Universitat Autònoma de Barcelona

Essays on cryptocurrencies

Obryan Poyser Calderón

Essays on cryptocurrencies

A thesis submitted in partial fullfilment for the degree of Doctor of Philosophy

Obryan Poyser Calderón

May 2019

Contents

[1] Poyser, O. Eurasian Econ Rev (2019) 9: 29. https://doi.org/10.1007/s40822-018-0108-2

List of Figures

List of Tables

Chapter 1

Introduction

As a product of information technology, cryptocurrencies had a delayed reaction from economic field, which brought an opportunity to shine a new light of some of the puzzles associated with a seemly innovative set of technological advances that fitted within the digital economy subfield. By the same token, these studies have a clear empirical scope, seeking to explore the variability, complexity and massively set of information that is recorded extensible, in real time, at an increasing rate and mostly in a non-structured and structured way. Moreover, it entails the inclusion of new methods to analyze such information with the goal of providing as robust as possible outcomes oriented on economic theory. For that sake, during the set of articles, there is an evolution from an explorative in nature study to a conceptual framework that makes economic sense to the cryptocurrency market. The past decade has been the rapid evolution of cryptocurrencies and as well as its derivative elements. This progress has not been absent from critiques, which made the topic even more interesting since it captures a wide range of factors and insights related human decision-making, that has been documented and studied in the past. In summary, the purpose of this project is to study the relationship between information processing, attention and individuals reaction in crypto-markets, focusing on the role of the wide access to information, the role of social media in diffusing information, public policies implicated, and the advanced statistical approaches to analyze the information.

The first chapter paper explores the association between Bitcoin's market price and a set of internal and external factors by employing the Bayesian structural time series approach (BSTS). The idea behind BSTS is to create a superposition of layers such as cycles, trend, and explanatory variables that are allowed to vary stochastically over time, additionally, it is possible to perform a variable selection through the application of the Spike and Slab method. This study aims to contribute to the discussion of Bitcoin price determinants by differentiating among several attractiveness sources and employing a method that provides a more flexible analytic framework that decomposes each of the components of the time series, applies variable selection, includes information on previous studies, and dynamically examines the behavior of the explanatory variables, all in a transparent and tractable setting.

The second chapter studies of behavioral finance aim to explain why investors in stock market settings act as they do. It is hypothesized that it is possible to explain cryptocurrencies market prices' puzzle from a behavioral finance perspective in which investors' cognitive biases play a major role to explain the volatility. In this context, this paper makes a literature revision on empirical and theoretical evidence in which investors' actions have been proved are not aligned with a rational benchmark, that can also serve as a parallelism to the crypto-market problem. Furthermore, this chapter seeks as well to shed light on the price setting puzzle by attributing movements to investors herding behavior, that is, a collective decision-making process in which prices "as is" are the coordination mechanism to investment decision making. According to the literature, herding can trigger the formation of speculative bubbles, thus, the main objective of this chapter is to study cryptocurrency market under the hypothesis that crypto-investors have limited resources to process information and weak prior knowledge, as a consequence they rely on others sources to valuate cryptocurrencies, which can unchain unexpected results. Moreover, it is suggested that cryptocurrencies' prices are driven by herding, hence this study test behavioral convergence under the assumption that prices "as-is" are the coordination mechanism. For this task, it has been proposed an empirical herding model based on Chang, Cheng, and Khorana (2000) methodology and expanding the model both under asymmetric and symmetric conditions and the existence of different herding regimes by employing the Markov-Switching approach.

The final chapter analyzed the impact of information shocks on behavioral convergence in cryptocurrency markets with the objective of composing a conceptual framework that helps to understand the nature of this market. In the second chapter, it has been proved that behavioral converge exists in cryptocurrency markets, and its magnitude differs in intensity conditional on current dynamics. Following the same line, the goal of this study is twofold, first, creating a Herding Index (hindex) that captures the magnitude of convergence under asymmetric conditions using State Space modeling. Second, providing a conceptual framework that represents the main traits of cryptomarkets and empirically provides Granger and Wold causal evidence of the dynamics within the system employing a structural vector autoregressive (SVAR) framework.

Chapter 2

Exploring the dynamics of Bitcoin's price: A structural time series approach[1]

Abstract

Currently, there is no consensus on the real properties of Bitcoin. The discussion comprises its use as a speculative or safe haven asset, while other authors argue that the augmented attractiveness could end up accomplishing money's properties that economic theory demands. This paper explores the association between Bitcoin's market price and a set of internal and external factors by employing the Bayesian structural time series approach (BSTS). The idea behind BSTS is to create a superposition of layers such as cycles, trend, and explanatory variables that are allowed to vary stochastically over time, additionally, it is possible to perform a variable selection through the application of the Spike and Slab method. This study aims to contribute to the discussion of Bitcoin price determinants by diferentiating among several attractiveness sources and employing a method that provides a more fexible analytic framework that decomposes each of the components of the time series, applies variable selection, includes information on previous studies, and dynamically examines the behavior of the explanatory variables, all in a transparent and tractable setting. The results show that the Bitcoin's price is negatively associated with the price of gold as well as the exchange rate between Yuan and US Dollar, while positively correlated to stock market index, USD to Euro exchange rate and diverse signs among the diferent countries' search trends.

[1] Poyser, O. Eurasian Econ Rev (2019) 9: 29. https://doi.org/10.1007/s40822-018-0108-2

2.1 Introduction

Digital currencies have been receiving public attention during past years, as result, it inevitably reached academia, finance, and public policy atmospheres. From the academics's perspective, the issue arises from the fact that digital currencies1 exhibit controversial features that challenge the status quo of what is considered money. Moreover, digital currencies also exhibits some other uses besides money, it can be defined as a protocol, platform, currency or payment method (Athey et al. 2016). Among digital currencies, Bitcoin (BTC) has been capturing almost all the attention, it was created in 2009 and serves as a peer-to-peer version of electronic cash that let to do transactions on the internet without the intermediation of the financial system (Nakamoto 2008).

Most of the interest in Bitcoin is associated with the age of information, a new economy in which the Internet strives to disrupt the way we interpret the world and behave in it. By the same token, Bitcoin's collection of technological properties can dramatically change our economy as well. Furthermore, it is important to underline that given that the conceptual foundation of digital currencies is attributed to Information Technology, a lagged interest was given to the research about the definition and scope from an economical point of view. On this matter, recently many authors have been studying the impact Bitcoin can exert on financial markets and fiat money. As Franco (2014) argues, whether the value of Bitcoin has a future within our economy or not relies on the forces driven by its application.

Bitcoin as well as alternative coins (Altcoins) has been vastly criticized due to its declared rejection of a centralized financial system, deriving to the inability of countries' central authorities to exert control over situations such as levy cash movements, money laundry and fighting illegal activities, among other issues. Another characteristic of Bitcoin is its high volatility behavior, which is consistent with typical speculative assets movements, an aspect that has also been criticized by many financial spokesmen. Events such as the PBoC[2] decision to close the main Chinese Bitcoin exchange offices due to concerns of illegal activities that might have been happening in China is an example. Other events including the bankruptcy announcement of Mt. Gox (one of the heads of Bitcoin trading) and recently the gain in legitimacy after the Brexit vote have only increased the need to study digital currency in depth (Bouoiyour and Selmi 2016; Halaburda 2016).

Despite all negative aspects aforementioned, there are also positive signs. In February 2017, cryptocurrency passed a milestone: Bitcoin's value surpassed the $1000 psychological threshold for the second time since the events of 2013 when it reached more than $1150 per BTC. Accordantly, some authors have argued that it is possible that

[2]The People's Bank of China

BTC is entering a mature phase identified by a decrease in the price volatility and an increment in the acceptance of BTC as a payment method by different businesses. Moreover, Bitcoin has been through government bans, hacks, and bad reputation but conversely, it is the most established cryptocurrency of the market. This behavior is generating a resilience perception around Bitcoin among users and investors that might be related to an increasing confidence in its future. As Böhme et al. (2015) claimed: for an economist, it is interesting to investigate the concept of Bitcoin because it has the possibility to *"disrupt existing payment systems and perhaps even monetary systems"*.

The goal of this paper is to explore which variables affect Bitcoin's price level given by search trends as a proxy for public interest, macro-financial, and Blockchain platform statistics. In order to achieve the objective, I chose to employ Brodersen et al. (2015) and Scott and Varian (2013) methodology of Bayesian Structural Time Series (BSTS). Particularly, one of the main contributions of this study is that BSTS approach allows to disaggregate Bitcoin's price into different components. Moreover, it has the ability to let the coefficients vary over time, permitting a more detailed detection of the data generating process. None of the existent research on Bitcoin has taken the differentiation of the elements that have dealt with the price dynamics over the time into account. Besides that, the condition that the search trend and magnitude vary greatly across countries has not been investigated either. This study innovates by applying data-driven methods to specify which groups of search trends have a relevant relationship with the price of Bitcoin. In summary, it is important to examine which social, financial and macroeconomic factors determine its price in order to know the scope and consequences for the economy.

This paper is organized as following: section one provides an introduction to the case study, section two describes the background of Bitcoin, while in section three it is going to be reviewed some of the most significant literature about price formation and estimation as well as the political and financial influence of Bitcoin. Section four shows the nuances of the data that is going to be used to estimate Bitcoin price measured by the exchange rate with USD. In the fifth section, the methodology putting noteworthy emphasis on the Bayesian Structural Time Series method will be explained. Section six shows the main results of the prediction and inference, whereas in section seven I will discuss the effect of each set of variables. To finish, section eight defines the core conclusions of the study.

2.2 Background

Foundations of digital currencies relies on cryptography advances. The capacity to secure communications drove many researchers to create digital currencies. However, they failed in their attempt due to their centralization, precious metal backing, counterfeiting and double-spend issues (Antonopoulos 2014). The first problem arose from the characteristic of being settled in specific physical spaces that were the reason prior digital currencies were susceptible to government prohibition and hacker's attacks. These issues regarding the trustiness of digital coins made it difficult to prove their authenticity, while the issue of preserving the property rights of a set of coins was also a great inconvenience. The two problems aforementioned were mostly solved by creating digital signatures under an appropriate technological architecture. Particularly, Bitcoin is the ultimate implementation of a proper technological architecture after decades of developments and technological applications of cryptography.

Bitcoin is an open-source computer program that was invented by an entity under the pseudonym of Satoshi Nakamoto in 2008. According to Antonopoulos (2014), Bitcoin is a set of technologies that established the framework to interchange money named bitcoins (lower case). In detail, it firstly consists of a decentralized peer-to-peer network, which implies that there is no intervention of the government nor financial system. Instead, it is a self-organized interconnected set of nodes, where each node represents a buyer or a seller, and these are the only parties involved in the transaction (Nakamoto 2008). Secondly, Blockchain serves as the public ledger for all transactions, where in this platform a set of rules are established regarding how to create, distribute, exchange, and validate the flow of block of transactions are established. Thirdly, the bitcoin is an inherent currency that has the function to represent value and serve as a reward for securing the distributed ledger to the operators in the network (Franco 2014). Regarding this issue, Nakamoto (2008) outlined the rules that determine the amount of "coins" produced over time and the method to create them. There is a determinist rule that specifies that the limit of bitcoins will be 21 million bitcoins in the year 2140.

Finally, it is precise to mention that the asymptotic limit of 21 million[4] Bitcoins derives from the *issuance of new bitcoins to reward operators (miners) in the network for securing the distributed ledger* (Franco 2014). Miners are individuals with high computational power used to solve algorithms that maintain the network organized by blocks of

[4]This limit can be depicted as a geometric series, and it is straightforward to find that the common factor is 0.5, thus we can calculate the maximum amount of bitcoins by:

$$S_n = \frac{a(1-r^n)}{(1-r)} = \frac{210000 * 50(1-0.5^{\infty})}{1-0.5} = 21x10^6$$

transactions. In exchange for their work, they receive a fixed but decreasing amount of bitcoins and an optional fee that will depend on current market activity. The former compensation was 50 bitcoins and this number is halved every four years. By extension, there will be nearly 210,000[5] blocks for each set of four years.

2.3 Literature review

The conventional economic approach to outline what is considered money is based on a set of basic functions. The first function is the medium of exchange, meaning an intermediary mechanism that aligns the demands for each pair of agents present in a trade event. The second function is the ability to work as a unit of measurement, needed to set comparability between the goods and services that are being traded through the interchange. Finally, the third function is the ability is to store the value over time. Several authors have been trying to interpret the role of Bitcoin from the previously mentioned function of money. For instance, Bjerg (2016) compared bitcoin to a set of typical theories of money[7]. Bjerg (2016) developed the analysis under the principle that bitcoin is *"a commodity money without gold, fiat money without State, and credit money without debt"*, and claimed that even though bitcoin is no gold, state or debt backing, it is a mistake to settle for counterfeit money. On the other side, Yermack (2013) argued that bitcoin does not have the possibility to meet the classical functions of money (especially on store of value) since it lacks intrinsic value, exerts long verification process of the transactions and high volatility prices.

Despite the heterogeneous arguments on Bitcoin's adequacy as a currency, almost all of them coincide in the fact that Bitcoin's future as a currency is mostly linked to the credibility and acceptance from users and merchants (Luther 2016). Further uses might end up turning Bitcoin into a platform for illicit activities or a speculative asset (Bjerg 2016; Ciaian, Rajcaniova, and Kancs 2016b; Raskin and Yermack 2016; Yermack 2013). Henceforward, the purpose of this study is to analyze Bitcoin's price drivers under a dynamic scope in order to shed light on the evolution of which variables affect the most (the variables that have most effect on its evolution). Most of the empirical literature addresses Bitcoin's price estimation by using social information, financial and macroeconomic variables, however, none of them considers time variance of these relationships.

In order to estimate Bitcoin's price drivers, two main branches of explanatory variables are included in the model: those papers which only include sentiment analysis

[5] This value is easily proved as there is a block each 10 minutes, hence, 144 per day, and given that there are 1460 days in four years, the result is 210.240 blocks.

[7] Another debate around bitcoin's digital currency and its appropriateness as money can be found in Böhme et al. (2015), Glaser et al. (2014), Rogojanu and Badea (2014), and Simser (2015)

(adoption and attractiveness) and others that employ macroeconomic and financial variables. However, especially the latter group has also included at least a proxy for investor's attractiveness. Within the first branch, Kaminski (2014) studies how emotions expressed on Twitter influence the digital currency market and argues that those sentiments have a moderate correlation with Bitcoin closing price and volume. In extension, the Granger causality analysis found that there is no statistical significance for Twitter signals as a predictor. Similarly, Yelowitz and Wilson (2015) collected Google Trends data and anecdotal evidence regarding Bitcoin users to examine the determinants of interest in Bitcoin. According to this paper, computer programming enthusiasts and unobserved illegal activities drive interest of Bitcoin, while political and financial variables' effect is less supported. Finally, another contribution was done by Kim et al. (2016) who analyzed social activity in cryptocurrency communities and constructed a sentiment analysis index in order to explain if those variables affect Bitcoin, Ethereum, and Ripple cryptocurrencies price. Their finding was that the proposed approach predicted variability in the price of low-cost cryptocurrencies.

Regarding the second branch, Garcia et al. (2014) and Kristoufek (2015) have been two of the most influential studies. These two papers address the analysis by differentiating between internal and external drivers of Bitcoin price. Specifically, Kristoufek (2015) formalizes the role of Bitcoin as a potential hedge or safe haven asset and describes the great influence of the Chinese market on it. By applying the wavelet coherence method, Kristoufek (2015) examines potential drivers, such as economical, transactional, technical and interest-related factors. Kristoufek opens the discussion of the duality property of Bitcoin (digital currency or speculative asset) by arguing that *"although the Bitcoin is usually considered a purely speculative asset, we find that standard fundamental factors -usage in trade, money supply, and price level-play a role in Bitcoin price over the long term."* This argument reinforces the idea that it is not all lost for now, however, the author also mentioned that, for the time being, it is a unique asset that goes from being a currency to being speculative asset without a clear differentiation.

Recently, other authors have been comparing Bitcoin with precious metals, analyzing volatility and adoption, and account for interest. For instance, Cheah and Fry (2015) found that Bitcoin is prone to substantial speculative bubbles, a result that was confirmed by Baek and Elbeck (2014) findings. However, the latter paper specifies that Bitcoin's importance is growing, thus it is likely to become more stable in the future. Another contribution was given by Georgoula et al. (2015) who applies time series analysis to study the impact of economic, technological and Twitter sentiment indicators on Bitcoin. According to their results in the short run, positive Twitter sentiment as well as Wikipedia search queries, and hash rate have a positive relationship with Bitcoin price, while USD to Euro exchange rate has a negative one. Through the employment of a VEC model, they found that in the long run Bitcoin price is positively related to bitcoins in circulation and negatively associated with S&P500 index. Other worthy studies can be seen in (Abad and Iyengar 2015; Bouoiyour and Selmi 2016; Bouri et al. 2017; Ciaian, Rajcaniova, and Kancs 2016b, 2016a; Dyhrberg 2016).

As has been shown before, most of the empirical work relies on Google trends and Twitter sentiment as a measure of attractiveness. However, I have found that the behavior of the search queries is not homogeneous across countries nor static over time. Henceforward, the disaggregation of investor's attractiveness is the main novelty of this paper alongside the empirical procedure to perform variable selection.

Following the framework proposed by other authors Ciaian, Rajcaniova, and Kancs (2016b, 2016a) and Kristoufek (2015) three types of drivers organized into internal and external factors are differentiated. By internal factors, we understand those factors that capture the supply and demand drivers that are directly derived from information of Bitcoin platform. On the other side, external factors are composed of attractiveness and macro-financial drivers. (Figure 2.1).

2.3.1 Internal factors

Bitcoin has a controlled supply of coins set by block height and block reward values, which is intrinsically related to the mining process. Given this situation, we can imply two things: firstly, bitcoin's supply is exogenously determined and secondly, it is constructed in a deflationary way [9]. The problem aforementioned has been exposed and the consensus is that it represents a serious drawback on its way to become a real currency, according to the economic principles (Böhme et al. 2015; Garcia et al. 2014; Yermack 2013). Given that supply is deterministic, only the demand side can affect Bitcoin's price (Baek and Elbeck 2014; Ciaian, Rajcaniova, and Kancs 2016b; Kristoufek 2015). Among the internal variables we can break down internal variables into bitcoins in circulation, transaction volume, hash rate and mining difficulty[10]

2.3.2 External factors

Other forces are hypothesized to influence Bitcoin price. Some authors have been studying the role of Bitcoin as a safe haven and hedge instruments.[11]. The theoretical argument about the existence of such assets is that investors have incentives to reduce losses in times of market stress.

[9] Many economists have stressed about the deflationary spiral that bitcoin represents to an economy. See [@Bohme2015; @Garcia2014; @Hanley2013] for a broader discussion.

[10] These variables will be explained in detail in the data section.

[11] Increasing risks in financial markets have established the need to invest in another type of assets, precious metals being the most frequent ones

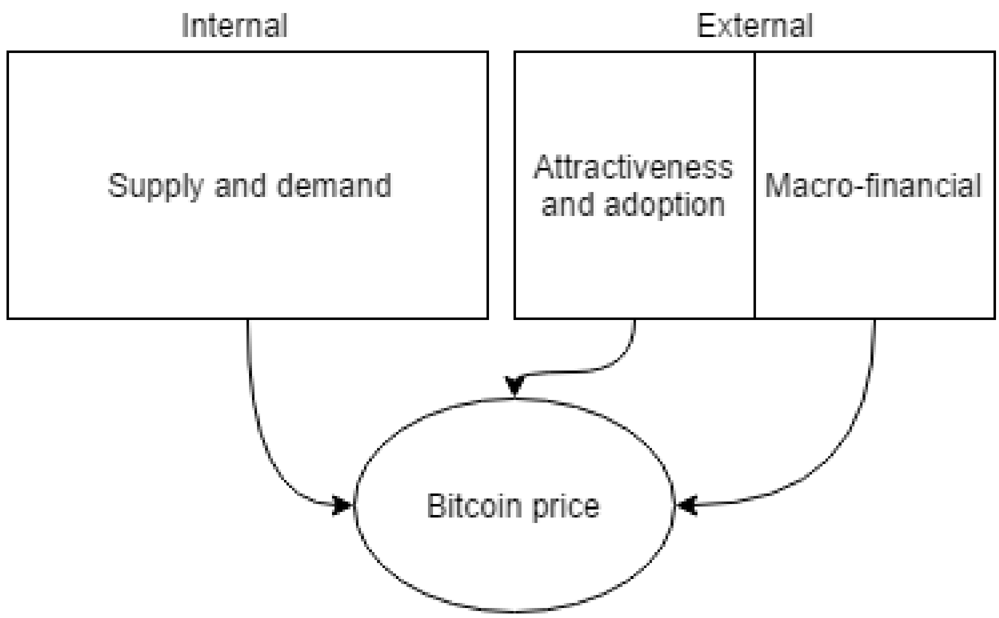


Figure 2.1. Bitcoin price drivers

We can distinguish between three types of assets: hedge, diversifier, and safe haven assets (Baur and Lucey 2010). Hence, a safe haven and hedge are both defined as assets that are uncorrelated or negatively correlated with another asset, with the distinction that the former behaves as such under the influence of stress and turmoil situations. Finally, a diversifier is positively correlated with another asset[12]. Bouoiyour and Selmi (2016) examined the relation between precious metals and Bitcoin with volatility in financial markets. They found Bitcoin appropriateness as a hedge and safe haven is not constant over time. Particularly, Bitcoin acts as a weak safe haven in the short run, and as a hedge in the long run. Moreover, in a recent paper Bouri et al. (2017) backed Abad and Iyengar (2015; Bouoiyour and Selmi 2016) results, the authors found that Bitcoin is positively associated in the presence of high deviations especially in the short run. Likewise, in a previous study, Kristoufek (2015) found one period of time that showed correspondence amongst the Financial Stress Index and Bitcoin price. A clear conclusion is the importance of studying Bitcoin's relationship with financial indicators and precious metal prices in a dynamic environment.

