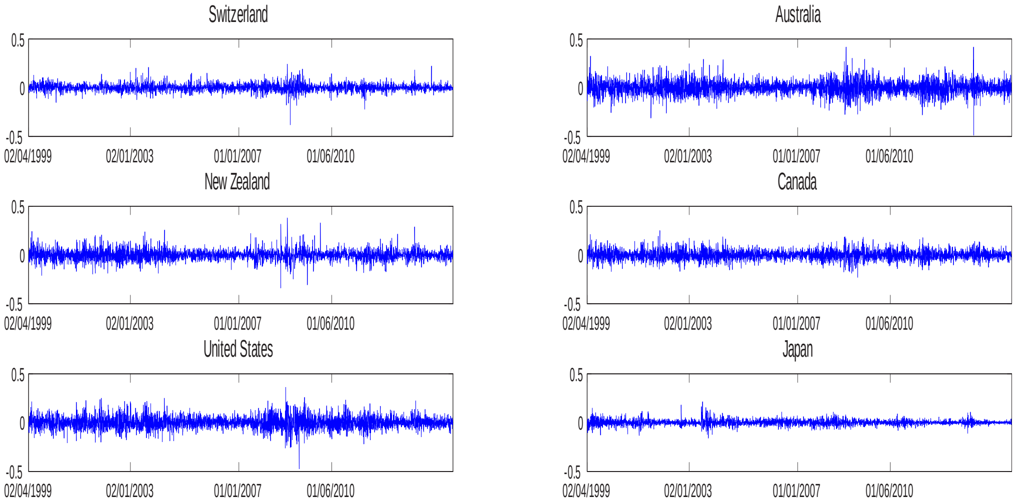

Figure 3-2: First difference of bond yields

Chapter 4

Conclusions: Main findings, policy implications and future lines of research

This chapter summarises the main conclusions from the empirical analysis that has been carried out throughout the thesis and the main policy implications that derive from it. This exercise allows us to devise some future lines of research that have appeared when working in the topics that have been studied in the thesis.

4.1 Main findings and policy implications

The main goal of this thesis is the study of the presence of international financial contagion. To achieve this goal, this thesis has focused on two main definitions of contagion. On the one hand, Chapter 1 uses the definition of contagion that centres on the transmission mechanisms of the crisis. On the other hand, Chapters 2 and 3 use the "shift contagion" definition of contagion focusing on two different markets. Specifically, Chapter 2 analyses the stock market crisis during the great recession, and Chapter 3 focuses on the European debt crisis that experienced most of the developed OECD countries in the same last recession.

Chapter 1 aims to identify the main channels of transmission of contagion during the Thailand, Russian and Brazil crises in the four main financial markets – i.e., exchange rate, interest rate, reserves and stock markets. This analysis has tried to identify the transmission channels of crisis and guide policymakers to create economic and financial structures in times of calm to prevent the main effects of contagion. The results that have been obtained showed that the structure of each financial market, depending on market forces or government intervention, in times of crises used different channels of transmission. Further, it has been shown that the contagion effect had different duration for each market. Second, the transmission of crisis by spatial clusters was the main channels of contagion, and there did not exist clear evidence that the economic fundamentals were the key of the Thailand, Russian and Brazil crises. These results will help policymakers to build a different policy to prevent contagion depending on government intervention in each financial market. Finally, the analysis revealed that the non-geographical channels of transmission were changing across the crises.

Chapter 2 focuses on the stock market crisis that was originated in the US in 2007 and developed into a long lasting great recession in many developing economies. These mortgage and stock crises collapsed large financial institutions, provoked the bailout of sick banks and downturns in stock markets and affected the stability of financial institutions which, in turn, required political interventions.[1] In Chapter 2, we use the "shift contagion" definition and the econometric approach allows us to use this definition without the need to estimate the channels of transmission. This approach has tried to find if the transmission of crisis was based on the normal interdependence among countries, or, whether it was due to an exceptional interdependence in the turbulent period. This sharp distinction guides policymakers to manage and mitigate crises and contagion during the turbulent period. The results showed the presence of global contagion of stock returns – i.e., the systemic risk change and increase in the crisis period – and also showed the presence of local contagion. This suggests that the transmission of crisis is