As previously stated, it is difficult to define Bitcoin due to its amalgam of characteristics. In most cases, authors have relied on Google search trends and Wikipedia article views (Glaser et al. 2014; Kristoufek 2015), Twitter sentiment analysis (Georgoula et al. 2015; Kaminski 2014) and online community reactions (Ciaian, Rajcaniova, and Kancs 2016b; Dwyer 2015; Kim et al. 2016). Among all the variables in the studies, the attraction has the most relevant variance explanation power. Nevertheless, none of the

[12]For a broader discussion on gold's and other assets application see Baur and Lucey (2010); Baur and McDermott (2010); Ciner, Gurdgiev, and Lucey (2013).

Figure 2.2. Bitcoin exchange rate with USD

previous works have realized that trends are not uniform across countries. Meaning that search trends in the United States are significantly different from China's and as far as I know this has not been accounted in the empirical literature on this topic. On this matter, this paper provides an innovation in comparison with other studies. The further description can be found in posterior sections.

2.4 Data

Bitcoin price level expressed as the exchange rate with the USD is the target variable. The price was extracted from www.blockchain.info website, which also provides Blockchain statistics (internal drivers). This site continuously records information about the BTC/USD on daily frequency (Figure 2.2).

It is important to mention that although www.blockchain.info is a reliable source of information, for this research it has been found that www.quandl.com platform provides a straightforward way to extract the information since there is an API wrapper package for R software that offers a direct interaction with the database.

Blockchain.info distinguishes between five types of platform descriptors: currency statistics, block details, mining information, network activity and blockchain wallet activity. All the variables within such categories have a daily frequency. For explanatory variables USD exchange trade volume (trvou) that represents the total USD value trading volume on major Bitcoin exchanges has been included. Among the block details, confirmation time (atrct) that records the median value that a transaction needs in order to be accepted into a block and added to the public ledger. The mining information, has been included the hash rate (hrate) that measures the power of miner's machines. Finally, in order to analyze the network activity, I will consider the number of transactions per day which account for unique trades per day excluding the 100 most popular addresses.

Attractiveness' proxy in most of the papers is represented as search trends and Wikipedia articles' views. However, Kristoufek (2015) found that both sources provide analogous results. This variable consists of weekly search queries for the word "Bitcoin", collected from Google Trends in the period January 2013 to May 2017 for 27 different countries. By providing proper filters as needed, this tool shows how regularly a particular search term is requested in comparison with the total search volume across countries and periods. The resulting number is expressed in a scaled range between 0 and 100 on a topic's proportion of all searches on all topics. The reason I decided to include several countries for search trends in opposition to other similar studies Yelowitz and Wilson (2015), Kristoufek (2015) and Bouoiyour and Selmi (2016; Abad and Iyengar 2015) is that behavior varies significantly across the series. This hypothesis was confirmed by applying the Dynamic Time Warping algorithm[14], which allow to visualize disparities across time series. For instance, the trends in China (CN), the second country in importance into trade volume of Bitcoin differs greatly from the United States (US). However, the latter seems to be more correlated with Canada (CA) and other European nations such as Great Britain (GB), Sweden (SE), and fairly stronger with France (FR), Germany (DE) and so on (Figure 2.3).

Finally, financial variables will try to capture Bitcoin's capabilities as safe haven, diversified or hedge assets. Hence, the S&P500 (indicator of the performance of a group of relevant stock market companies), Chicago Board Options Exchange (CBOE) Volatility Index (VIX) (expresses market's expectation of one month ahead volatility), bearish sentiment from the AAII Investor Sentiment Survey, and the price of gold will be employed as potential driver from the financial market perspective. From a macroeconomic perspective, it is essential to account for movements in the exchanges rate of the euro with the dollar, and more relevantly, the US Dollar with the Yuan, which it is hypothesized that it might affect Bitcoin price due to capital controls that China has been introducing in order to control speculation. China has a fundamental protago-

[14]Dynamic Time Warping (DTW) is a technique to find optimal alignment between time-dependent sequences. This method is particularly useful to measure similarity and, by extension in classification problems. For a broader explanation and application of this method, please review Kate (2016) and Vaughan (2016)

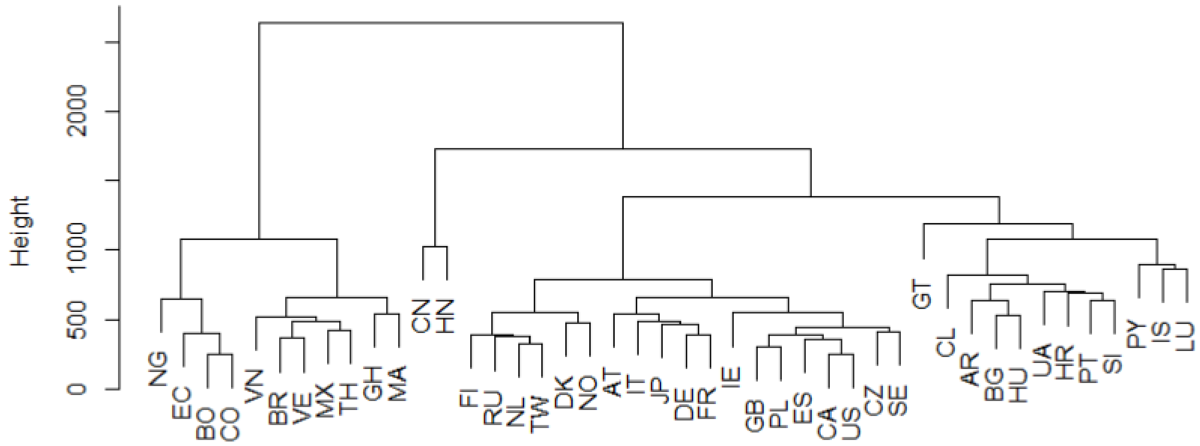


Figure 2.3. Clusters of attractiveness by country

nist, since more than 90% of the bitcoins are traded with the Yuan, and more than 70% of the mining takes places there (Geoffrey Smith 2017).

2.5 Methodology

In this section, I will present Bayesian Structural Time Series (also named state space form models) framework in order to make inferences about the variables that affect BTC price, together with a description of some side tools that can provide a better understanding of the problem.

2.5.1 Structural time series models

When we study a signal (time series) it is useful to visualize it as a product of aggregating different components, hence, the process of decomposing each layer provides an attractive method to bring a direct individual interpretation to the model. A basic additive form of given series can be expressed as:

$$observed = trend + seasonal + error \tag{2.1}$$

Therefore, a state space model (SSM) is equivalent to a dynamic system composed by a seasonal and trend element and perturbed by random disturbances Parmigiani, Petrone, and Campagnoli (2009). In his comprehensive book, Harvey (1990) highlights the salient properties of this framework due to its capability to reflect characteristics of the data, make diagnostic tests and makes it consistency with previous knowledge. By extension, the framework allows to expand prediction power by adding explanatory variables as a separate component. As expected, other relevant layers such as cycles and interventions can also be included in the model if needed.

Moreover, SSM method handles missing observations, the inclusion of stochastic explanatory variables can be permitted to vary stochastically over time, no extra theory is required for prediction since all that is needed is to project the Kalman filter forward into the future Durbin and Koopman (2012). In summary, the idea behind SSM is to create a "superposition", that is, a modular set of equations in which each layer forms part of the observed stochastic process, this is the reason they are also named as SST (Harvey 1990; Parmigiani, Petrone, and Campagnoli 2009).

A Gaussian SSM can be expressed in several notations, I have found the one presented by Durbin and Koopman (2012) and used as well in Scott and Varian (2013) and Brodersen et al. (2015) the most comprehensible:

$$y_t = Z_t \alpha_t + \varepsilon_t \qquad \varepsilon \sim N(0, H_t) \tag{2.2}$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \qquad \eta_t \sim N(0, Q_t) \tag{2.3}$$

Then, the equation 3 is the observation equation where y_t is a $p \times 1$ vector of observations, Z_t is a known $p \times m$ matrix, ε_t is an independent Gaussian random error with mean zero and variance H_t, and α_t is an unobserved $m \times 1$ vector named state vector. On the other side, equation 4 is called the *state equation* which is an autoregressive model of α_t, defined as an unobservable Markovian process imprecisely measured by y_t. In this equation T_t is a known $p \times p$ matrix called the state/transition matrix, R_t is a $p \times m$ error control matrix (indicates which rows of the state equation have nonzero disturbance terms), and η_t is the innovation, another independent Gaussian random error with zero mean and variance Q_t. Finally, SSM is that the underlying stochastic process is determined by α_t, nevertheless, since this latent system is not observable, we have to rely on the vector of observations to solve the system. There is an initial (prior) information assumed to be known for α that follows a normal distribution with mean α_t and variance P_0 which is also independent of ε_t and η_t for $t = 1, 2, ., n$.

2.5.1.1 Posterior inference and prediction

For a given SSM the key task is to generate predict future observations in the unobserved states, these values are computed from conditional distributions from sequential information as it is available. In this regard, the filtering[17] process compute conditional densities $\pi(\alpha_t|y_{1:t})$ as the data arrives, that is, it estimates the current value in the state vector given the disposable information in the observation vector and generates $\pi(\alpha_{t+1}|y_{1:t+1}), \pi(\alpha_{t+2}|y_{1:t+2}), \pi(\alpha_{t+3}|y_{1:t+3}), ..., \pi(\alpha_{t+n}|y_{1:t+n})$. In this case, since we are interested in predicting BTC price level, one-step-ahead (OSA) predictions of the $btcprice_{t+1}$ are based on previous data, it is needed to estimate α_{t+1} then, based in this value generate the observation $btcprice_{t+1}$. Finally, from a starting point $\alpha_0 \sim \pi(\alpha_0)$ it is possible to recursively compute $t = 1, 2, ..., n$ until obtaining the OSA state predictive density $\pi(\alpha_{t+1}|t_{1:t})$ and OSA predictive density $\pi(y_{t+1}|y_{1:t})$. The aforementioned problem can be solved elegantly through the Kalman filter, by taking advantage of the Markovian structure of the SSM and the assumption that the random state and observation vectors, as well as the marginal and conditional distributions follow a normal distribution.

One common problem that arises in SSM formulation is that system matrices Z_t, T_t, H_t, Q_t are unknown. When all the system matrices are known it straightforward to compute densities by using Maximum Likelihood Estimators (MLE), however, it gets promptly complicated when uncertainty about an unknown parameter is included (Parmigiani, Petrone, and Campagnoli 2009; West and Harrison 2006). In this regard, a Bayesian approach provides a solution, this is the reason simulation-

[17]It differs from the smoothing since this problem computes recursively the conditional distribution of given.

based methods have been gaining attention due to maximum likelihood limitations,[18] and by extension one of the most prominent factor that has led to the increasing interest number of applications STS methods. For instance, Markov chain Monte Carlo (MCMC[19]) helps to analyze the efficiency of the process. (Parmigiani, Petrone, and Campagnoli 2009; Durbin and Koopman 2012) methods provide a straightforward yet powerful way to simulate posterior densities when direct methods are not available West and Harrison (2006). In particular, Gibbs sampling algorithm (appendix 2) iteratively simulate and approximate filtering densities and probabilities π, from the full conditional distributions $\pi(\alpha_{0:t}|\psi, y_{1:t})$ and $\pi(\psi|\alpha_{0:t}, y_{1:t})$ where ψ is the unknown parameter. Hence, *"this approach solves at the same time the filtering, smoothing, and forecasting problems for a DLM with unknown parameters."* (Parmigiani, Petrone, and Campagnoli 2009).

In general terms, the proposed framework is a powerful tool to recursively generate estimations of the problem of interest. Harvey (1990) emphasized in the desire to ensure that the prediction reflects the true features of the data. In this study, we aim to introduce an improve to SSM formulation proposed in Brodersen et al. (2015) and Scott and Varian (2013) that led to select the best model out a set of possible explanatory variables. The relevance of the implementation in this study arise from the variable selection problem of the set of attractiveness drivers, it is expected that it will handle uncertainty about which country truly play a substantial role.

2.5.1.2 Bayesian variable selection

One of the most crucial aspects of SSM is the definition of the most appropriate model, hence, the inclusion of apparently set of clustered attractiveness indexes demands a variable selection approach that assesses for the best model variable's subset. The variable selection has been a common problem in statistics but not too much in econometrics. During the last years, econometric models commonly have a set of "true" theory specified explanatory variables, however, nowadays the "empirical revolution" in economics has changed the vision of how to do research. One problem that stems frequently in statistics is the selection of a subset of variables in a given model for the sake of interpretability or reducing variance[20]. SSM framework there is an attractive

[18] See Parmigiani, Petrone, and Campagnoli (2009) and West and Harrison (2006) for a further discussion.

[19] MCMC samplers must be checked in order to prove the distributional assumptions about the simulation, and it has to be stable over several draws. In most cases reduce by thinning (eliminating the burn-in iterations in compliance with parameter stability.)

[20] Among the discrete version, we have the forward/backward stepwise selection that filters through all possible subsets, nevertheless is computationally costly when the number of predictors becomes large. On the other side, penalized shrinkage methods such as LASSO (Tibshirani 1996) or Ridge (Hoerl and Kennard 1970) are more generally recommended, especially in high-dimensional settings.

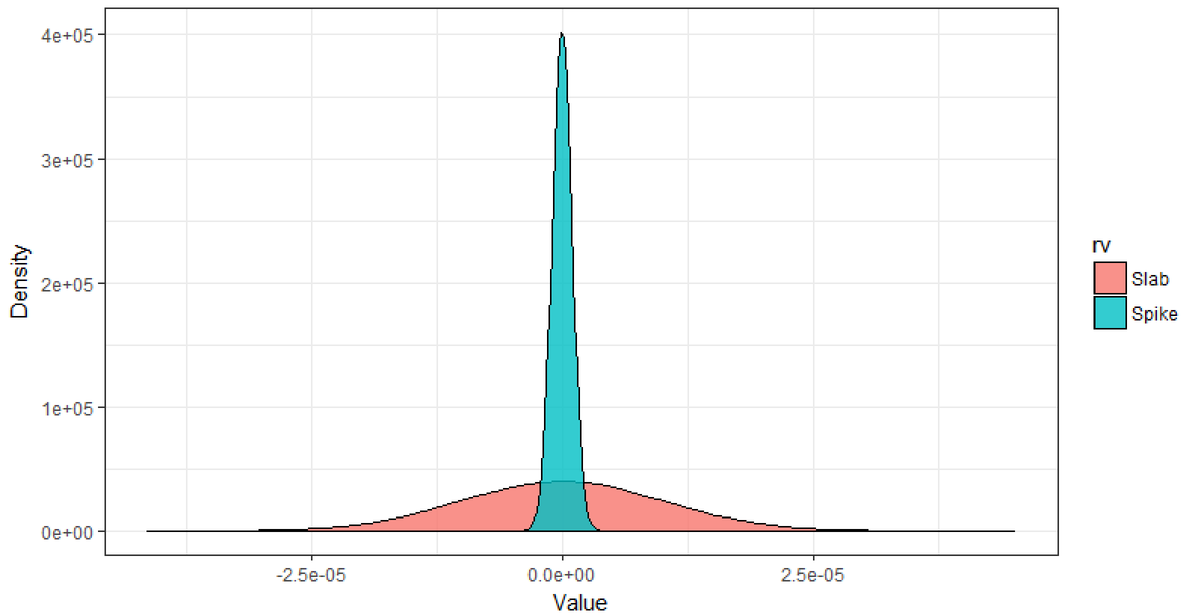


Figure 2.4. Spike and Slab priors

implementation that works well with MCMC and recursive estimations of the Kalman filter.

The Spike and Slab (SS) is a hierarchical Bayesian model, where the spike refers a center of mass concentrated around or nearly to zero, while the slab is represented as a wide (high variance) normally distributed prior. As Ishwaran and Rao (2005) mentioned, these names were originally proposed by Mitchell and Beauchamp (1988), who also designed the application to follow a Gaussian distribution with the purpose of enabling efficient Gibbs sampling of the posterior conditional distributions. One popular version of the SS model was introduced by George and McCulloch (1993) that describes the system as a mixture of two normal distributions (similar to Figure 2.4):

$$p(\beta_j, \gamma_j) = p(\gamma_j)p(\beta_j|\gamma_j) \qquad p(\beta_j|\gamma_j) \sim (1-\gamma_j)\,N(0,\tau_j^2) + \gamma_j\,N(0, c_j\tau_j^2) \tag{2.4}$$

The idea behind SS is to zero out β_j coefficients that are truly 0 by making their posterior mean values small. Small hypervariances τ_j^2 sets $\gamma_j = 0$ and asymptotically set the β_j as 0, while large values of τ_j^2 and c_j derive into $\gamma_j = 1$, generating a non-zero estimate of which means that are going to be selected as being part of the final model. In summary, through Bayes' rule, the probabilities are updated in order to generate a joint posterior distribution of the variables with the higher marginal posterior inclusion probabilities (Harvey 1990; Owusu et al. 2016; Scott and Varian 2013; Brodersen et al. 2015). It is important to highlight that in this study we consider predictors with a considerable level of collinearity (search trends) *"which intercorrelations* *between predictors (multicollinearity) undermine the interpretation of MLR weights in terms of predictor contributions to the criterion"* (Nimon and Oswald 2013) and standardized variables help model selection in the presence of S&L approach since as it was stated reduces the variability of the estimates by shrinking the coefficients and reduction of collinearity (Merlise 1999; Ročková and George 2014)

2.5.1.3 Spike and slab priors' specification

Bayesian analysis requires explicit specification of a prior on the parameters. Non-informative priors are commonly used by researchers because it is difficult to find a universally justifiable subjective prior. The choice of priors is often complex, although empirical Bayes approaches can be employed as well (Ishwaran and Rao 2005; Chipman, George, and McCulloch 2001). Koop, Poirier, and Tobias (2007) supports the idea of using empirical Bayes methods to select hyperparameters values in opposition to non-informative ones, nonetheless, it warns about the "double-counting" problem, that is, using the same data in previous draws to generate priors in posterior simulations.

In this work, it has been decided to follow an empirical selection hyperparameters selection. Hence, in the first step, it will be run multiple draws of the model using the what George and McCulloch (1993) of assigning for each independent γ_j a Bernoulli(γ_j) random variables a, inclusion/no-zero prior probability equal to 0.5. The decision of setting such prior derives from the assumption of having no information about the presence of the variables considered, or in other words a complete indifference or uninformative priors. The second step is to generate a joint distribution from n simulations draws generated with the same model specification and inclusion prior. Finally, it is going to generate new priors and test for the convergence and sensibility.

2.5.2 Model specification

As I describe in the last chapter, the additive structure of the SSM models allow organizing the components following the idiosyncratic characteristics of the phenomena in the study. For the sake of simplicity, the measurement equation will be presented in regular form rather than state space form:

$$\begin{aligned}
y_t &= \mu_t + \sum_{i=1}^{k} \lambda_{it}\varpi_{it} + \sum_{j=1}^{p} \beta_{jt}x_{jt} + \iota_t + \varepsilon_{y,t} && \varepsilon_{y,t} \sim N(0, \sigma^2_{\varepsilon_y}) && (2.5)\\
\mu_{t+1} &= \mu_t + v_t + \varepsilon_{\mu,t} && \varepsilon_t \sim N(0, \sigma^2_{\varepsilon_\mu}) && (2.6)\\
v_{t+1} &= v_t + \varepsilon_{v,t} && \varepsilon_{\mu,t} \sim N(0, \sigma^2_{\varepsilon_v}) && (2.7)\\
\lambda_{i,t+1} &= \lambda_{i,t} + \varepsilon_{\lambda_i,t} && \varepsilon_{\lambda_i,t} \sim N(0, \sigma^2_{\varepsilon_\lambda}) && (2.8)\\
\beta_{j,t+1} &= \beta_{j,t} + \varepsilon_{\beta_j,t} && \varepsilon_{\beta_j,t} \sim N(0, \sigma^2_{\varepsilon_\beta}) && (2.9)\\
\iota_{1,t+1} &= -\iota_{1,t} - \iota_{2,t} - \iota_{3,t} + \varepsilon_{\iota,t} && \varepsilon_{\iota,t} \sim N(0, \sigma^2_{\varepsilon_\iota}) && (2.10)\\
\iota_{2,t+1} &= \iota_{1,t} && && (2.11)\\
\iota_{3,t+1} &= \iota_{2,t} && && (2.12)
\end{aligned}$$

Regarding the variances σ^2, they are typically modeled as an inverse gamma distribution of the precision (σ^{-2}), hence:

$$\frac{1}{\sigma^2} \sim gamma(\frac{v}{2}, \frac{s}{2}) \tag{2.13}$$

Where μ_t is the local level component, this component is analog to the intercept in a classical regression model with the difference of being able to change over time, while v_t represents the angle of the trend line that also varies over time. The i intervention or shocks variables that are going to be included in the model are denoted as λ_{it} for $i = 1, 2, ..., k$, this component will capture suddenly changes in the level at the time point where the event happened. There are three possible situations after an intervention, a level shift which means a permanent structural form in the series, slope shift which means that the value of the slope showed a permanent change after the intervention and finally pulse, where the value of the level suddenly changes at the moment of the intervention, and immediately returned to the value before the intervention. In order to study the effects of other variables, a set of explanatory variables are going to be included where β_{jt} is an unknown regression weight for $j = 1, 2, ..., k$. Finally, ι_t captures the seasonal component of the series, in this case, it is expected that BTC price has quarterly periodicity.

2.5.2.1 Standardized variables

Standardization is the process of taking the sample mean of a random variable and dividing the result by its standard deviation, expressed as:

$$\frac{Y_i - \overline{Y}}{S_Y} = \left(\beta_1 \frac{S_1}{S_Y}\right) \frac{X_{i1} - \overline{X}_1}{S_1} + ... + \left(\beta_k \frac{S_k}{S_Y}\right) \frac{X_{ik} - \overline{X}_k}{S_k} + \frac{\epsilon}{S_Y} \tag{2.14}$$

The use of standardization of the covariates and response variable has been part of a long-time discussion in statistics. Detractors' main critic is around the use of standardized coefficients as a comparative importance measure among a different class of variables due to the "unitless" property of standardized variables. Mainly, when independent and dependent variables differ greatly from their distribution (Greenland et al. 1991; Nimon and Oswald 2013). However, besides some details in the estimation of covariances (Appendix 1), it offers a set of advantages. For instance, in a regression model, a coefficient of unstandardized variables measures the expected change in the dependent variable when the independent variable change in one unit. Conversely, when both variables are standardized, the interpretation differs, thus, the modified coefficient measures the expected standard deviation variation in the response variable associated with one standard deviation change in the covariate. In time series analysis, studying the deviations movements makes more sense than levels, hence standardized coefficient offers an attractive characteristic, beyond the comparability across different type of variables that in this research presents.

2.5.2.2 Assessing seasonality

Several authors have concluded that Bitcoin time series seems to behavior unlike, any other asset, as a result, it demands a closer look at the structure of trend and seasonal components. In order to test for the latter component, it will be tested a periodogram that is used to identify the dominant periods (or frequencies) of a time series. This might be a helpful tool for identifying the dominant cyclical behavior in a series, particularly when the cycles are not related to the commonly encountered monthly or quarterly seasonality (Shumway and Stoffer 2010).

2.6 Results

In this section, it is going to be compared to one-step-ahead predictions estimates with STS method and actual series for the period 01/2013 until 05/2017. A naïve local level model without explanatory variables is starting specification (the basic form in the state space framework), where the unobserved level μ_t (equation 7) has an irregular component, defined as a random walk with the form $\mu_{t+1} = \mu_t + \varepsilon_{\mu,t}$. As it can be noticed in the local level model (equation 7) it is assumed to be zero, this term is now included as a new state equation for modeling the slope v_t (also called drift) which measures the angle of the stochastic trend line. Regarding seasonal component, it has been discovered that BTC price does not have a recurring pattern over time, this conclusion arises from the periodogram analysis (Figure 2.10) where the highest periodic signal peak appears at 960, which is in this case, meaningless given that the time series number of observations is 1620. The now-casting performance will be described in Table 2.1 by the usual accuracy measures.

Table 2.1. One step ahead prediction accuracy according to the different specification

Model		sMAPE	MAE	MSE
Local level	LL	3.146	12.749	506.992
Local level with time-invariant regressors	LLTI	4.874	12.139	457.65
Local level with time-variant regressors	LLTV	4.181	14.588	702.588
Local linear trend	LLT	2.97	12.026	499.041
Local linear trend with time-invariant regressors	LTTI	4.134	11.782	455.146
Local linear trend with time-variant regressors	LLTTV	3.825	12.73	540.861

The process of superposing features in a structural model provides a flexible, tractable and intuitive process to analyze the behavior of BTC price. Prediction accuracy results for the period 01/2013 to 05/2017 are presented and compared in the Table 2.1 above. According to the symmetric mean absolute percentage error (sMAPE[24]), the naïve local linear trend model provides the best fit to the in-sample data with an error of 2.970%, followed by the local level of 3.146%. The effects of introducing regressors decrease precision when we account only for sMAPE as an indicator, however, predictors let to analyze the association with potential drivers, which is one of the objectives of this study. On the other side, the mean absolute error (MAE[25]) and the squared

[24] The symmetric mean absolute percentage error (sMAPE) is an accuracy measure based on relative errors, it is evaluated as: $\frac{100}{n} \sum_{t=1}^{n} \frac{|\hat{Y}_t - Y_t|}{(|Y_t| - |\hat{Y}_t|)}$

[25] The mean absolute error (MAE) is as its name describe $\frac{\sum_{t=1}^{n} |\varepsilon_i|}{n}$

Figure 2.5. One step ahead predictions of Bitcoin's price

error (MSE[26]) indicators, points to the LLTTI model since it has the lowest value for both, followed by LLT model. In this study, it has been decided to follow the superposition of LLTTV model, given that it provides the prospect to dynamically analyze the association of price drivers.

Prediction results for the LLTTV model are shown above. Here it can be seen that the model predicts reasonably well, however when it tends to overestimate local maxima and local minima values, this is one of the reasons why the MSE measure was relatively bad in comparison with other specifications since the square weighs heavily the presence of extreme values. This aspect is confirmed by the SMAPE measure in Table 2.1, that locate in terms of prediction power on the third position.

Figure 2.6 below illustrates the contribution of each of these components, where we can highlight the slope trend signal estimated recursively by the Kalman filter. The medium panel shows the effect of time-invariant regressors that provided prediction power to explain Bitcoin price by the end of 2013 and beginning of 2014, with an overall level of uncertainty (perceived by vaguely noticeable gray ribbon). Similarly, the time-variant regressors contributed heavily to price variation, mainly in the first semester of 2014 and 2017 up to the end of the period of analysis.

As it has been mentioned, one of the main features of the state space framework is its

[26]The mean squared error (MSE) is represented as $\frac{\sum_{t=1}^{n} \varepsilon_i^2}{n}$

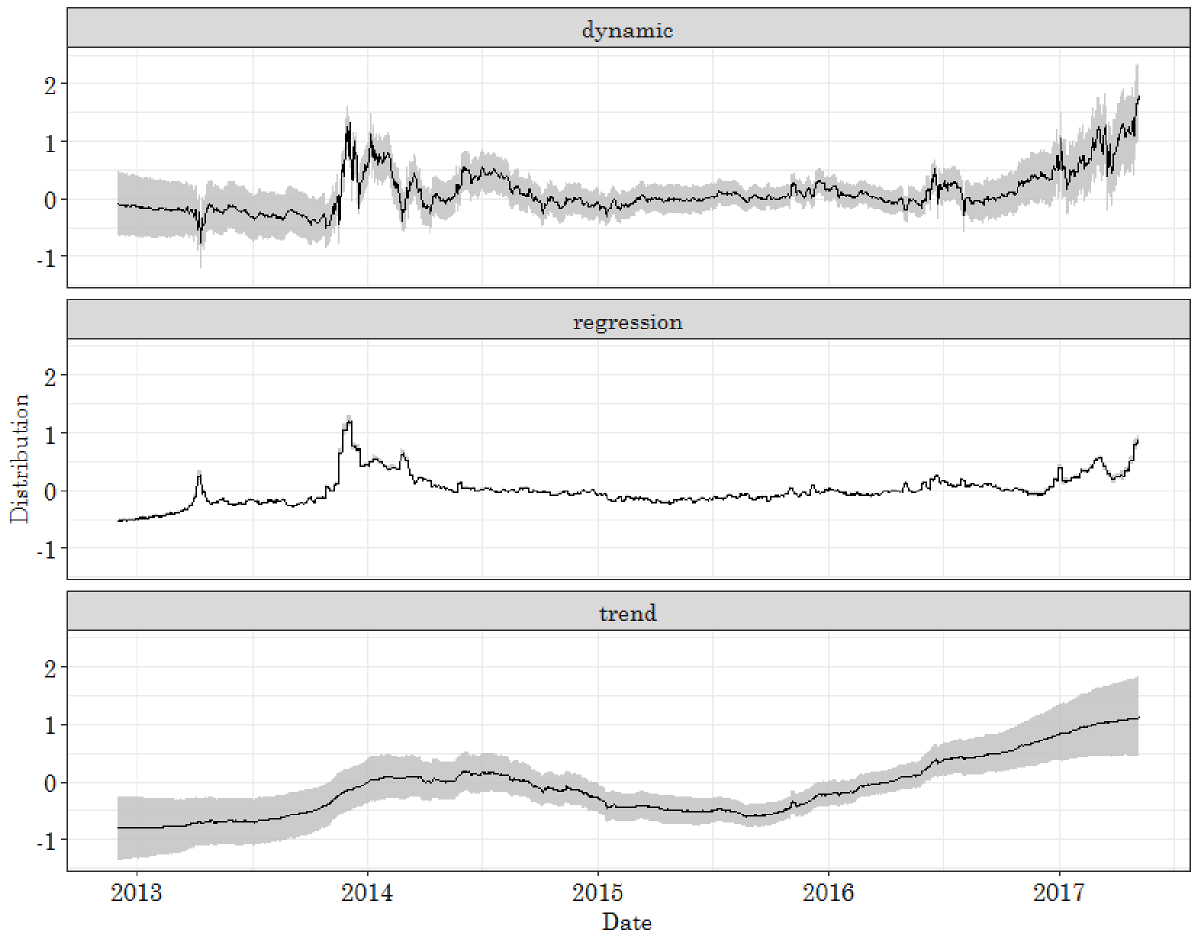


Figure 2.6. Decomposition of the LLTTV model for Bitcoin price

ability to decompose the prediction into diverse components. Figure 2.6 above illustrates the contribution of each of these components, where we can highlight the slope trend signal estimated recursively by the Kalman filter. The medium panel shows the effect of time-invariant regressors that provided prediction power to explain Bitcoin price by the end of 2013 and beginning of 2014, with an overall level of uncertainty (perceived by vaguely noticeable gray ribbon). Similarly, the time-variant regressors contributed heavily to price variation, mainly in the first semester of 2014 and 2017 up to the end of the period of analysis.

2.6.1 Posterior estimates results

It has been conducted an estimation of Bitcoin's price based on a set of internal and external demand factors. However, it is precise to organize the empirical analysis in five sections in order to present clearly the process of the methodology. In the first part I will provide a description of the hyperparameters and prior calibration, in the second part, I describe the results of the variable selection procedure, thirdly, the static and dynamic coefficient estimates and final the prediction comparison across models.

2.6.2 Hyperparameters and priors calibration

In the variable selection section, it was stated that the Spike and Slab method discriminate coefficients based on the values of τ, where the prior for this parameter follows a Bernoulli distribution. In this study, it has been run 30 different MCMC simulations with 3000 (discarded 981 draws as they represent burn-in period) iteration each (Figure 2.12) with an uninformative prior of 0.5 as the authors suggested, and a prior mean equal to 0 for all variables. This process was done in computationally terms it is imperative to use multiple "seeds", that is, different random number generators in order to learn about the "true" posterior probabilities.

In Figure 2.12 can be denoted that there are a group of variables that commonly have a fairly stable non-zero coefficient, that is the case of gold price, S&P500 and search trends from Colombia (trend_co), while Hash Rate of VIX is asymptotical to zero and unstable. Since one of the most attractive characteristics of the Spike and Slab approach is the possibility to learn from the posterior distribution, and incorporate the information as a prior for further analysis, the best guess for the prior to incorporate in a unique MCMC simulation used as a base for the model is to mean inclusion probability a coefficient means values. This process is usually called as "empirical Bayes" that is, utilize previous information results to "shrinkage" subsequent simulations[28]. This procedure intends to address the problem of limited computational power to estimate through a single MCMC "true" posterior probabilities, hence, I integrate information at multiple simulations to provide more accurate inference for the reference model[29].

Figure 2.7 shows the density of the variables whose mean inclusion probabilities surpassed the 80% for six distinct simulations with 10000 MCMC iterations (discarding a burn-in it would effectively 8129).

As it was stated before, previous research on this topic has been conducted using search trends as an attractiveness proxy, but only considering the signal of all countries on Google, however, the behavior varies significantly across countries. Hence, the variable selection procedure helps us to discern which series have higher prediction power.

2.6.3 Marginal posterior regression estimates

Following the methodology, I estimate a Bayesian Structural Times Series model of Bitcoin's price drivers, in this model the dependent variable is the standardized level of Bitcoin's price, not the returns. Table 2.2 summarizes the statistics associated with estimating the change in the standard deviation of Bitcoin's price given one standard

[28] Stability of the further simulation was proved given the update of the priors (Figure 2.13)
[29] Extension of the process are described in detail in (Xi et al. 2016)

deviation change in the. Estimation was constructed from the updated prior, marginal posterior means, medians (both are nearly identical since the distributions are seemly symmetrical), 95% highest density intervals (HDI) as well as non-zero probability. The first thing to note regarding the results in Table 2.2 is the zero in the intercept, this result derives from the standardization of the variables, additionally we can see the presence 17 relevant variables out of the 55 that we have considered in first place. Additionally, it has been estimated the dynamic coefficient for those variables that have a relevant non-zero probability of being part of the model.

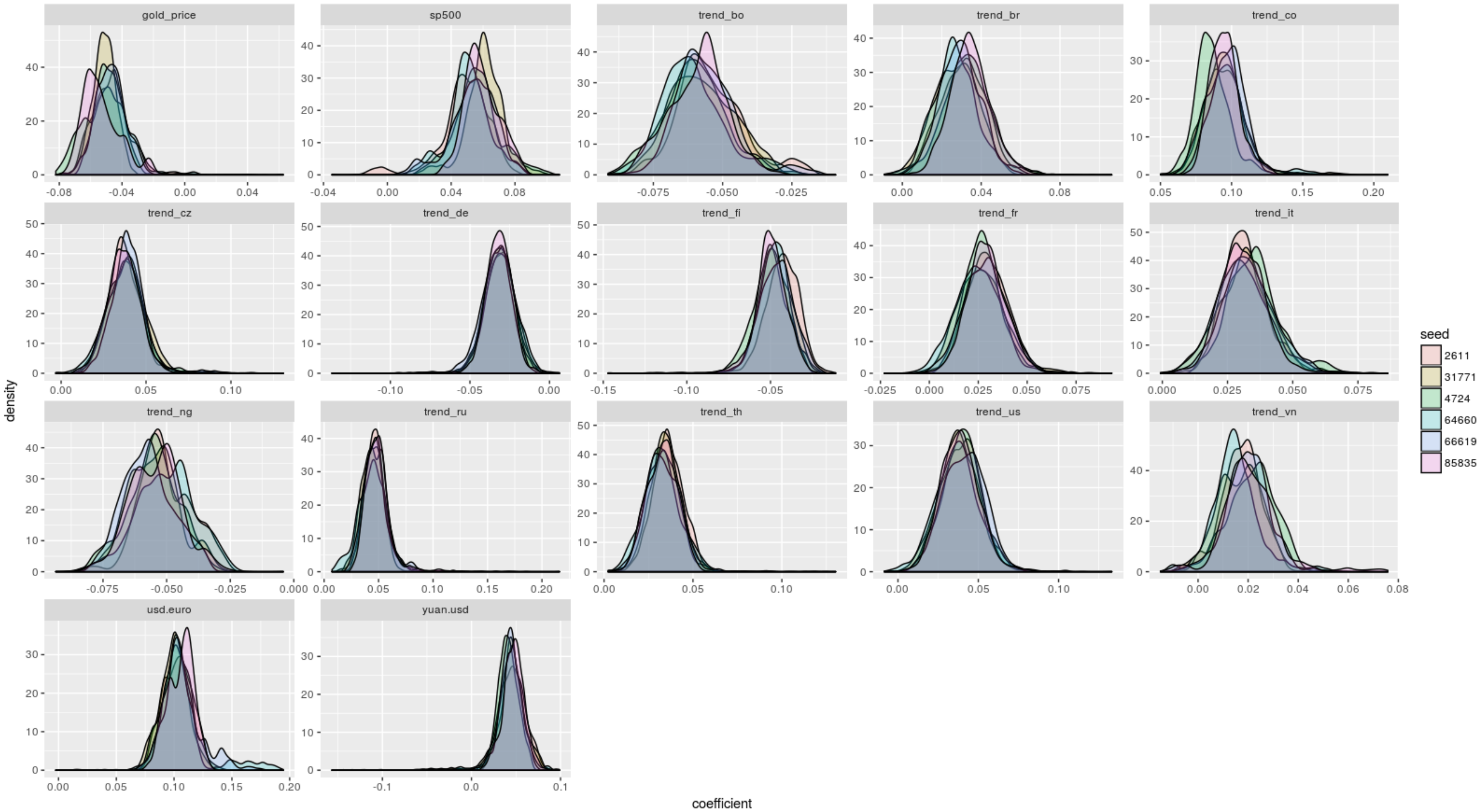


Figure 2.7. Multiple simulation posterior densities for the non-zero inclusion probability variables

2.7 Discussion

An estimation of Bitcoin price based on a set of internal and external demand factors has been conducted. This section focuses on the analysis of BTC price given the different explanatory variables.

2.7.1 Internal determinants

Among the internal variables that are directly related to bitcoin, I have not found any relevant effect on Bitcoin price. It was expected that the daily median time take for transactions to be accepted into a block would have a negative association with the price. However, one change in the standard deviation had zero effect, with an inclusion probability of just 0.07%. Similarly, the hash rate which measures the productivity and difficulty of the blockchain had had a very low non-zero probability of being part of the model. This result differs from Kristoufek (2015) and Georgoula et al. (2015) who found a positive, however, small (and diminishing in the case of Kristoufek (2015)) effect on Bitcoin price. Other variables such as transactions excluding popular addresses and trade volume had a slightly higher inclusion probability (2.3% and 3.9%) than hash rate and confirmation time, however negligible.

2.7.2 Attractiveness determinants

In this section, the outcomes for the attractiveness or interest for Bitcoin will be provided. Before starting the analysis, it is precise to highlight that popularity of Bitcoin, and by extension the interest measured by search trends, indisputably exhibits several limitations as an attractiveness proxy. First of all, we do not know the true reasons why people from different countries search the internet. Secondly, the fact that a person is interested in gaining information does not necessarily mean that he or she is going to actively participate in the market. Nonetheless, given that it is almost impossible to distinguish where the transactions take place, search trends provide a good approximation. As was stated, there is a great difference in the behavior of the signal across countries, an aspect that has not been analyzed in empirical studies. Hence, this characteristic can be interesting and can provide further detailed results, since the different governments have been developing policies either to provide a legal framework or to limit the use of Bitcoin.

Among the countries in consideration, 13 out of 44 had a high probability of being part of the final model. Additionally, the interest appears to differ significantly in sign and magnitude amid the selected series. The marginal posterior mean and HDI for Colombia is 0.092 [0.075, 0.105], that is 1 standard deviation change in the searches for "Bitcoin" in Google from this country is associated with almost 0.1 standard deviations

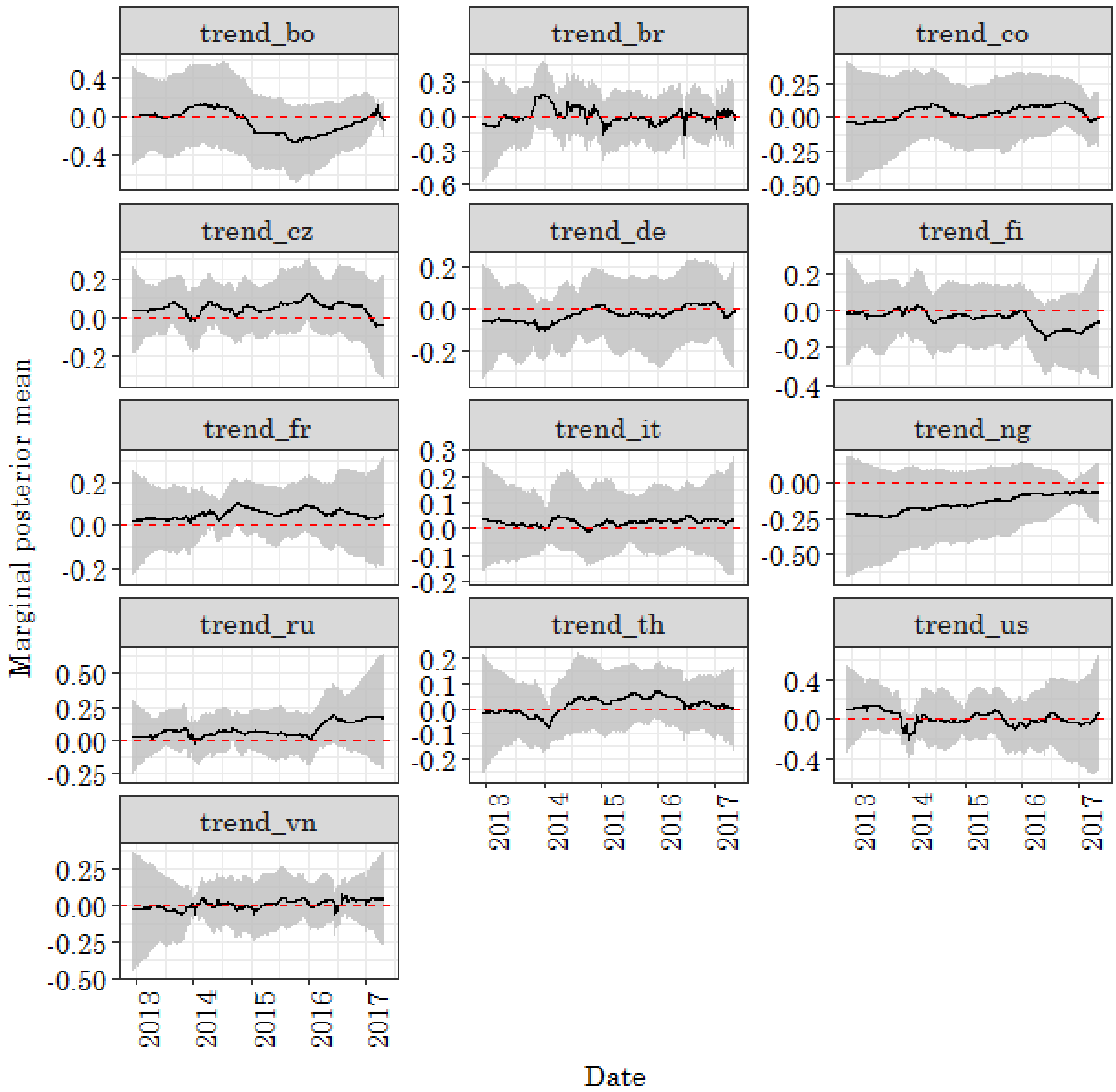


Figure 2.8. Dynamic standardized coefficients for attractiveness drivers

change in Bitcoin price. Furthermore, the aforementioned country has a common cluster's leaf with two other selected trends which show nearly identical posterior means, Bolivia (-0.058 [-0.073, -0.041]) and Nigeria (-0.057 [-0.070, 0.044]). Both countries' governments have emitted a formal warning about the use of Bitcoin to make transactions since it is not a legal tender. The dynamic regression results (Figure 2.8) provide a more accurate description of the marginal probability distribution over time of the standard deviation effect of search trends. For instance, the coefficient of Bolivia switched from positive to negative at the end of 2014, while Nigeria's negative effect has been fading since 2013.