[1] See Markose, Giansante, Gatkowski, and Shaghaghi (2010) for the analysis of too big to fail and the system risk.

through the crisis-contingent transmission channels, such as those based on multiple equilibria, endogenous liquidity, or political economy. These results permit to cast some doubts about the portfolio diversification in crisis period and guide policymakers to create specific policies in times of crisis. These short-run isolation policies, such as capital controls, may be able to stop or slow down the transmission of a crisis from one country to another and reducing a country's vulnerability to shocks elsewhere in the world.

In Chapter 3, we focused on the consequences of the political intervention during the great recession on public debt markets. In this chapter, we also used the "shift contagion" definition since it allows us show if the crisis is based on crisis-contingent transmission channels or non-crisis-contingent transmission channels which, in turn, define different policy implications. The results showed that long run global interdependence in the OECD market debt exists in the calm period but this long run interdependence disappears in the crisis period. Once again, these results cast some doubts about the portfolio diversification in crisis period. Finally, the local short run analysis showed that the local short run interdependence does not disappear in crisis period and it is similar in calm and crisis periods. These results suggest that the recent debt crisis appears to have been transmitted mainly through non-crisis-contingent channels. Therefore, specific short-run policies may be able to delay the contagion, but they cannot avoid the necessary fundamental adjustment.

4.2 Future lines of research

The research that has been conducted in this thesis has given rise to further topics of research that should be addressed in the future. In what follows, we describe some of these promising avenues of research that might developed in the upcoming years. Concerning the study in Chapter 1, the spatial econometric analysis might be affected by the endogeneity that might exist between the definition of the economic weights and the objective variable. Therefore, it would be interesting to assess whether such endogeneity problem exist and, if so, try to devise a robust procedure that avoid this problem. The application of new spatial econometric techniques that address this potential endogeneity issue and that cover the criticism raised by Rigobon (2002) defines interesting extensions of the study addressed in this chapter. One limitation of the analysis that has been conducted in Chapter 1 comes from the short sample of observations that have been used, which might be affecting the empirical power of the test statistics that are applied. In this regards, it would be desirable to extend the sample and check the robustness of the conclusions. Related to this issue, we have used low frequency data, which prevented us from analyzing the behavior of the markets during the crisis period more accurately. Thus, it would be interesting to extend the analysis using high frequency data and see if it is possible to obtain a better characterization of the crises. Finally, Chapter 1 assumed that the contagion in the markets do not change between calm and crisis periods, an assumption that might be relaxed.

Chapter 2 studies the financial contagion on stock markets and part of the analysis is done conditional on the exogenous determination of the beginning of the crisis – i.e., assuming that the date of the structural break is known. The natural extension of this research thus is defined by the endogenous selection of the beginning of the crisis for each country, which will suppose a better characterization of the contagion effects for each country. Finally, we have used an approximate linear common factor model to perform part of the analysis, although it would be possible to consider the specification of non-linear common factor models to cover non-linearities that might be present in the data.

Finally, Chapter 3 focuses on the financial contagion on debt markets using the econometric framework defined by pice-wise linear cointegrating relationships. The analysis has assumed that there is one structural break affecting the parameters of the VECM specification that is used, although it would be the case that there might be more than one structural break. Consequently, it would be possible to extend this analysis considering more than one structural break. Although this generalization will increase the degree of non-linearity of the model specification, an interesting extension of the research would explore the use of non-linear cointegration analysis. We hypothesize that this type of models could cover situations where the markets are connected (interdependence) and disconnected with simple specifications. One important contribution offered in this chapter is the endogenous selection of the beginning of the crisis within the system defined by the VECM specification. However, the implementation of this econometric technique has been done only for bivariate systems and a straightforward modification can be introduced to cover systems of higher dimension. Finally, the global contagion was analysed taking into consideration only seven markets. In this regard, it would be desirable to define systems of variables of higher dimensions, which will provide a deeper analysis of the global contagion covering a broader set of markets.

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