Among the marginal posterior means estimates Russia (RU) has one the highest effects on of the price with 0.051 [0.036, 0.066] (Table 2.2), with a special aspect to consider.

By the beginning of 2016, the marginal posterior mean jumped to 1 standard deviation in the search trends from Russia, which has been linked with nearly 0.15 standard deviations change in Bitcoin's price. A possible explanation of this movement can be attributed to an increasing depreciation of the Ruble against the USD, occasioning a further reaction from the public to look for ways to preserve their wealth. Furthermore, Russian government's explicit opposition exposed by harsh fines might have fueled and extended the fads and interest rather than reducing it. Another country where BTC has an important relevance is Venezuela (VN), where the time-invariant marginal posterior mean shows that 1 SD change in a number of queries in Google is associated with 0.031 [0.020, 0.041] SD's in the BTC price. According to the news[32], the political and economic conjuncture, loss of government fate and uncertainty, have been producing interest in Bitcoin for its use for multiple purposes. Firstly, the job of so called "bitcoin miners" is especially attractive since the earnings are protected from bolivar's (Venezuela's currency) extreme inflation. Secondly, buying basic needs (after being exchanged for dollars) inside and outside the country and as a safe haven asset. As can be noted in Figure 2.12 in the appendix, the trade volume of Bitcoin has been increasing rapidly after 2016. As for the United States (US), France (FR), Italy (IT) and Czech Republic (CZ) the results indicate a clear-cut positive association of Bitcoin's volatility, with a higher participation of US with 0.054 [0.039, 0.069] standard deviation change in the price. The time-variant marginal posterior means (Figure 2.8) show for this group positive relationship over in the years 2013-2017 but on the other hand, a short period of negative impact can be distinguished and was evidenced in 2014, especially in the US where it reached -0.2 standard deviation change.

2.7.3 Macro-financial determinants

Macroeconomic variables such as exchange rate also play a relevant role in uncovering the current use of BTC. By now I have proven that internal factors are not relevant, while attractiveness in almost half of the countries does present a high probability of being part of the final model that describes standard deviations movements on BTC price. Although several attractiveness variables may have contributed to answering the question if drivers also played a significant role. Among the variables in this group, I have found that the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) together with Bearish sentiment were excluded from the final model with only 0.8% and 0.9% probability of being selected (Table 2.2). This result differs from Bouri et al. (2017) outcomes since the authors found that uncertainty has a significant negative

[32]Articles referring details about this situation can be reviewed in "The Guardian" Growing number of Venezuelans trade bolivars for bitcoins to buy necessities, "Business Insider", Venezuela is cracking down on 'bitcoin fever' and "The Washington Post" Bitcoin mining' is big business in Venezuela, but the government wants to shut it down.

impact on BTC returns and by extension being a hedge against that uncertainty. However, the results of this study show that the gold price, S&P500 and bilateral exchange rates are related to Bitcoin price.

Even though Bitcoin is a recent invention, it has been gaining attention as an investment asset. Correspondingly, Bouoiyour and Selmi (2016) hypothesizes that even though there is plenty of literature of how precious metals can act as a safe haven or hedge, few authors have tried to answer if Bitcoin behaves in the same way as gold or silver in risk situations in the stock market given their fair stability over time. This hypothesis is shared by Bouri et al. (2017) and Dyhrberg (2016) who states that "generally, economists have compared bitcoin to gold as they have many similarities". Additionally, Abad and Iyengar (2015) argues that transcendental political events (Trump election specifically) might generate stock market due to geopolitical uncertainty, an event that could generate interest in Bitcoin.

According to the results shown in Table 2.2, one SD change in the gold's price is linked to -0.051 [-0.062, -0.040] SD's change in BTC price, with an inclusion probability of 100%. Henceforth, given that a hedge is an asset that is marginally negative correlated with another asset Baur and Lucey (2010), the coefficient suggests that Bitcoin acts as a hedge in relation to the gold, plus the prospect characteristic of being the "digital gold", these results are similar to Dyhrberg (2016). The results in Figure 2.9 indicate that the dynamic coefficient has been typically negative during the period in the study, where the effect started to diminish from the third quarter of 2014 and regaining its previous state until the first quarter of 2017. In between a positive standard deviation variation opening 2016 can be observed.

Looking at the relationship to the stock market indicator, the model shows that one SD variation in the S&P500 index is on average associated with 0.057 [0.044, 0.069] SD change in BTC price. However, from the time-variant estimation (Figure 2.9) the negative association can be noticeable (yet small) from 2013 until the second semester of 2014. Posteriorly there is a switch in the sign that lasted up to 2017, then it became negative again. From the jargon proposed by Baur and Lucey (2010), can be determined that Bitcoin has been performing as a diversifier and hedge, with a tendency converge at the end of the period of analysis to the latter.

Regarding exchange rates, there are two aspects that deserve further attention. Firstly, following credibility intervals it is straightforward to conclude that the effect on Bitcoin is reasonably stronger in comparison with any other price driver studied. Secondly, there is a substantial difference both in the sign and behavior of time-variant coefficients over time of both bilateral exchange rates into consideration. The results suggest that one SD change in the USD-Euro exchange rate is linked to 0.099 SD's change in BTC price, with a 95% probability that this value is going to be positioned

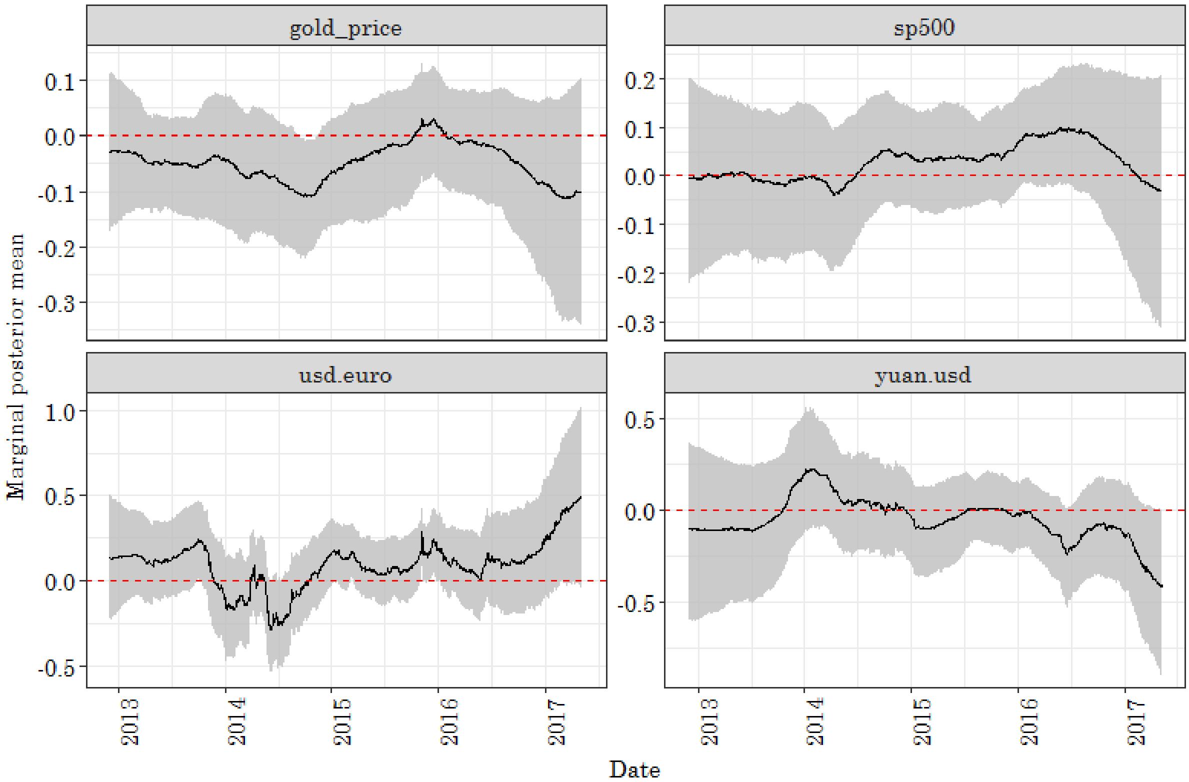


Figure 2.9. Time-variant standardized coefficients for macro financial drivers

in the range 0.088-0.112. On the other side, one SD change in the Yuan-USD exchange rate is associated with 0.039 [0.027, 0.054] change in the SD of BTC price. Nonetheless, dynamic coefficients provide a more informative perspective of BTC relationship with exchange rates, which is the case for the last two months of 2013 when the price reached $1242 per BTC (surpassing for a small period of time gold's price), incident that attracted global attention towards cryptocurrencies. The lowest row of graphs in Figure 2.9 depict the effect of the sudden rise in BTC price on exchange rates, in USD-Euro case, the effect switched signs from nearly 0.23 to -0.17 SDs in BTC price given one SD change in USD-Euro exchange rate, followed BTC price behavior in the second rise that took place in midst 2014. Regarding Yuan-USD exchange rate[34] 1 SD increase in this variable leads to an increase of 0.039 [0.027, 0.054] SDs in BTC price. However, this might seems deceptive given results exposed in Figure 2.9, it happens due to the dependency of the prior selection, and hence the time-variant marginal posterior provides a proper interpretation of the relationship. As described in the graph, a positive unit change in the SD in Yuan-USD leads over most of the time to a negative impact on BTC price volatility, with an acceleration by the end of the period of analysis.

[34]This value can be misleading since as depicted in Figure 2.13 in the appendix, the marginal posterior distribution for Yuan-USD is bimodal, that is, with two local maxima, one negative around -0.03 and other positive around 0.08. Since the Slab component on *SL* variable selection is normally distributed, I have decided to keep the prior distribution as it is and set a naïve approximation for the mean of the bimodal distribution.

From a macro-financial factor driver's point of view, it seems that BTC price variation is more sensible to exchange rates than stocks market deviations. Additionally, the results seem to be related to (Dyhrberg 2016) in the sense that BTC has properties that range between a currency and a commodity.

2.8 Conclusion

Bitcoin represents an amalgam of attributes that have demanded a deep meditation of each portion in order to understand its role in the contemporary economic scene. Hence, as digitization is call to disrupt the status quo in many areas, Bitcoin has been positioning as a significant yet not for now overwhelming rival to formal alternatives from the payment systems perspective. And even though the volume of transactions is currently negligible in comparison with bank related exchanges it already defiance prevalent conceptions several times. On the other side, Bitcoin is also considered as a financial instrument, and an attractive product for speculators, situation that have been increasing in complexity due to its scale and volatility of its price since it began in 2008. This study undertake the problem of finding the determinants or drivers for Bitcoin price measured by the exchange rate with the dollar for the period January 2013 to May 2017. I have used a combination of Spike and Slab variable for variable selection and Structural Time Series for the estimation of both static and time-variant coefficients. In general terms, the research revealed that Bitcoin possesses a multi-faceted property, however none of the internal factors have a relevant impact on the price, instead it responds to attractiveness in selected countries and most macro financial variables. The dynamic analysis of the BTC price has yielded new insights about the relationship between different factors. Regarding the attractiveness as a currency or investing asset, this research found evidence of different effects between countries and deviations in within time with a significant consideration of Brazil and United States during the first time that Bitcoin's price skyrocket and Russia positive impact in the beginning of 2016. It has been speculated that Bitcoin might be entering in a new phase (Bouoiyour & Selmi 2016b), in this regard the increasing effect of attractiveness may be an indicative prospect of such argument. For macro-financial factors, this study found that in absolute terms Bitcoin's price is more affected by exchange rates than a commodity like gold or stocks indicator. On this subject, according to the results yuan depreciation with the dollar has been generating an increase in Bitcoin price in the first quarter of 2017. Generally, it has been found that Bitcoin behaves as a financial instrument with tendency to be a speculative asset, but this study also had shed light into the existence of an increasing mass of potential users as a currency or capital flight instrument.

2.9 Appendix

2.9.1 Appendix 1: Standardized coefficients effects on interpretation

Standardization of both sets of regressors and independent variables leads to several changes in interpretation and results. Here I present some of the very common:

1. The coefficient between x and y standardized variables will be equal to the covariance of them.

$$\beta^*_{yx} = \frac{cov(z_y, z_x)}{var(z_x)} = \frac{cov(z_y, z_x)}{1} = cov(z_y, z_x)$$

2. As expected, the covariance of x on y is equal to the covariance of y and x

$$\beta^*_{xy} = \beta^*_{yx}$$

3. The covariance between two standardized variables is equal to the correlation between them

$$\rho_{xy} = \frac{cov(z_y, z_x)}{\sigma(z_x)\sigma(z_y)} = cov(z_x, z_y)$$

2.9.2 Appendix 2: Gibbs sampling

Gibbs sampling generates posterior samples by smoothly moving through each variable to sample from its conditional distribution with the remaining variables fixed. The algorithm does not sample from the posterior directly, insteads, it simulates samples from one random variable at a time. According to MCMC theory, the Gibbs sampler will converge to the target posterior (Yildirim 2012). For X_D random variables the algorithm works as:

$$Initialize\ x^0\ q(x)\ for\ iteration\ i = 1, ..., do$$

$$\begin{aligned}
x_1^1 &\sim p(X_1 = x_1 | X_2 = x_2^{i-1}, X_3 = x_3^{i-1}, ..., X_D = x_D^{i-1}) \\
x_2^1 &\sim p(X_2 = x_2 | X_1 = x_1^{i-1}, X_3 = x_3^{i-1}, ..., X_D = x_D^{i-1}) \\
&\vdots \\
x_3^1 &\sim p(X_3 = x_3 | X_1 = x_1^{i-1}, X_2 = x_2^{i-1}, ..., X_D = x_D^{i-1})
\end{aligned}$$

Table 2.2. Time-invariant statistics of the standardized coefficients

Variable	Mean	2.5%	97.5%	Inc.Prob.
(Intercept)	0.000	0.000	0.000	0.000
Median conf. time	0.000	-0.002	0.003	0.007
Bearish sentiment	0.000	-0.003	0.001	0.008
Gold's price	-0.051	-0.062	-0.040	1.000
Hash rate	0.000	-0.011	0.009	0.016
My wallet trans.	0.000	-0.003	0.006	0.014
Trans. excl. popular	0.000	-0.006	0.016	0.023
S&P500	0.057	0.044	0.069	1.000
Trend Argentina	0.000	-0.011	0.001	0.027
Trend Austria	0.000	-0.011	0.013	0.019
Trend Bulgaria	0.000	-0.013	0.004	0.026
Trend Bolivia	-0.058	-0.073	-0.041	1.000
Trend Brazil	0.042	0.028	0.056	1.000
Trend Canada	0.000	-0.010	0.013	0.019
Trend Chile	0.000	-0.007	0.006	0.018
Trend China	0.000	-0.002	0.001	0.005
Trend Colombia	0.092	0.075	0.105	1.000
Trend Czech Republic	0.041	0.027	0.054	1.000
Trend Germany	-0.033	-0.047	-0.019	1.000
Trend Denmark	0.000	-0.008	0.007	0.011
Trend Ecuador	0.000	-0.006	0.005	0.009
Trend Spain	0.000	-0.006	0.007	0.012
Trend Finland	-0.038	-0.051	-0.025	1.000
Trend France	0.042	0.028	0.056	1.000
Trend United Kingdom	0.000	-0.007	0.011	0.014
Trend Ghana	0.000	-0.009	0.003	0.013
Trend Guatemala	0.000	-0.002	0.001	0.003
Trend Honduras	0.000	-0.001	0.002	0.003
Trend Croatia	0.000	-0.007	0.006	0.015
Trend Hungary	0.000	-0.007	0.005	0.021
Trend Ireland	0.000	-0.007	0.006	0.010
Trend Iceland	0.000	-0.002	0.002	0.005
Trend Italy	0.031	0.018	0.044	1.000
Trend Japan	0.000	-0.007	0.008	0.011
Trend Luxembourg	0.000	-0.002	0.007	0.016
Trend Morocco	0.000	-0.006	0.008	0.019

Variable	Mean	2.5%	97.5%	Inc.Prob.
Trend Mexico	0.000	-0.005	0.006	0.007
Trend Nigeria	-0.057	-0.070	-0.044	1.000
Trend Netherlands	0.000	-0.005	0.013	0.015
Trend Norway	0.000	-0.006	0.004	0.010
Trend Poland	0.000	-0.010	0.007	0.011
Trend Portugal	0.000	-0.002	0.006	0.011
Trend Paraguay	0.000	-0.002	0.004	0.005
Trend Russian Federation	0.051	0.036	0.066	1.000
Trend Sweden	0.000	-0.010	0.005	0.015
Trend Slovenia	0.000	-0.004	0.002	0.006
Trend Thailand	0.036	0.024	0.050	1.000
Trend Taiwan	0.000	-0.005	0.004	0.009
Trend Ukraine	0.000	-0.011	0.004	0.016
Trend United States	0.054	0.039	0.069	1.000
Trend Vietnam	0.000	-0.006	0.008	0.013
Trend Venezuela	0.031	0.020	0.041	1.000
Exchange Trade Volume	0.000	0.000	0.012	0.039
USD-Euro exchange rate	0.099	0.088	0.112	1.000
VIX	0.000	-0.003	0.003	0.009
YUAN-USD exchange rate	0.039	0.027	0.054	1.000

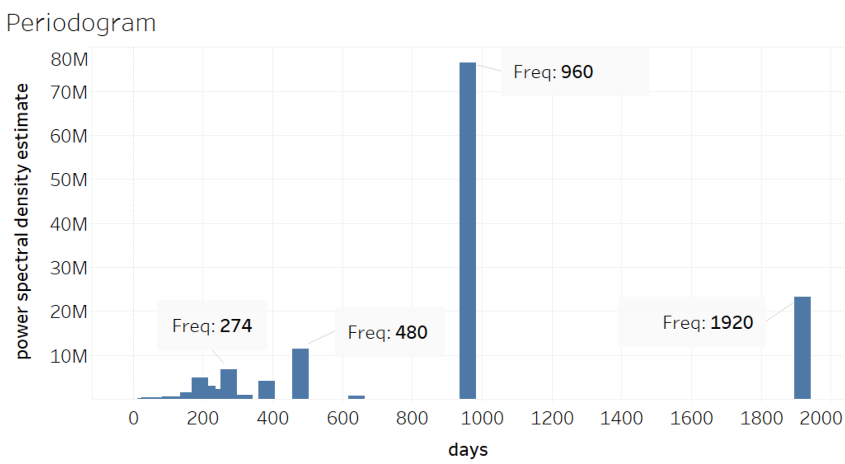


Figure 2.10. Periodogram of Bitcoin's price

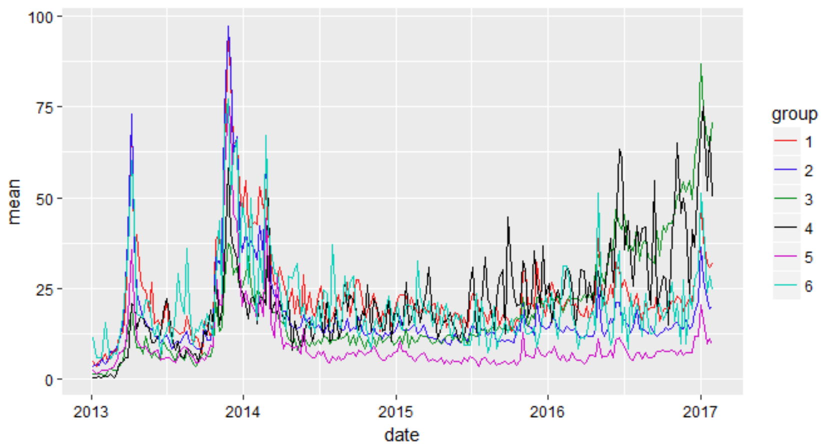


Figure 2.11. Average search trend values by cluster

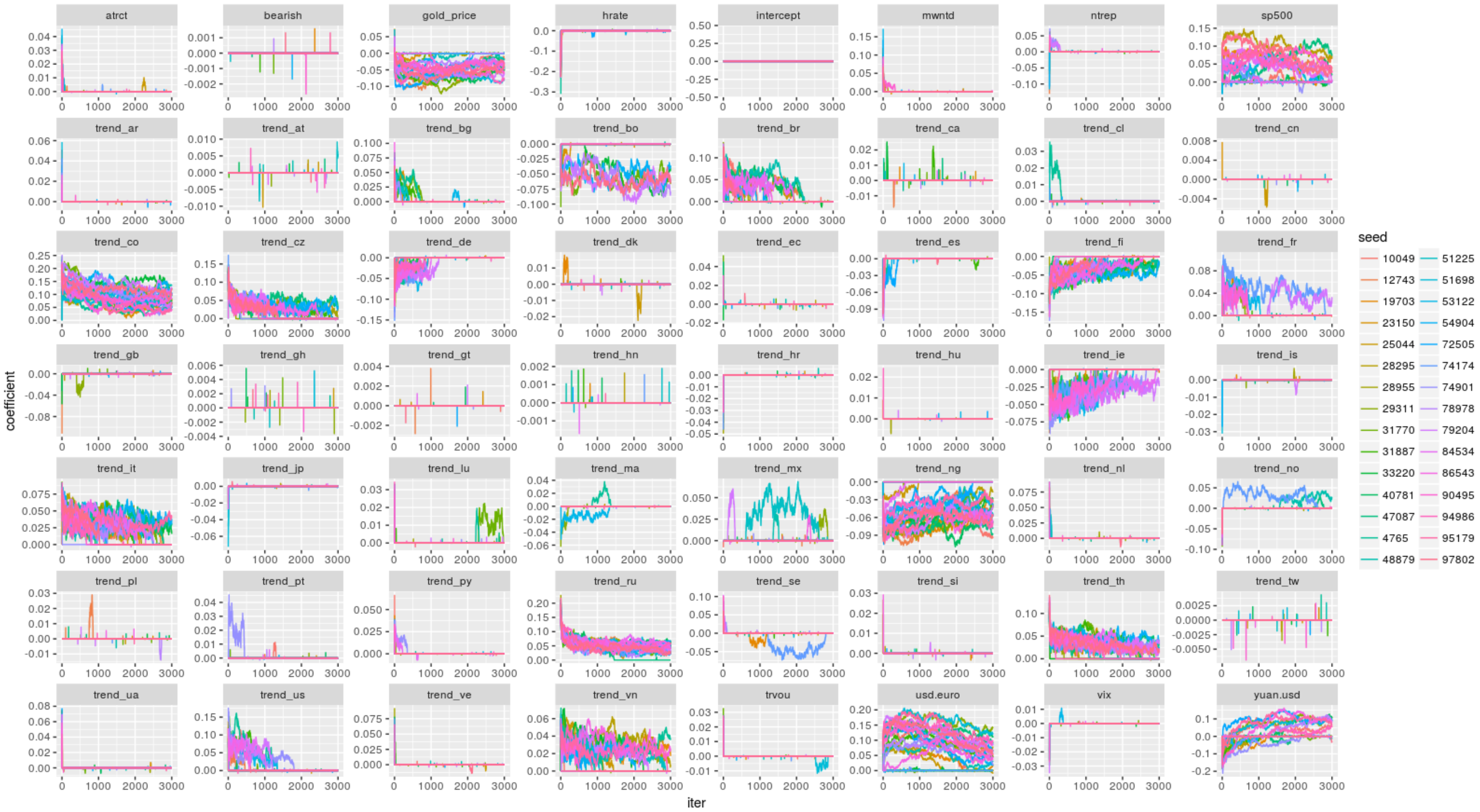


Figure 2.12. Markov chain and Monte Carlo Simulations for time-invariant β coefficients

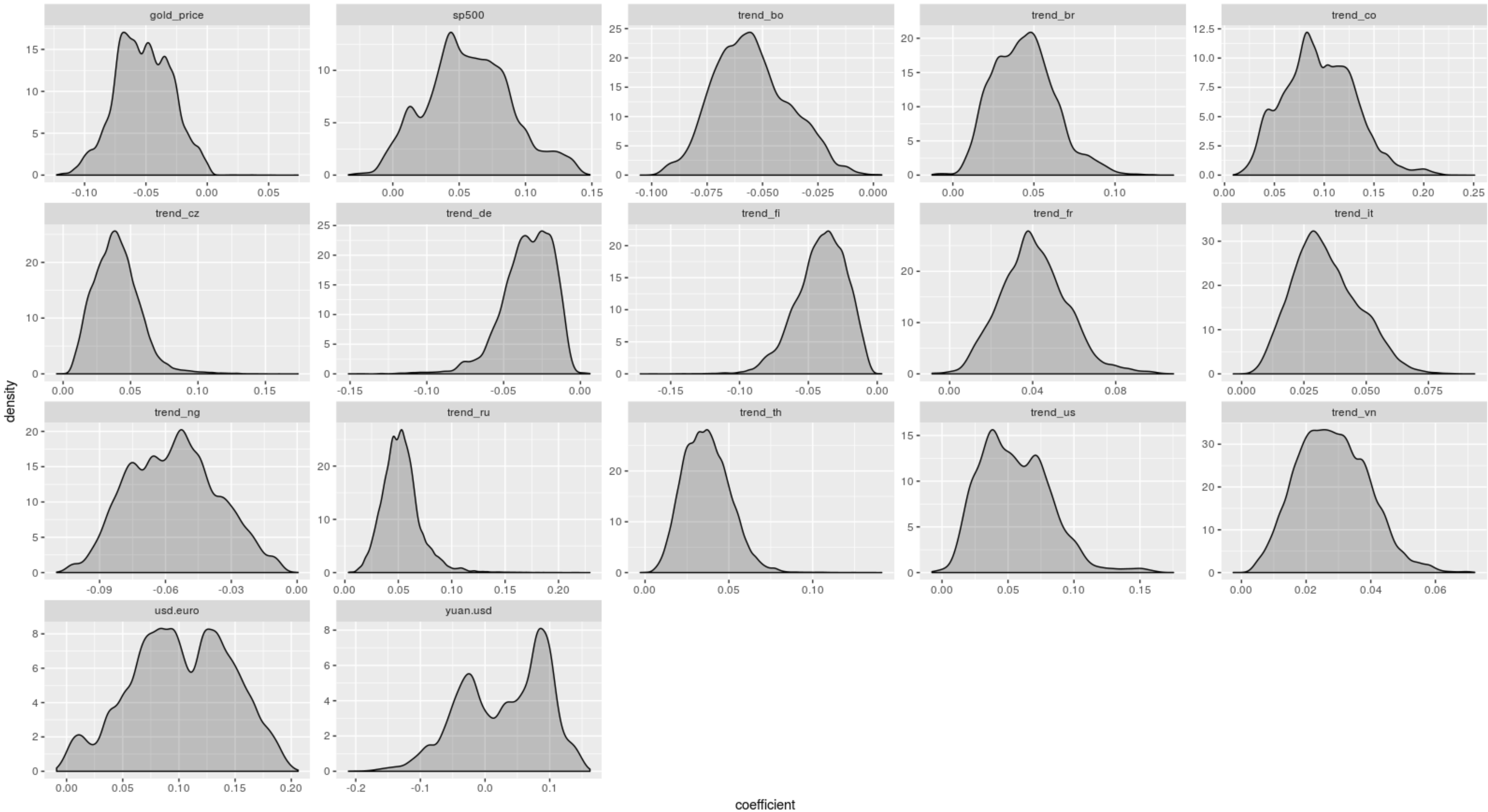


Figure 2.13. Marginal posterior distributions employed to generate priors

Chapter 3

Investors' biases and herding behavior in the cryptocurrency market

Abstract

Crypto-markets lack of fundamental value, henceforth, individuals interacting within are presumably bias-prone as it has been documented in financial-like markets. This study objective is two-fold. Firstly, it aims to describe how theory on behavioral economics serves as a framework to to understand crypto-markets. Secondly, it is suggested that cryptocurrencies' prices are driven by herding behavior. Concretely, this study test for behavioral convergence under the assumption that prices are the coordination mechanism. For this task, it has been proposed an empirical model to assess for herding behavior under asymmetric and symmetric market conditions and accounting for the existence of stochastic states by employing the Markov-Switching approach. The results show that herding is a *regularity* instead of an *anomaly* of crypto-markets; therefore, individual usually ignore their own priors and follow the aggregate market consensus.

keywords: Cryptocurrencies, Herding, Biases, Markov Switching
JEL: G40, G41, C32, D81, D83

3.1 Introduction

The digital economy has been increasing the exposure of state-of-art ideas, opportunities, and changes in economic paradigms. Cryptocurrencies as well as Blockchain's technology, and other potential applications are, without any doubt, a relevant concept that has emerged on this "new economy." One could assure that most of the interest in cryptocurrencies was fueled by Bitcoin, the first successful implementation of a peer to peer network that could serve as a payment method or an asset. The responsiveness from the public has been trigger in part from the extreme upswings and downswings in prices, which has also been illustrated to some degree by other alternative coins such as Ethereum, Ripple, Tokens or Initial Coin Offering (ICO's). As portrayed by chapter 2, it is difficult to align a future in which cryptocurrencies make a significant economic change under current extreme price movements exhibited without the existence of salient announcements.

The understanding of crashes in stock markets has been difficult for economists for several years. Theoretical foundations in financial economics rely ultimately on the assumption of the efficiency of markets. Nonetheless, several studies have found empirical evidence that contradicts what could be considered the cornerstone of efficient markets. The behavioral economics uncover systematic deviations from rationality exposed by investors by arguing individuals are the victim of their cognitive biases, leading to the existence of financial market inefficiencies, fragility, and anomalies. Particularly, crypto-currency market has several common characteristics that fit to the criticisms on financial markets exposed by behavioral finance advocates.

Studies of behavioral finance aim to explain why investors in stock market settings act as they do. In this work, it is hypothesized that it is possible to explain crypto-market prices' puzzle from a behavioral finance perspective in which investors' cognitive biases play a significant role to explain the market dynamics. In this context, this paper makes a literature revision on empirical and theoretical evidence in which investors' actions have been proved are not aligned with a national benchmark, serving as a parallelism to the crypto-market problem. Furthermore, this paper seeks to shed light on the price setting puzzle by attributing price movements to investors herding behavior, that is, a collective decision-making process in which prices "as is" are the coordination mechanism to investment decisions. According to the literature, herding can trigger the formation of speculative bubbles, thus, the main objective of this chapter is to study cryptocurrency market under the hypothesis that crypto-investors have limited resources to process information and weak prior knowledge, as a consequence they rely on others sources to form beliefs and expectation on crypto-markets.

The most striking result that stems from the symmetric model is that herding is not an unusual phenomenon or *anomaly*; instead it is a *regularity* of the crypto-market. There is a tendency to either herding or scattering (commonly named adverse-herding as well) dynamics, representing an opposition to what a rational asset pricing would expect where investors follow their private information. Crypto-investors herd when market is exibiting positive negative returns, nonetheless, the magnitude in which they react to declining conditions is almost three times greater than what could be seen in increasing conditions. Crypto-investors seem to be more affected by the likelihood of losing money, henceforth, they outweight "bad news," conveyed by a seemly declining evolution of the coordination mechanism.

Moreover, it has been concluded that passing from regimes typically characterized by adverse-herding behavior to regimes have a non-neglibible probability of passing to another regime where the is consensus either due to extreme returns and uncertainty. Another interesting result is that if the market does follow a strong aggregate positive feedback strategy, there is a high likelihood that the next state will be strong herding as well. This means that once there is evidence of people to ignore their own priors substantially, herding propagates in the market, which is unlikely to be corrected back to the "normal" state. Herding is ubiquitous to crypto-markets, but there is evidence of being stronger when the market is declining, unveiling a unique decision-making process to respond to a negative outlook.

The layout of this chapter is as follows: section two discusses the idiosyncracy of cryptocurrency market behavior and how some speculative-triggering elements resembles what has been historically seen in the past. Section three provides an overview of the most relevant literature to understand the biases and tendency to form trading strategies following a positive feedback strategy, namely: herding behavior. Section four describes the methodology and the data which is going to be used for this work. Section five shows the the empirical results and discussion on herding behavior. Finally, section six summarizes the main outcomes of this research.

3.2 Background

It has been said that theory on financial economics formally started in 1900 with Bachelier (1900), who was interested in the application of random motion to explain the movements of prices of a popular investment tool named "perpetuity bond." In order to explain price dynamics, he implemented the random walk, that is, a path created by the succession of random uncorrelated steps in which a given equal probability buffets each move. The first insight present in Bachelier (1900) is that prices movements will tend to be on the average (zero) given an equal probability of going "up" or "down," therefore the trajectories are neutralized or canceled. Additionally, the level in which prices fluctuate is named *"fundamental value"*, and the so-called Gaussian distribution[1] governs any deviation or fluctuation created by the forces of the market (active participation from multiple investors) around this value. Hence, any possibility of predicting future values is impossible, and therefore, there is no deterministic chance to arbitrage both for sophisticated and unsophisticated investors. This result is possible due to the constant feedback dynamics products of the constant participation, that is, any strategic information in the hands of an investor is quickly recognized and eliminated by others in the market who analyze prices[2]. Up to now, it has been described the cornerstone characteristics of the Efficient Market Hypothesis (EMH) which had been intensively improved by other significant contribution of Eugene Fama, Stephen Ross, Robert Merton, Myron Scholes, William Sharpe, among other whom works set the basis to the contemporaneous modern finance theory.

Several conclusions stem from the statements exposed above, first, financial prices embed inside the sum of all information publicly provided over time, hence assets price are always correct, and any deviation is only product of the active market interchange[3]. Second, it is not possible to forecast any further price change; therefore, one could not systematically beat the market (Read 2012).

A reasonable question to bear about is if such theory is indeed a good starting point to describe crypto-markets. Speculation has been a concern that takes back upon the times of John Maynard Keynes, who proposed a tax on financial transactions that were excessively speculative. With the purpose of limiting the market to be composed by legitimated investors and thus mitigate the impact on the economy in case a potential burst (Keynes 1936; Read 2012). Speculative bubbles have been increasing in attention since modern finance cannot explain how events such as Black Monday, Dot-Com and the financial crisis in 2008. Along the same line, Robert Shiller has assured that the financial market is driven exclusively by behavioral issues among the participants (speculative component outbound fundamental component).

[1]Nowadays there is consensus on the idea that there is no need to be attached to a Gaussian distribution.

[2]Fama (1965) describes accurately what an efficient market means by saying: *"An efficient market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the several sophisticated participants leads to a situation where, at any point in time, actual prices of individual securities reflect the effects of information based both, on events that have already occurred and current ones, that form expectations. In other words, in an efficient market at any point in time, the actual price of a security will be a good estimate of its intrinsic value"*

[3]In Shiller (2015), the author severely criticized such assumption by saying: *"price may appear to be too high or too low at times, but, according to the efficient markets theory, this appearance must be an illusion."*

3.3 Literature review

A basic tenet of classical economic theory is that investment decisions reflect agents' rationally expectations; that is, decisions are made efficiently using all available information. A contrasting view is that investors are also driven by herd behavior, which weakens the link between information and market outcomes (Devenow and Welch 1996; Scharfstein and Stein 1990). In one sense, the EMH was so successful because it seemed to dispel the previously dominant notion of an irrational market driven by herds[4]. The perceptions of Mackay (1852) and Kindleberger and Aliber (2005) follow the line that there was convincing evidence of "bubbles" of mass errors caused by the fickle nature of herds.

To some extent, what has been happening with cryptocurrencies is closely related to the criticisms on the rationality of investors. Having said that, behavioral finance tries to unveil market outcomes under the existence of a large group of irrational investors by studying real-world investors' beliefs and valuations. Naturally, new (and old) investors are dependent on information on fairly diversified sources, that is, individuals interested in cryptocurrencies usually form beliefs, trading strategies based on two primary sources: news and social media. Nowadays, many trends start in specific forums; in these spaces, users share impressions about last news and recent issues like unexpected upswings or downswings in cryptocurrencies price or innovations in the Blockchain platform. That is a case of Reddit, a social news aggregation website in which people discuss a wide range of topics, particularly the community of cryptocurrencies is the biggest one among the internet, with more than 600.000 subscribers. There are a wide variety of users (sophisticated and unsophisticated); as a result, opinion formation on this community unveil different investment strategies such as discovering a new altercoin or "smartly" recognize price patterns.[5]

Expectations' formation on other's investor's opinions has been widely studied for years, for instance, Keynes (1936) wrote an apt metaphor to describe the heuristics' individuals performed to invest in stock markets and newspapers competition for the most beautiful women among many options during the thirties:

"...so that each competitor has to pick, not those faces which he finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of

[4]Keynes (1936) famous adage was that the stock market was mostly a beauty contest in which judges picked whom they thought other judges would pick, rather than whom they considered being most beautiful

[5]Another type of feedback formation occurs in specialized websites that impulse new users to follow *" experienced"*, *"professional"* and *"successful"* investors, thus, disregarding private information, and following others' actions is precisely an apparent contradiction with the EMH that states randomization irrational investors' decisions.

one's judgment, are the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligence to anticipating what average opinion expects the average opinion to be. Moreover, there are some, I believe, who practice the fourth, fifth and higher degrees."

The scenario described by Keynes[6] seemly relates to cryptocurrencies market, both on price determination and which of them to choose invest. Discerning the degree of compliance within the community is a challenging task since experienced users can take advantage over unsophisticaed ones in diverse settings, an aspect that it will consider further. Nowadays, we count on more evidence supporting on Keynes' anecdotal arguments thanks to empirical and experimental evidence (Kahneman and Riepe 1998). Until now, it has been described some of the belief formations on feedback, which has been widely studied behavioral finance literature; thus, it seems that this field is an excellent fit to describe Bitcoin market since efficiency is hardly possible for the existence of many contradictions with the statements of the Efficient Market Hypothesis.

It is relevant to describe common biases in judgments and decision-making, also identified as cognitive illusions that people usually reflect in economic tasks and how limited are individuals be their computational power (bounded rationality) concept attributed to (Kahneman and Riepe 1998; Simon 1982). He was concerned with the human decision making *"shortcuts"* that could lead to suboptimal outcomes. Naturally, there is a large set of systematic behavioral biases that characterize individuals in financial-like markets such as crypto-markets; however, they emerge from a setting in which heuristics are altered by market participants and mixed signal to noise cues. Moreover, it has been proved that in asset markets the existence of irrational investors generates deviations from fundamentals, hence, under the particular case with cryptocurrencies the absence of a parameter of value creates a different puzzle. At this point, it is relevant to classify the different cognitive biases found in the literature on which people are affected. Hence, this study aims to create an accurately standardized aggregation based on literature reviews studies on behavioral finance (Kahneman and Riepe 1998; Kumar and Goyal 2015; Shiller 1999; Stracca 2004; Subrahmanyam 2008).

A crucial starting point in decision-making framework is to distinguish between beliefs and preferences. Beliefs are salient in expectation formation, and usually, people develop non-optimal judgments in what to believe due to a set of experimentally proved systematic errors called biases (Kahneman and Riepe 1998). The hypothesis of this study, it that crypto-investors presumably suffer from several of the same judgment biases that have been documented in financial markets settings, which can even

[6] Another concept attributed to Keynes is *"animal spirits"* which originally described business calculation, which he considered the role of confidence, uncertainty and framing on investment heuristics is inexorable due to our human nature, more precisely of *"... a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities."*

get intensified by crypto-market idiosyncratic uncertainty and complexity. The next subsection wil try to describe the most relevant ones.

3.3.1 Overconfidence and optimism

Within financial market, individuals oftenly display exacerbated trust on their abilities, knowledge, and skills, are entitled as overconfidence. Moreover, this self-reliance on personal judgments entails concepts such as miscalibration, over-precision, which are at the same time associated with an overreaction to random events, and over-optimism (Barber and Odean 2013; Barberis and Thaler 2005; Kahneman and Riepe 1998). A classic illustration of overconfidence bias is the "better than the average": a perception of being better than the mean for certain activities, for instance, Svenson (1981) found that 90% of Swedish car drivers considered themselves better than the average. Another example is to generate narrow uncertainty values; in other words, people assign significantly less likelihood on rare events than really occur. The typical example is when people were asked to evaluate 1 and 99 percentiles of an index such as exchange rates a year from the reference point, the resulting 98% percent confidence interval captured far less the expected value in comparison with expected intervals (Alpert and Raiffa 1982). Particularly, in the aforemetioned study it has been proved that uncertainty is considerable high; in fact, the surprise rate[7] is about 20% where the accurate calibration would yield 2%. Also, Barber and Odean (2001) found on the premise that men are more prone to overconfidence than women, that the former gender trade more and display lower return than women. Other significant contributions can be found in Daniel, Hirshleifer, and Subrahmanyam (1998) and Daniel and Hirshleifer (2015), which also stated how unlikely is the purely rational model to explain variability in stock prices due to systematic departures from rational behavior.

3.3.2 Herding behavior

None of the theory on behavioral or EMH-grounded financial economics has considered the scenario in which there is no reference to be attached. To the authors' view, there are three levels of convictions regarding positions about markets. The first is associated with the rational expectations assumption that conveys investors react coherently to announcements that affect fundamentals. The second degree stems from the debatable conjecture that prices movements are genuinely ruled by fundamentals, in which Shiller (2015) has been severely criticized by showing evidence of an excess of volatility. Finally, we reach a third-degree exceptionally exposed by crypto-markets, in which by construction there is no fundamental value, then prices will be

[7] Deviations between expected future value and actual ones

determined in large extension by collective valuation and coordination. Noting the crypto-markets nature, and the compelling evidence regarding human behavior systematic biases exposed in financial-like markets, which represent the most evidence supported the economic theory, there is a final question to solve: in the absence of reference points to prices, how do individuals make decisions in crypto-markets?

In a broad context, comparing the information or digital economy to the industrial, Shapiro and Varian (1999) stated that the old economy differs from the new in the substitution of economies of scale by the economics of networks. That is, in a technological world, one finds utility as far other people's preferences are aligned to ours. For instance, a messaging app has as the primary purpose of communicating with a counterpart that can be a group or individual. Nevertheless, if those whom ones want to communicate with does not find the same platform valuable, makes it worthless for me too. According to the same authors, in the beginning, it is essential to reach a certain amount of users or critical mass, and positive feedback behavior drives the mechanism to increment the number.

It seems coherent to hypothesize that one detonating factor that has converted Bitcoin into the leading cryptocurrency independently of being the first successful cryptocurrency implementation is a combination of positive feedback mechanism and self-fulfilling prophecy. The sociologist Merton (1948) defined a self-fulfilling prophecy as *"...a situation, evoking a new behavior which makes the originally false conception come true."*, translating this situation to our case, it can be interpreted as those initial opinions which featured digital currencies, particularly Bitcoin as a milestone of a new era, even though few people then (probably now too) understand it. Indeed, little of the main foresight have been fully realized, but reality seems blurry enough to keep the fad going on. Merton adds: *"For the prophet will cite the actual course of events as proof that he was right from the very beginning."* This is potentially related to market value foresight exposed in social media and forums that declared excessive markups such as 10.000 or 20.000 dollars per BTC that eventually came true.

Indiviuals' thoughts and actions are usually forged by what others do, this mimicking process is triggerd by a transmission mechanism, such as: word-of-mouth communication, news and social media exposition, in-place observation, or second-degree (indirect) manifestations like market prices (Grossman and Stiglitz 1976). From the behavioral economics perspective, the literature on crowd behavior has been defined as herding, positive feedback, or informational cascades, but they all relate to decision-making scope characterized by mimicking actions of others (Graham 1999). Concretely, Kumar and Goyal (2015) defines it as a *"situation wherein rational people start behaving irrationally by imitating the judgments of others while making decisions."*, it is also defined as any behavior similarity/dissimilarity conveyed by the interaction of individuals (Hirshleifer and Hong Teoh 2003).[8] One crucial feature herding or behavioral convergence is that it entails a coordination mechanism, it can be a social learning heuristic by observing other decision-makers or coordination based on some signal such as price movements (Devenow and Welch 1996). Moreover, the among the range of situations where it has been reviewed we mentioned investor trading, managerial investment, financing choices, analyst following and forecasts, market prices, market regulation, bank runs, bubbles, and welfare (Brunnermeier and Oehmke 2013; Hirshleifer and Hong Teoh 2003).

According to (Graham 1999), the herding literature can be organized into four distinct categories: informational cascades, reputational herding, investigative herding, and empirical herding, and all of them with a common conceptual ground. For instance, an informational cascade is described as a process that stems when someone (optimally) choose to ignore her private information and instead jump to the bandwagon by mimicking the actions of individuals who acted *previously* (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Graham 1999). In Bayesian reasoning context, it is the process of updating posteriors by gradually shrinking prior's weight as new and supposedly reliable information is presented sequentially. Cascades assume that public to private signal ration are unbounded, as a result, it is likely that individuals in the further chain of events will also fall into mimicking the consensus due to the overwhelming mass of common beliefs, unchaining non-useful information for the latter observers/actioners.

Among the most related and relevant theoretical contributions, is Banerjee (1992) who found that decision rules chosen by optimizing individuals will be characterized by herd behavior. Bikhchandani, Hirshleifer, and Welch (1992) provided proofs that informational cascades could explain conformity, fads, fashions, booms, and crashes. Along the same lines, Scharfstein and Stein (1990) stated that in individual investment environments, managers usually disregard private information and adopting a follow-the-crowd strategy which is an inefficient behavior from the market perspective. Similarly, Welch (1992) results show that in Initial Public Offering (IPO) investors based their buying decisions guided by previous counterparts' actions, and by extension forming informational cascades. Among the causes of herding, we can mention limits of attention (exposed earlier in this study), which increases the probability of herding due to the difficulty to process information accurately (Hirshleifer and Hong Teoh 2003).

Several attempts have been made to describe crowd behavior in investing settings,

[8] Some other authors include payoff externalities (network externalities) models that show that the payoffs to an agent adopting an action increases in the number of other agents adopting the same action Devenow and Welch (1996). Further literature can be viewed in Hirshleifer and Hong Teoh (2003)

notably, De Long et al. (1990) seminal article reintroduced the concept of *"noise"*[9]. According to De Long et al. (1990) perspective, "noisy trader" represents the irrational alter ego of the sophisticated investor, an investor which misperceive expected returns and generate beliefs and heuristics to buy and sell following a simple feedback rule to form insights about market dynamics (Lux 1995). Among the results exposed by De Long et al. (1990) the one that asserts that noisy traders can earn higher returns than sophisticated investors even though their distorting prices practices, this generates as a consequence anomalies such as an excess of volatility and mean reversion.

Another interesting study was performed by Welch (2000) who found that analysts herd in their stock recommendations from data about buy and sell (reputational herding), exposing the significant positive correlation between adjacent analysts. Additionally, Welch showed that analyst's elections are correlated with the current forecast and asymmetry towards a tendency to herd under the existence of optimism or positive news, concluding that this situation can create fragility and further crashes. Those results are aligned with a famous phrase in Keynes (1936) which says: *"Worldly wisdom teaches that it is better for the reputation to fail conventionally than to succeed unconventionally"*. Stracca (2004) explains that several factors may reinforce a tendency to herding, including reputation in a principal-agent context if the performance of the portfolio manager (the agent) is costly to monitor, and the fact that compensation is often computed comparing with other investors performance, pushing risk-averse traders to conform to the "average" assessment of the market

Herding in crypto-markets could stem through price as the coordination mechanism that is it can be (errors are implicit) the most efficient social learning model. This is described by empirical herding category, which has been studying investors' behavior when they do a momentum-following or positive feedback investment that is, taking decision-based on price patterns (Sornette 2017). In order to capture herding behavior under second-degree coordination mechanism (or aggregate indicators such as prices) one has to make some assumptions, particularly establishing a reference point. In the methodology section it has been explained the most common approach to test for herding following the method proposed by Chang, Cheng, and Khorana (2000).

3.3.3 Strategies and price bubbles

The last two sections were focused on describing common biases and heuristics to crypto-investors. It has been determined that individuals in crypto-markets have several incentives to chase the action and rely on their investments by observing prices and using them as a coordination mechanism due to the lack of salient information

[9] formerly attributed to Black (1986) who defined as the *"opposite of information"*

or fundamental announcements. This scenario seemly relates to the Internet Bubble (also known as dot-com, or Y2K) when companies like Amazon, eBay, and Yahoo! emerged. An over-expectation of future profits characterized it, as a product of recent rises prices for internet related firms, investor were eager to invest in companies that were associated with e-commerce, fiber optics, servers, chips, software, improved hardware, telecommunications or any prefix that could sound as part of the *"new economy"* Kindleberger and Aliber (2005). A rapid increasing NASDAQ Composite index characterized the bubble, coming from 1300 in 1996 to 5400 only three years later[10]. According to Ofek and Richardson (2001) rational explanations had little power to explain what happened since internet stock prices significantly deviated from their underlying fundamentals and volatility of prices were out/bounded expressing the over-optimistic sentiment, lack of caution, and the panic of *"not being part"* among the investors. Particularly, on the last element, cryptocurrency slang has a special acronym to express this behavior, it is known as #FOMO or *"Fear of Missing Out"*, that is, the anxiety of not actively participate in the market when an unexpected event unchains a rapid valorization of a certain digital coin. Another example about investors' irrationality was Black Monday, the crash that took place in October 29 of 1987, on this matter Shiller (1987) expressed that nothing seemed to be different during those days among the investors whom he surveyed, perhaps, a perception that the market was overpriced, he also emphasized in the existence of large price movements without any news breaks, which is not consistent with the EMH which had been criticized for other authors (De Bondt and Thaler 1985). Shiller insisted in stating that crashes[11] seems to be determined endogenously by investors, either by a reaction to others' actions or manifestations expressed in prices (from here devised the concept of positive feedback trading). Moreover, some investors affirmed they rely on *"gut feeling"* as their forecasting method (in contraposition to fundamental or technical analysis). One of the main aspects to consider in such scenarios is the impact of speculative price movements, particularly Kindleberger and Aliber (2005) stated that:

"The insiders destabilize by driving the price up to and up and then sell at or near the top to the outsiders. The losses of the outsiders necessarily are equal to the gains of the insiders. [. . .] But the professional insiders initially destabilize by exaggerating the upswings and the downswings; these insiders follow the mantra that the 'trend is my friend.' At one stage, these investors were known as 'tape watchers;' more recently, they have been called 'momentum investors.' The outsider amateurs who buy high and sell low are the victims of euphoria that affects them late in the day. After they lose, they go back to their ordinary occupations to save

[10]It is relevant to highlight that during December 1996 Alan Greenspan (chairman of the Federal Reserve Board) coined the famous concept of *"Irrational Exuberance"* to illustrate the effect of psychology in stock markets.

[11]Consistent with the argument that noisy participants can affect markets in a non-transitory fashion.

for another splurge five or ten years in the future."

On one side, those who think markets are rational and efficient, are explaining deviations as an exceptional movement from fundamental value. The other side is composed of those who believe psychological behavior as the main driver. The way investor believes they act as they are more intelligent as the average investor in the market, hence having a big chance to take out the money safe and the sound is described by Read (2012) who mentioned:

"Since the crash is not a certain deterministic outcome of the bubble, it remains rational for investors to remain in the market provided they are compensated by a higher rate of growth of the bubble for taking the risk of a crash, because there is a finite probability of 'landing smoothly', that is, of attaining the end of the bubble without crash."

In this work, it has been hypothesized that price dynamics in regard of its type (crytocurrencies, token or ICO's) are governed by herding behavior or positive feedback trading strategies, and not by an independently and private-formed valuation. In this case, the coordination mechanism are the past prices, which potentially cause price manipulation and market destabilization as a product of exaggerated successive upswings and prices decrease to make the less informed to buy high and sell low, making them only victims of the euphoria (Shiller 1999, 2015; Shleifer 2004).

3.4 Methodology

To date, few methods have been developed to test for empirical herding using aggregate data. In the literature review section, it has been mentioned that direct observation on investors' actions is the best approach to test for herding since the coordination mechanism and the potential tilting towards the social convention is transparent from the flow of information dynamics within individuals. Nonetheless, in the cryptocurrency market, this is almost impossible due to its privacy, hence this study will follow prices as a coordination mechanism.

This limitation is not unique; in several financial settings analyzing stocks or exchanges rates almost impossible to get information about market participants. Given that herding cannot be measured directly from financial markets, the literature has developed different proxies for detecting herding behavior based on the return's regression tests. This study employs the methodology present in Chang, Cheng, and Khorana (2000), which is an improvement from the original methodology offered by Christie and Huang (1995). Christie and Huang (1995) suggested the use of Cross-Sectional Standard Deviation of returns (CSSD) to identify herding behavior in financial markets; it is defined as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n} (R_{i,t} - \bar{R}_{m,t})^2}{N-1}} \tag{3.1}$$

Where R_i is the observed stock return on a firm i (in our study it is described as c as presented in the data section below) at time t, while $CSSD_t$ is the cross-sectional average of the returns in the aggregated portfolio at time t, and N the number of cryptocurrencies at time t. The implicit indication of the CSSD is that it quantifies the average proximity of individuals' returns to the mean, by extension, CSSD will always be equal or above zero, where a value tied to the lowest bound expresses a situation when all returns flow in harmony while a deviation from the zero marks represents dispersion.

According to Christie and Huang (1995) it is possible to test for herding under market stress (large upswings and downswings) events by exploiting investors' tendency to overturn their own beliefs in favor of the market consensus. This conclusion stems from a rational the Capital Asset Pricing Model[12] (CAPM) which predicts that the dispersion will increase with the absolute value of the market return since individual assets differ in their sensitivity to the market return. On the other side, if herding

[12] The CAPM relates to the risk of an investment and the expected returns given a market benchmark, which in stock market settings is for many cases the S&P500, deriving a measure of sensibility and asset is in comparison to the movements of the market. In this study It has been established it as a baseline to denote rationality in cryptocurrency markets.

exists, individual returns will not differ greatly from the market results. Christie and Huang (1995) empirical tests is estimated as the Equation 3.2:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \tag{3.2}$$

where:

$D_t^L = 1$ if the market return on day lies in the extreme lower tail of the distribution, or zero otherwise $D_t^U = 1$ if the market return on day lies in the extreme upper tail of the distribution, or zero otherwise

This model was developed to capture differences in investor behavior upon extreme upswings or downswings in comparison to what it is expected to be *"normal"*, expressed as the 90% or 98% percent of the distribution. Nonetheless, this methodology has two main drawbacks, firstly, it is too sensitive to outliers, and secondly, it is completely arbitrary what is considered as *"extreme"* since the 1% and 5% rule might not fit good for all distributions. Consequently this study will followed an version to Christie and Huang's model proposed by Chang, Cheng, and Khorana (2000)[13] which is based on the Cross-Sectional Absolute Deviations defined as:

$$CSAD_t = \frac{1}{N}|R_{i,t} - \bar{R}_{m,t}| \tag{3.3}$$

CSAD is a measure of dispersion that takes the absolute difference between the individuals to return and the average market returns, which makes it far less sensitive to return's outliers than quadratic one. Moreover, it is important to highlight that N does change over time, the different i at time t is increasing because new cryptocurrency is added to the calculation, this is an important feature that it has not been mentioned in previous studies. Chang, Cheng, and Khorana (2000) demonstrated *"that rational asset pricing models predict not only that equity return dispersions are an increasing function of the market return but also that the relation is linear"*. Moreover, they rely on the following intuition: *"if market participants tend to follow aggregate market behavior and ignore their priors during periods of large average price movements, then the linear and increasing relation between dispersion and market return will no longer hold. Instead, the relation can become non-linearly increasing or even decreasing…"* This model has been recently employed by several papers, for instance, Arjoon and Shekhar (2017) examined herding in the context of frontier market, Chiang and Zheng (2010) found herding behavior in advanced stock markets, Demirer, Lee, and Lien (2015) empirically tested for herding commodity financialization settings and Balcilar, Balcilar, Demirer, and Hammoudeh

[13] Chang, Cheng, and Khorana (2000) stated that Christie and Huang (1995) approach *"requires a far greater magnitude of non-linearity in the return dispersion and mean return relationship for evidence of herding than suggested by rational asset pricing models"*.

(2013) who studied for herding in Gulf Arab stock markets. Following the line of the papers as mentioned earlier, this study starting with a reference model specified as:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.4}$$

The model exposed in Equation 3.4 aims to detect significant dispersion of returns during markets stress. Hence, a statistically significant negative coefficient of γ_2, indicates that herding is likely to be occurring, whereas a significant positive implies a presence of scattering. On identification of herding Kabir and Shakur (2018) highlights what Gebka and Wohar (2013) stated about a possible situation when investors *" overemphasize their view or focus on views dominant among subset of actors (who may herd jointly moving in and out of positions) excessively ignoring market information, it results in increased dispersion in returns across assets leading to scattering"*. It is essential to clarify that as many other authors that had been studying herding behavior (Arjoon and Shekhar 2017; Chiang and Zheng 2010; Economou, Katsikas, and Vickers 2016) this model employs Newey and West (1987) smart solution to account for heteroscedasticity and autocorrelation consistent standard errors in regression coefficients, besides the inclusion of lagged dependent variables (to guarantee that effects are not a consequence of autocorrelation dynamics.

3.4.1 Model

Other authors have proposed the application of CSAD methodology to measure the degree and directionality of herding behavior in cryptocurrency markets, for instance, in a recent paper da Gama Silva et al. (2019) analyzed herding behavior and contagion phenomena in cryptomarkets using a State Space model, similarly, Stavroyiannis and Babalos (2019) followed a time-varying parameter quantile regression to study idiosyncratic characteristics of cryptocurrency moments such as long tail distribution of returns. In this regard, this study is similar to the articles as mentioned above, but it provides a more robust specification of the regression by accounting to volatility and lagged effects which are important characteristics of any cryptocurrency. Besides, it relies on Markow Switching (MS) approach to identify stochastic structures that vary significantly in high-frequency data, which is not always possible to define in time-varying coefficients when the parameters are updated as the information arrives, that is, it has "memory", however, it does not adjusted to local structures that may be as small as few days. Formelly, MS regression is a useful method to express adjustments which are more pronounced in high-frequency data, moreover, it offers advantages to reveal patterns commonly hidden in data such as non-linearity and provides an edge over the linear models due to their ability to reveal patterns beyond traditional stylized facts, which only nonlinear models can generate. For the sake of describing the basic functioning of an MS, a two-state MC can be described as:

$$P = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,j} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ P_{i,1} & P_{i,2} & \cdots & P_{i,j} \end{bmatrix} \tag{3.5}$$

where $P(S_t = j|S_{t-1} = i, S_{t-2} = b, ..., \Omega_{t-l}) = P(S_t = j|S_{t-1} = i) = P_{ij}$, p_{ij} transition probability of the Markovian chain that represents the likelihood of being in regime S at time t given that the in S_t the regime is equal to j, and j will only depend on the previous state i. Finally, Ω represent all the parameters necessary to describe the Data Generating Process (DGP)

Having said that, a symmetric Markovian switching herding model can be illustrated in Equation 3.6 as:

$$\begin{aligned} CSAD_{t,1} &= \gamma_{0,1} + \gamma_{1,1}|R_{m,t}| + \gamma_{2,1}R^2_{m,t} + \gamma_{3,1}Vol_t^{R_{m,t}} + \gamma_{3+k,1}CSAD_{t-k} + \varepsilon_{t,1} \\ CSAD_{t,2} &= \gamma_{0,2} + \gamma_{1,2}|R_{m,t}| + \gamma_{2,2}R^2_{m,t} + \gamma_{3,2}Vol_t^{R_{m,t}} + \gamma_{3+k,2}CSAD_{t-k} + \varepsilon_{t,2} \\ &\vdots \\ CSAD_{t,s} &= \gamma_{0,1} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}R^2_{m,t} + \gamma_{3,s}Vol_t^{R_{m,t}} + \gamma_{3+k,s}CSAD_{t-k} + \varepsilon_{t,s} \end{aligned} \tag{3.6}$$

Where $\varepsilon_{t,s}$ is an i.i.d innovation term with mean 0 and standard deviation σ for regime $S = s$. Therefore, know the model will be able to identify when exhibits herding or not, besides different magnitudes this behavior.

Several of the recent empirical studies coincide in the important to distinguish between herding behavior under irregular market dynamics, in other words, account for asymmetric reaction in face of downswings and upswings in the market returns (Arjoon and Shekhar 2017; Chiang and Zheng 2010; Demirer and Kutan 2006; Economou, Katsikas, and Vickers 2016). In order to test whether crypto-investors react differently on days when the median returns are positive or negative, it has been created a dummy variable coded as Equation 3.7:

$$H(up, down) = \begin{cases} (1-D)R^2_m & if\ R_{m,t} \geq 0 \\ DR^2_m & if\ R_{m,t} < 0 \end{cases} \tag{3.7}$$

Which leads to a new specification given by:

$$
\begin{aligned}
CSAD_{t,1} =& \gamma_{0,1} + \gamma_{1,1}|R_{m,t}| + \gamma_{2,1}DR^2_{m,t} + \gamma_{3,1}(1-D)R^2_{m,t} + \\
& \gamma_{4,1}DVol_t^{R_{m,t}} + \gamma_{5,1}(1-D)Vol_t^{R_{m,t}} + \gamma_{5+k,1}CSAD_{t-k} + \varepsilon_{t,1} \\
CSAD_{t,2} =& \gamma_{0,2} + \gamma_{1,2}|R_{m,t}| + \gamma_{2,2}DR^2_{m,t} + \gamma_{4,2}(1-D)R^2_{m,t} + \\
& \gamma_{4,2}DVol_t^{R_{m,t}} + \gamma_{5,2}(1-D)Vol_t^{R_{m,t}} + \gamma_{5+k,2}CSAD_{t-k} + \varepsilon_{t,2} \\
& \vdots \\
CSAD_{t,s} =& \gamma_{0,s} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}DR^2_{m,t} + \gamma_{3,s}(1-D)R^2_{m,t} + \\
& \gamma_{4,s}DVol_t^{R_{m,t}} + \gamma_{5,s}(1-D)Vol_t^{R_{m,t}} + \gamma_{5+k,s}CSAD_{t-k} + \varepsilon_{t,s}
\end{aligned} \tag{3.8}
$$

Regarding the number of regimes, the definition is not a straightforward task, on this matter, Psaradakis and Spagnolo (2003) states that dynamic models with parameters that are allowed to depend on the state of a hidden Markov chain have become a popular tool for modeling time series subject to changes in regimes, nonetheless, the determination of an adequate number of states to characterize the observed data it is not conclusive. In Psaradakis and Spagnolo (2003) view, a rule of thumb for autoregressive models based on Information Criterion (Akaike, Schwarz, among other) values do provide an excellent instrument to choose the correct state dimension.

3.5 Data

According to the site www.coinmarketcap.com up to May 2019, there were 2177 different cryptocurrencies available in the market; nonetheless, this study dampens the sample to the first 100 leading ones which in aggregated terms account for nearly 96% of total cryptocurrency's market capitalization. Getting cryptocurrencies' prices, market capitalization, and descriptions is not a completely easy task. The easy way would be to buy information on specialized websites that sell datasets; however, it has been scraped the website www.coinmarketcap.com. The original data includes open, close, highest, and lowest prices, besides its current market capitalization given a day for each CC. Since crypto-markets are relatively new, it is easy to deduce that not all 100 original presented CC have the same starting dates, mainly, the two with more observations (2120) are Bitcoin and Litecoin which extends from 2013-05-09, and ends as all the rest on 2019-03-01.

Measuring herding intensity by analyzing prices demands to work with returns, thus I determined the daily return of each c cryptocurrency arithmetic as follows (Equation 3.9):

$$R_{c,t} = \frac{CP_{c,t} - CP_{c,t-1}}{CP_{c,t-1}} \tag{3.9}$$

Where $R_{c,t}$ denotes the price returns of cryptocurrency c on the day t, and CP is the closing price of the cryptocurrency. One of the most iconic features of cryptocurrencies is the existence of significant deviations from the mean; this volatility is exposed by the existence of long tail distribution for most of the sample CC this study considered. For instance, taking into account the subsample seen in table 1, the *"grand"* average return is 1.3%, while the average median is -0.1%, as a result, is no surprise to find a third moment average of 3.7.

Additionally, the uncertainty of current market conditions has been estimated using a Generalized Autoregressive Conditional Heteroskedasticity model to approximate the volatility of $R_{m,t}$ with the method Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) that accounts for fourth moment idiosyncrasy of crypto-markets returns that commonly present long tail distributions, besides of the expected clustering of volatility. The Table 3.5 describes the parameters' estimates and Figure 3.4 the diagnostics for the same model.

3.6 Results

As mentioned earlier, the testing methodology proposed by Chang, Cheng, and Khorana (2000) is based on the CAPM as the reference point of rational asset pricing model; therefore, any evidence that contradicts the expected results is interpreted as an anomaly, which in this case is associated with behavioral convergence or herding. Following the CAPM specification, it has been tested if the expected crypto-asset returns behave as the benchmark, or instead, is light of abnormal crypto-market returns there is a tendency or not to react in consensus (lower dispersion). As a consequence, if one observes negative values for γ_2 in Equation 3.6 it means that crypto-investors ignore their own priors and behave in conformity, on the other side, positive values of γ_2 means that individuals have strong priors, and not react towards the consensus, therefore the overall market dispersion increases. The specification as seen in Equation 3.6 does not differs between current positive and adverse market conditions (this is the reason which it will herein refer to it as the symmetric model), henceforth, it is impossible to evaluate if crypto-investors tend to herd during "bad times" and "good times." To solve this problem, the Equation 3.8 introduces a binary indicator that defines below or above average market returns conditions. This is an important trait, since one might expect that loss aversion pushes people to be risk averse and react toward market aggregate consensus, however, this behavior contradicts the popular "HODL" strategy that establishes that in the existence of negative perspectives, one might keep calm, which is the same as a having strong priors. In this regard, γ_3 and γ_4 in Equation 3.8 captures herding (negative sign) and scattering (positive sign) under decreasing and increasing market conditions, respectively.

One important aspect of the specification exposed above is that as in other studies of herding in crypto-markets they have ignored the role of uncertainty, that is, high volatility in current market returns will cause crypto-investor to be unsure of how to react to positive and negative cues, henceforth, their beliefs and trading strategy will be presumably affected.

3.6.1 Herding behavior under symmetric market states

The analysis begins with herding behavior under symmetric conditions and four-regime switching models according to the specification seen in Equation 3.6, whose results are shown in Table 3.1. As it has been explained before, the CAPM framework defines that dispersion and absolute market returns are linearly and positive related, which is verified by our estimates with a significant positive coefficient of 0.203 (8.955) at a 1% threshold either for OLS and robust autocorrelation and heteroskedasticity consistent estimates (HAC)[14]. This particular estimate is not of our interest; however, one does have to verify that the sign is consistent with the specification exposed by Chang, Cheng, and Khorana (2000). The results for the different regimes support the theoretical assumptions.

Under the assumption that dispersion and the absolute market returns are linearly related, we must center the attention on the coefficient γ_2 associated with extreme market returns $R^2_{m,t}$, since it captures herding behavior under market stress. The second column of Table 3.1 shows that there is enough statistical evidence against the null hypothesis of "no-herding" or "diffuse" behavior with a negative coefficient of -0.212 (-2.361) which means that under market stress the crypto-investors behave following a positive feedback strategy, or in other words, in presence of extremely upswings, individuals tend to follow the consensus and inducing to a lower dispersion across the 100 leading cryptocurrencies. The relevance of this result lies in the informational properties of crypto-markets since one has to rely on current market conditions to define and shape the expected value of any cryptocurrency, *prices are the coordination mechanism*. Bear in mind, that the estimate of γ_2, does not hold statistically significant if we estimate the standard errors with a robust covariance matrix method, the possible explanation is a high degree of variability that cancels the effect across the sample; for this matter, it is useful to rely on the Markov Switching estimates that account stochastic dynamics in the parameters.

[14]The coefficients are were estimated using Newey and West (1987) methodology, to achieve heteroscedastic and autocorrelation consistent standard error estimates for the leading 100 cryptocurrencies according to their market capitalization

Table 3.1. Regression estimates of herding behavior under symmetric market conditions

Term	OLS	OLS^{HAC}	Regime 1	Regime 2	Regime 3	Regime 4
γ_0	-0.007***	-0.007***	-0.006***	-0.005***	-0.016***	-0.001
	(-8.503)	(-7.517)	(-4.960)	(-11.692)	(-12.409)	(-0.792)
γ_1	0.203***	0.203***	0.024	0.142***	0.715***	0.191***
	(8.955)	(5.647)	(0.639)	(3.355)	(6.503)	(3.248)
γ_2	-0.212**	-0.212	0.416***	-0.540***	-1.615***	-0.545**
	(-2.361)	(-1.315)	(4.438)	(-2.779)	(-4.020)	(-2.048)
γ_3	-0.303***	-0.303***	-0.155	0.063	-0.290	-0.647***
	(-3.348)	(-2.787)	(-1.016)	(0.470)	(-0.698)	(-3.098)
γ_4	-0.566***	-0.566***	-0.682***	-0.486***	-0.761***	-0.125**
	(-26.533)	(-16.385)	(-18.596)	(-6.510)	(-35.233)	(-2.450)
γ_5	-0.373***	-0.373***	-0.708***	0.114***	-0.504***	-0.249***
	(-16.427)	(-10.554)	(-6.411)	(43.408)	(-6.589)	(-4.689)
γ_6	-0.208***	-0.208***	-0.667***	0.164***	-0.178**	-0.061
	(-10.167)	(-6.720)	(-9.435)	(3.383)	(-2.539)	(-1.482)
Multiple R^2	0.318		0.824	0.649	0.457	0.185
AIC	-9997.570		-10926.980			

This table presents estimates of $CSAD_{t,s} = \gamma_{0,1} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}R^2_{m,t} + \gamma_{3,s}Vol_t^{R_{m,t}} + \gamma_{3+k,s}CSAD_{t-k} + \varepsilon_{t,s}$ testing for the existence of herding behavior. Where OLS stands for Ordinary Least Square estimation and OLS^{HAC} shows the Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, being both referred as static models. Alternatively, the columns referred as regimes 1-4 describe the Markov-Switching estimates of herding behavior where all variables are allow to change stochastically. The numbers in parenthesis are t-statistics, ***, ** and * stands for significance at 1%, 5% and 10% levels respectively, and finally, Multiple R^2 estimates and Akaike Information Criterion (AIC) are described for each model.

Columns ranging from 4 to 7 in Table 3.1 presents estimates for the four-regime switching under symmetric herding states.[15] The results provide evidence of both herding and adverse herding for the period under study. The latter case is represented in the first regime, where $\gamma_{2,1}$[16] is 0.416 (4.438) , which means that an increase in average market returns is associated with lower dispersion. Now we can provide a more in-depth description of herding behavior than the static model by looking at the smoothed probabilities in Figure 3.1 where regime number 1 is represented by the dark blue color. In this graph, it has been discovered that adverse herding is more prominent towards the end the of the sample period, in fact, the probability of being in this state of the regime is around 20.37% on average for 2013 and increasing up to 27.47% during 2019. As it can be seen in columns 5 to 7, there is statistical

[15]It is important to mention that coefficients γ_4, γ_5, and γ_6 were included in the model to control for autocorrelation effects, henceforth their interpretation is irrelevant. It applies the same to other further tables where those variables where included.

[16]Recall that the notation to define a regime s for variable p is given by $\gamma_{p,s}$

evidence in favor of herding behavior since the estimates for $\gamma_{2,2}$, $\gamma_{2,3}$ and $\gamma_{2,4}$ have a negative sign, meaning that crypto-investors behave in aggregate consensus in the existence of extreme market returns. The three regimes mentioned earlier are different in the magnitude of herding, being the regime 3 three-fold the effect of regime 2 $\gamma_{2,3}/\gamma_{2,2} \sim 2.99$, as well as $\gamma_{2,3}/\gamma_{2,4} \sim 2.96$, and almost 4-times greater than adverse herding $|\gamma_{2,3}/\gamma_{2,1}| \sim 3.88$. This is an interesting result, since it has been found that herding is ubiquitous to crypto-markets, but there is a visible stronger tendency to follow the consensus in comparison to outweigh private market perspectives over public states (adverse herding). In Figure 3.1 it is seen that the probability of finding herding behavior (adding the probabilities of being in regimes 2 to 4) is over 70% for all the sample period; nonetheless, we can identify peaks (described in yellow) of extreme herding during the last quarter of 2013 and 2014, as well as the second quarter of 2015.

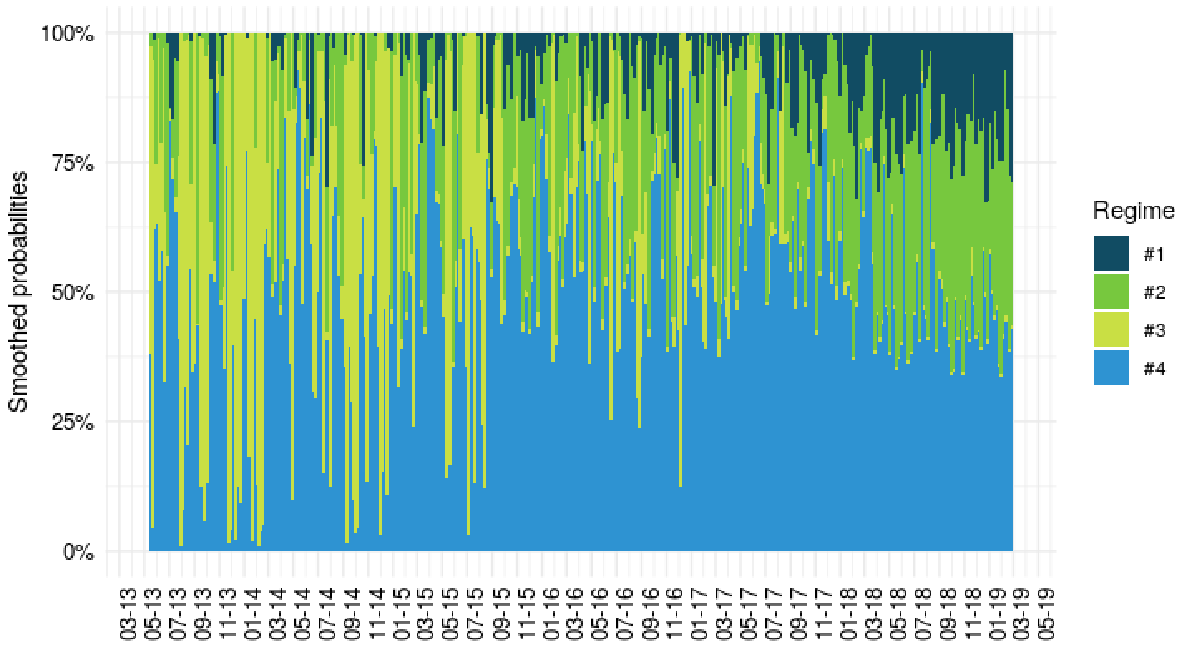


Figure 3.1. Regime switching smoothed probabilities under symmetric herding behavior

The estimate for the volatility term $\gamma_3 = -0.303$ in Table 3.1 in the static model, denote that when risk and uncertainty rises, crypto-investors respond by abandoning their private information (if any), trading following the aggregate consensus, this result has been found to be consistently significant with robust standard errors as well. As mentioned earlier, there is little difference in terms of coefficient estimates for herding between regimes 2 and 4, in fact, the differential element lies in the volatility term in regime 4, meaning that not only their trading strategies converge during high market stress periods, they also react to uncertainty in the same fashion as the significant coefficient $\gamma_{3,4} = -0.647$ (-3.098) denotes.

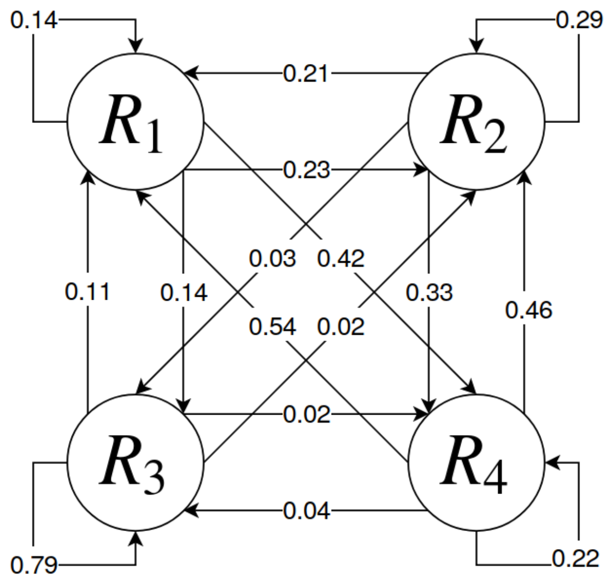


Figure 3.2. Transition probabilities in a four-regime of herding behavior model under symmetric market conditions

The set of regimes of symmetric Markov-Switching model captures certain idiosyncracies of the data generating process. For instance, regime one is characterized by representing adverse herding, while the rest of regimes captured herding behavior as stated earlier, differentiating themselves by the magnitude of $\gamma_{2,s}$ and the significance of uncertainty to explain the dispersion of returns. Having said that, a relevant question associated market correction is to respond: *how likely is to observe herding, given that the previous regime was characterized by no-herding or adverse herding?* Figure 3.2 describes the P_{ij} transition probabilities (see Equation 3.5) between i and j regimes within the model/system estimated in Table 3.1. For the sake of simplicity, it has been decided to declare global characteristics for each regime according to a combination of herding triggers, henceforth: R_1 is associated to moderated adverse-herding, R_2 moderated herding, R_3 strong herding and concluding with R_4 moderate herding and uncertainty.

From Figure 3.2 is concluded that passing from a state of adverse-herding (R_1) to a state characterized by following the consensus either due to extreme returns and uncertainty is 42.40%, whereas to staying with strong priors is 14.31%. Another interesting result is that if the market does follow a strong aggregate positive feedback strategy (R_3), there is a high chance (78.58%) that the next state will be strong herding as well. This means that once there is evidence of people to ignore their own priors substantially, herding propagates in the market, which is unlikely to be corrected back to the "normal" state. To mention other relevant transmission probabilities, from state of herding due to returns/uncertainty are $R_4 \longrightarrow R_1 = 53.78\%$, $R_4 \longrightarrow R_2 = 46.11\%$ and moderate herding $R_2 \longrightarrow R_4 = 32.86\%$, $R_2 \longrightarrow R_1 = 21.26\%$ and $R_2 \longrightarrow R_2 = 29.19\%$.

Up to now, the most striking result that stems from the symmetric model is that herding is not an unusual phenomenon or *anomaly*; instead it is a *regularity* of the crypto-market. From Figure 3.1, it can be seen that by far the most considerable amount of time cryptocurrency market exhibits dynamics opposite to what a rational asset pricing would expect, where investors follow their private information.

3.6.2 Herding behavior under asymmetric market states

This investigation began to test the presence of herd behavior in a sample of the 100 leading cryptocurrencies according to their market capitalization. In the past section, it has been found that dispersion decreases when extreme returns are present in the market; nonetheless, it remains to distinguish between the directions in which returns go. Several studies have emphasized in the argument that herding can stem vary either in direction and magnitude when the market is rising or declining (Arjoon and Shekhar 2017; Chang, Cheng, and Khorana 2000). To capture this behavior, it has been created a binary variable D that takes the value of 1 if $R_{m,t} \leq 0$ or 0 otherwise, as denoted earlier in the methodology section. Additionally, to gain more insights about herding behavior there has been estimated other two specifications, the first one in Table 3.3 describes the model a smaller version of Equation 3.8 that takes out the term of volatility of average market returns and the second Table 3.4 interacting uncertainty proxy ($Vol^{R_{m,t}}$) and extreme market returns indicator ($R^2_{m,t}$). It is relevant to mention that for the sake of consistency with the model under symmetric states, it has been decided to maintain four regimes in all the specifications.

Table 3.2 reports the regression estimates for herding under asymmetric conditions for the static and regime switching models. The static estimate of the parameter of herding under declining market conditions (or "bear market" in financial jargon) is represented by γ_2 while γ_3 shows the aggregate tendency to herd or not, in the presence of a bull market. The parameter of the static model $\gamma_2 = -0.464$ (-4.224) provides evidence of herding behavior when market returns are declining, and when it is compared to the specification described in Table 3.3 where volatility was included in the model, the parameter that captures herding behavior under declining conditions is $\gamma_2 = -0.459$ (-4.164), while $\gamma_2 = -0.460$ (-4.104) in table Table 3.4 being all of them statistical significant at a 1% threshold, also considering heteroscedasticity and autocorrelation consistent standard errors.

Interestingly, there is also evidence of crypto-investors to ignore their priors and follow the consensus when market is increasing as seen in the coefficient $\gamma_3 = -0.168$ (-1.875), -0.176 (-1.977) and -0.168 (-1.813) in tables 3.2, 3.3 and 3.4, respectively. However, none of them remains significant with robust standard errors. This result implies that crypto-investors herd under in both directions; nonetheless, the magnitude in which they react to declining conditions is almost three times greater than what could be seen in increasing conditions. Crypto-investors seem to be affected by the likelihood of losing money, henceforth, they shape outweigh "bad news," conveyed by a seemly declining evolution of the coordination mechanism. The fact that when cryptocurrency markets face extreme negative returns individuals follow the consensus, it implies that the *"HODL"* strategy (popular among specialized websites) is not consistent with the data since crypto-investors do not keep their trading strategies, an outcome that would have been associated to a higher dispersion.

Table 3.2. Regression estimates of herding behavior under asymmetric market states (specification 1)

Term	OLS	OLS^{HAC}	Regime 1	Regime 2	Regime 3	Regime 4
γ_0	-0.005***	-0.005***	-0.005***	0.002	-0.003*	-0.017***
	(-5.628)	(-5.526)	(-3.920)	(0.737)	(-1.908)	(-3.895)
γ_1	0.232***	0.232***	0.063**	0.094	0.114*	0.669***
	(9.652)	(6.849)	(1.971)	(1.577)	(1.851)	(7.188)
γ_2	-0.464***	-0.464***	-0.257	0.568*	-1.266***	-1.061***
	(-4.224)	(-3.000)	(-1.617)	(1.890)	(-3.009)	(-3.598)
γ_3	-0.168*	-0.168	0.163	-0.645	1.598***	-1.123***
	(-1.875)	(-1.191)	(0.771)	(-1.539)	(2.933)	(-4.646)
γ_4	-0.593***	-0.593***	-0.746***	-0.196***	-0.658***	-0.674***
	(-29.232)	(-17.754)	(-19.703)	(-3.578)	(-8.756)	(-13.248)
γ_5	-0.393***	-0.393***	-0.703***	-0.288***	0.065	-0.473***
	(-17.797)	(-10.972)	(-20.944)	(-4.272)	(1.061)	(-8.355)
γ_6	-0.217***	-0.217***	-0.632***	-0.080*	0.029	-0.236***
	(-10.731)	(-6.903)	(-23.417)	(-1.672)	(0.446)	(-4.425)
Multiple R^2	0.327		0.864	0.109	0.691	0.415
AIC	-10024.070		-10948.560			

This table presents the estimated coefficients of the specification $CSAD_{t,s} = \gamma_{0,s} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}DR^2_{m,t} + \gamma_{3,s}(1-D)R^2_{m,t} + \gamma_{3+k,s}CSAD_{t-k} + \varepsilon_{t,s}$ testing for the existence of herding behavior, where OLS stands for Ordinary Least Square estimation and OLS^{HAC} shows the Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, being both referred as static models. Alternatively, the columns referred as regimes 1-4 describe the Markov-Switching estimates of herding behavior where all variables are allow to change stochastically. The numbers in parenthesis are t-statistics, ***, ** and * stands for significance at 1%, 5% and 10% levels respectively, and finally, Multiple R^2 estimates and Akaike Information Criterion (AIC) are described for each model.

Table 3.3. Regression estimates of herding behavior under asymmetric market states (specification 2)

Term	OLS	OLS^{HAC}	Regime 1	Regime 2	Regime 3	Regime 4
γ_0	-0.006***	-0.006***	-0.005***	-0.002	-0.001*	-0.019***
	(-5.795)	(-5.692)	(-2.895)	(-1.595)	(-1.819)	(-3.941)
γ_1	0.238***	0.238***	0.053	0.162***	0.069***	0.691***
	(9.895)	(6.989)	(1.267)	(4.341)	(3.189)	(6.552)
γ_2	-0.459***	-0.459***	-0.120	-0.034	-0.031	-0.946***
	(-4.164)	(-3.096)	(-0.809)	(-0.216)	(-0.094)	(-2.869)
γ_3	-0.176**	-0.176	0.366***	-0.290	0.017	-1.226***
	(-1.977)	(-1.277)	(3.508)	(-1.148)	(0.098)	(-3.411)
γ_4	-0.062	-0.062	-0.152	0.152	0.252	-0.364
	(-0.359)	(-0.328)	(-0.568)	(0.552)	(1.340)	(-0.711)
γ_5	-0.288**	-0.288**	-0.061	-0.335**	-0.356***	-0.150
	(-2.407)	(-1.977)	(-0.323)	(-2.383)	(-2.650)	(-0.339)
γ_6	-0.570***	-0.570***	-0.685***	-0.432***	-0.356***	-0.661***
	(-26.922)	(-16.413)	(-17.407)	(-11.038)	(-5.554)	(-11.702)
γ_7	-0.376***	-0.376***	-0.743***	-0.230***	-0.308***	-0.418***
	(-16.642)	(-10.254)	(-21.258)	(-6.140)	(-4.913)	(-7.040)
γ_8	-0.209***	-0.209***	-0.675***	-0.115***	-0.057***	-0.188***
	(-10.280)	(-6.603)	(-25.773)	(-4.277)	(-5.000)	(-3.092)
Multiple R^2	0.331		0.163	0.893	0.890	0.421
AIC	-10032.960		-10960.830			

This table presents the estimated coefficients of the specification $CSAD_{t,s} = \gamma_{0,s} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}DR^2_{m,t} + \gamma_{3,s}(1-D)R^2_{m,t} + \gamma_{4,s}DVol_t^{R_{m,t}} + \gamma_{5,s}(1-D)Vol_t^{R_{m,t}} + \gamma_{5+k,s}CSAD_{t-k} + \varepsilon_{t,s}$ testing for the existence of herding behavior, where OLS stands for Ordinary Least Square estimation and OLS^{HAC} shows the Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, being both referred as static models. Alternatively, the columns referred as regimes 1-4 describe the Markov-Switching estimates of herding behavior where all variables are allow to change stochastically. The numbers in parenthesis are t-statistics, ***, ** and * stands for significance at 1%, 5% and 10% levels respectively, and finally, Multiple R^2 estimates and Akaike Information Criterion (AIC) are described for each model.

Focusing the attention at Markov-Switching estimates[17] it is noted that the parameter that captures herding behavior under declining market conditions is as expected: time-dependent. There is a mixture of adverse herding and herding in a model that seemly to expose crypto-investors to follow the consensus only, that is the case of $\gamma_2 = -0.464\ (-4.224)$ in Table 3.2 since there is evidence of them outweighting their private information in $\gamma_{2,1} = -0.257\ (-1.617)$ given that it is not statistically significant. Nonetheless, regimes 2, 3 and 4 denote a different outcome; for instance, there is

[17] it is relevant to mention that the regimes not necessarily capture the same data generating process, for instance, a combination of parameters that reflect certain structure in regime 1 in a given specification, does not necessary would be regime one in another one, it could be $S-1$

evidence in favor of adverse herding within the regime 2 with $\gamma_{2,2} = 0.568$ (1.890) that also is associated with "no-herding" with a non-significant $\gamma_{3,2} = -0.645$ (-1.539). Conversely, there is mixed evidence of bi-directional herding in regimes 3 and 4, that is the case of $\gamma_{2,3} = -1.266$ (-3.009) and $\gamma_{3,3} = 1.598$ (2.933) both significant at the 1%, this means that crypto-investors reacted strongly towards the consensus in down-swings situations, but they also outweigh their private information when the market shows rising returns. On the other side, the regime 4 denote strong significant herding either under declining and increasing market conditions as seen in Table 3.2 with $\gamma_{2,4} = -1.061$ (-3.598) and $\gamma_{3,4} = -1.123$ (-4.646).

Comparing these estimates to the specification in Table 3.3 and Table 3.4 there seems to be that uncertainty is the driver of herding and not necessary extreme market returns. Table 3.3 presents the similar results ($\gamma_2 = -0.459$ (-4.164) and $\gamma_3 = -0.176$ (-1.977)) for the static model in Table 3.2 when testing herding behavior under increasing and increasing market states, even after controlling for the volatility of market returns that presumably affects the risk calculations and beliefs. Nonetheless, there are distinct states when comparing Markov-Switching outcomes between specifications, that is the case in regime 1 when there is evidence of adverse herding under increasing conditions only ($\gamma_{3,1} = 0.366$ (3.508)). While in regime 2 and three is it uncertainty what seems to guide crypto-investors to ignore their priors and follow the consensus when the market is rising with $\gamma_{5,2} = -0.335$ (-2.383), a similar conclusion could be extracted by the results found in regime 3 with $\gamma_{5,3} = -0.356$ (-2.650). After including volatility of returns ($R_{m,t}$) as a proxy of uncertainty, the only regime 4 found to captured herding behavior in both market conditions with $\gamma_{2,4} = -0.946$ (-2.869) and $\gamma_{3,4} = -1.226$ (-3.411).

Table 3.4. Regression estimates of herding behavior under asymmetric market states (specification 3)

Term	OLS	OLS^{HAC}	Regime 1	Regime 2	Regime 3	Regime 4
γ_0	-0.006*** (-5.777)	-0.006*** (-5.511)	-0.004*** (-3.676)	-0.005*** (-3.129)	0.001 (0.840)	-0.018*** (-3.948)
γ_1	0.237*** (9.840)	0.237*** (6.740)	0.033 (1.230)	0.223*** (3.816)	0.041 (0.943)	0.805*** (10.469)
γ_2	-0.460*** (-4.104)	-0.460*** (-3.022)	0.304*** (2.854)	-0.918*** (-5.347)	-0.250 (-1.451)	-0.757 (-1.153)
γ_3	-0.168* (-1.813)	-0.168 (-1.161)	0.383*** (5.322)	0.147 (0.967)	0.238 (1.398)	-1.934*** (-5.936)
γ_4	0.019 (0.083)	0.019 (0.074)	0.534** (2.215)	-0.396* (-1.812)	0.464* (1.874)	0.340** (2.237)
γ_5	-0.267* (-1.934)	-0.267* (-1.801)	-0.138 (-1.016)	-0.065** (-2.249)	-0.323 (-1.563)	-0.860 (-1.592)
γ_6	-2.648 (-0.277)	-2.648 (-0.273)	-22.111*** (-2.645)	49.261*** (3.665)	-0.485 (-0.086)	-98.288 (-0.693)
γ_7	-2.048 (-0.282)	-2.048 (-0.249)	9.655 (1.462)	-40.818*** (-4.250)	-17.401*** (-2.888)	54.546** (2.062)
γ_8	-0.572*** (-26.808)	-0.572*** (-16.035)	-0.677*** (-19.483)	-0.682*** (-12.672)	-0.172*** (-2.937)	-0.690*** (-12.405)
γ_9	-0.376*** (-16.596)	-0.376*** (-10.450)	-0.746*** (-22.195)	0.085* (1.821)	-0.265*** (-5.155)	-0.484*** (-8.004)
γ_{10}	-0.209*** (-10.281)	-0.209*** (-6.775)	-0.686*** (-25.042)	-0.024 (-1.043)	-0.065* (-1.717)	-0.217*** (-3.372)
Multiple R^2	0.331		0.166	0.446	0.738	0.892
AIC	-10029.710		-10940.590			

This table presents the estimated coefficients of the specification $CSAD_{t,s} = \gamma_{0,s} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}DR^2_{m,t} + \gamma_{3,s}(1-D)R^2_{m,t} + \gamma_{4,s}DVol^{R_{m,t}} + \gamma_{5,s}(1-D)Vol^{R_{m,t}} + \gamma_{6,s}DVol^{R_{m,t}}R^2_{m,t} + \gamma_{7,s}(1-D)Vol^{R_{m,t}}R^2_{m,t} + \gamma_{7+k,s}CSAD_{t-k} + \varepsilon_{t,s}$ testing for the existence of herding behavior, where OLS stands for Ordinary Least Square estimation and OLS^{HAC} shows the Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, being both referred as static models. Alternatively, the columns referred as regimes 1-4 describe the Markov-Switching estimates of herding behavior where all variables are allow to change stochastically. The numbers in parenthesis are t-statistics, ***, ** and * stands for significance at 1%, 5% and 10% levels respectively, and finally, Multiple R^2 estimates and Akaike Information Criterion (AIC) are described for each model.

To conclude the analysis, the Table 3.4 describes the interaction between volatility ($R_{m,t}$), extreme market returns ($R^2_{m,t}$) and the dummy variable that defines market conditions D. As mentioned earlier, the static parameter for herding behavior under declining market states is robust to the specification and consistent standard errors. The parameter γ_2 and γ_3 describes "pure" herding behavior associated exclusively to extreme market returns, having said that, there is evidence of adverse herding in regime 1 with $\gamma_{2,1} = 0.304$ (2.854) significant at a 1% statistical threshold, on the other side in regime there is strong evidence in favor of herding as seen in $\gamma_{2,2} = -0.918$ (-5.347). When the market is increasing, there is evidence of adverse herding in regime 1 $\gamma_{3,1} = 0.383$ (5.322) and herding in regime 4 $\gamma_{3,4} = -1.934$ (-5.936). Crypto-investors seemly react to uncertainty by either following the aggregate behavior or keep their priors strong, this is concluded when we take a look at the parameters γ_4 and γ_5 that capture the interaction between volatility and negative/positive market returns, particularly, there is evidence of adverse herding when it is considered uncertainty in declining conditions as seen in regimes 1, 3 and 4 with $\gamma_{4,1} = 0.534$ (2.215), $\gamma_{4,3} = 0.464$ (1.874), and $\gamma_{4,4} = 0.340$ (2.237) respectively, all the coefficients statistically significant at a 1% level, finally, there is evidence of herding as it can be concluded from $\gamma_{4,2} = -0.396$ (-1.812). Conversely, due to the interaction of rising market states and volatility, the estimates of the static model provide evidence of herding with $\gamma_5 = -0.267$ (-1.801), with similar results in regime 2 $\gamma_{5,2} = -0.065$ (-2.249). Finally, the parameters γ_6 and γ_7 were specified to bring information about the three variables interacting. The static model has not found evidence of herding; nonetheless, this is likely associated with conflicting data processes that cancel each other. For instance, this is visible in regime 1 where the parameter associated to *declining* $\times$ *uncertainty* $\times$ *extreme returns* is $\gamma_{6,1} = -22.111$ (-2.645) significant at a 1% statistical threshold, and $\gamma_{6,2} = -49.261$ (3.665). Alternatively, the parameter that captures *rising* $\times$ *uncertainty* $\times$ *extreme returns* found to affect market dispersion as it can be verified regimes 2 ($\gamma_{7,2} = -40.818$ (-4.250)) and 3 ($\gamma_{7,3} = -17.401$ (-2.888)) both for evidence in favor of herding and regime 4 for adverse herding ($\gamma_{7,4} = 54.546$ (2.062)). Figure 3.3 describes the smoothed probabilities of being in each regime.

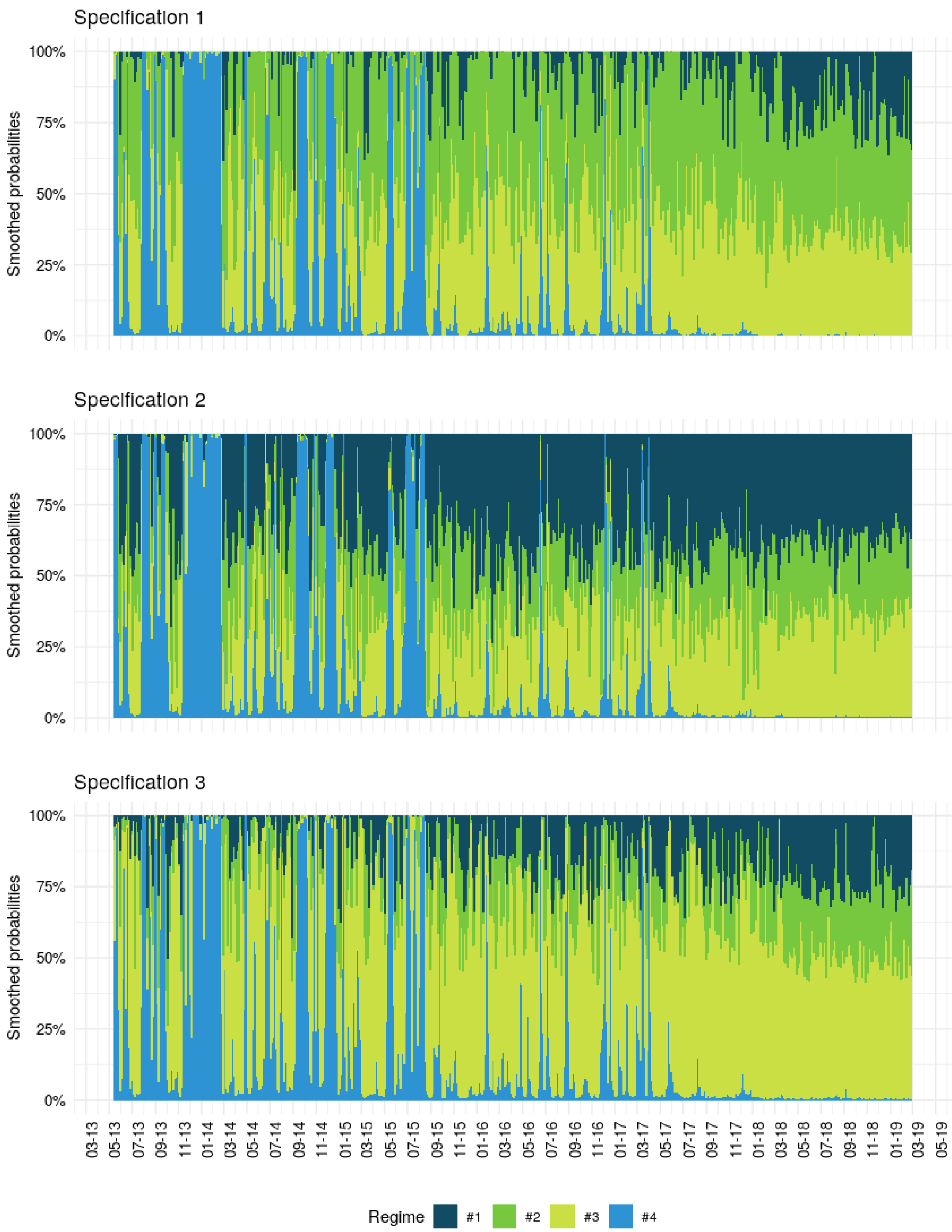


Figure 3.3. Regime switching smoothed probabilities under asymmetric herding behavior

Even though herding behavior under increasing returns situations was significant at a 1% level in the static model with, the extension of the model of Markov-Switching that account for interactions between uncertainty, market states and extreme returns unveiled the in-depth dynamics inside the data generating process. The results are similar to what it has been analyzed from Figure 3.1 being by top peaks of strong herding behavior in December of 2013, January/February/December 2014, and October 2014 with average probabilities of 97.1%, 96.2%, 78.3%, 73.0%, and 69.3% respectively. Other regimes found to be related to a mixture of "causes", not directly associated to market upswings and downswings.

These estimates of herding behavior under asymmetric market conditions corroborate the previous findings of the symmetric model. Herding is ubiquitous to crypto-markets, but there is evidence of being stronger when the market is declining, unveiling a unique decision-making process to respond to a negative outlook.

3.7 Conclusion

This essay was undertaken to evaluate the pertinence of behavioral finance as a framework to explain price dynamics in crypto-markets taking as a central point a series of potential biases in decision making from the investors. To solve the objective exposed above, it has been reviewed the literature on cognitive biases that have brought evidence of the existence of anomalies, or deviations from what a rational could be expected in related financial environments. Among the different possible explanations of price movements from a behavioral perspective, the theory of herding which consists in a situation when individuals ignore their private information and instead follow the consensus is under prior consideration a great approach to start the discussion. Herding behavior is challenging to measure with aggregate data; henforth, the explanation market dynamics demanded the task of finding an empirical model that serves to study the phenomena when only prices were the coordination mechanism. The former, and most relevant methodology to test for herding when only prices are available is attributed to Christie and Huang (1995), then it had been improved for Chang, Cheng, and Khorana (2000) among other authors, this study follows the same line.

The evidence from this study suggests that investors frequently deviated from the rational asset pricing benchmark, and instead follow the consensus in market stress situations. These findings have essential insights; first, herding is a *regularity* instead an *anomaly* of crypto-markets, second, it provides a framework to explain the price formation puzzle from crypto-markets, third, it unveils a signal that contradicts the Internet legend which asserts that there is a group of sophisticated crypto-investors that are not sensitive to significant price movements in cryptomarkets, which action make market corrections, results that is unlikely in light or the results of this study.

3.8 Appendix

Table 3.5. Generalized Autoregressive conditional heteroskedasticity for volatility estimation of average market returns for the leading 100 cryptocurrencies

Parameter	Estimate	SE	t-stat	p-value
μ	0.003	0.002	2.115	0.034
ar_1	0.926	0.012	80.247	0.000
ar_2	0.058	0.012	5.028	0.000
ma_1	-0.959	0.001	-833.437	0.000
ω	0.000	0.000	3.113	0.002
α_1	0.117	0.021	5.436	0.000
β_1	0.875	0.020	43.421	0.000
$shape$	3.697	0.318	11.631	0.000
Robust Standard Errors				
μ	0.003	0.002	1.790	0.073
ar_1	0.926	0.014	65.989	0.000
ar_2	0.058	0.016	3.572	0.000
ma_1	-0.959	0.001	-663.031	0.000
ω	0.000	0.000	2.622	0.009
α_1	0.117	0.023	5.031	0.000
β_1	0.875	0.024	36.039	0.000
$shape$	3.697	0.323	11.436	0.000
LogLikelihood		3700.378		
AIC		-3.474		
BIC		-3.452		

The table above describes the GJR-GARCH(1,1), ARFIMA(2,0,1), model to get the estimated volatility of average market returns $R_{m,t}$. Additionaly, this table provides the parameters and their standard errors (SE) and robust version which produces asymptotically valid confidence intervals.

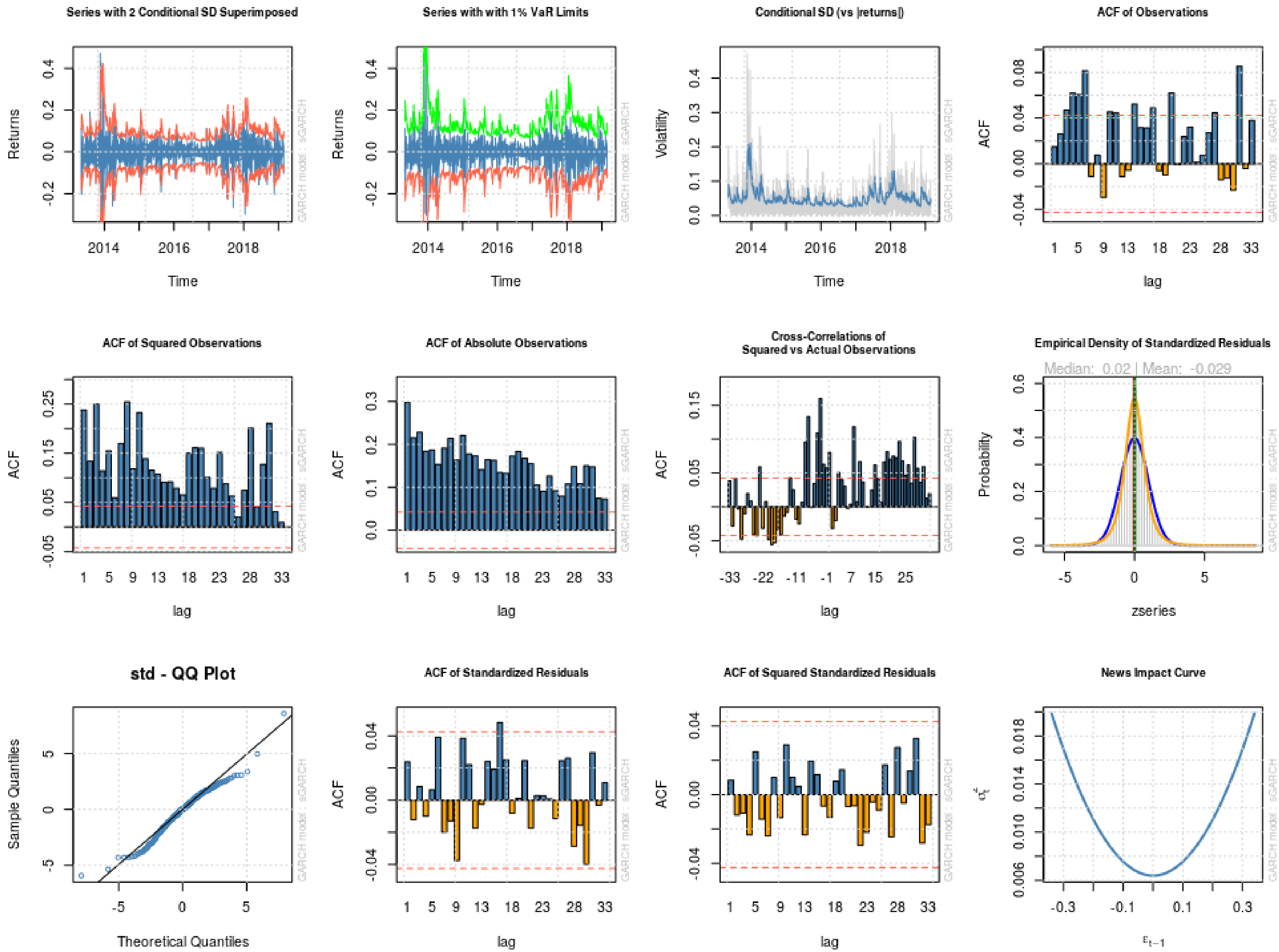


Figure 3.4. GARCH diagnostics for volatility estimates on average market returns

Chapter 4

Attention, meta-information and behavioral convergence in cryptocurrency markets: A SVAR analysis

Abstract

This paper aims to provide a conceptual framework that helps to understand decision-making within crypto-markets based on a small set of fundamental traits: attention-grabbing, behavioral convergence (herding), and uncertainty. The goal of this study is two-fold: first, propose a Herding Index (hindex) that captures the degree of consensus across market participants in face of asymmetric market conditions using time-varying state space modeling. Second, bringing a conceptual framework that links the essential traits of crypto-markets and empirically test for their contemporaneous relationship by applying Structural Vector Autoregressive (SVAR) framework, and estimate Granger and Wold methods to approximate a causal interpretation systems' dynamics. It has been found that the transmission between attraction proxies and market consensus is mild and dies quickly, while Bitcoins' meta-informational idiosyncrasy affects all traits causing a feedback loop that intensifies momentum that lasts for several periods. Finally, the conclusion is that there is little chance of market correction in absence of fundamental value, therefore the market is prone to generate bubbles and fads.

keywords: Herding; SVAR; Momentum; Cryptocurrency; State Space

4.1 Introduction

Regardless of the economic predicament individuals' might be involved, there are ubiquitous and natural constraints on the amount of computational and temporal resources that can be assigned to undertake a decision-making task (Kahneman 1973). The optimal distribution of cognitive resources implies *attention*, which ultimately will play a relevant role on the expected outcomes. Within behavioral finance literature is has been ascribed the term "anomalies" to designate non-negligible deviations from expected outcomes stemming from a rational model. Conversely, the so-called anomalies are so prevailing in cryptocurrency markets that one is tempted call them "regularities".

A growing body of literature has examined the economic responses of an agent's degree of attention. Mostly as a response of the urgency to design pragmatic policies by including known and proved psychological-based violations onto rational economic models. Attention is without a doubt an relevant element to take into account to economic modeling, besides it can also serve as a "bridge" and capture derived behavioral phenomena such as inattention to prices, taxes, probabilities, samples sizes, future (hyperbolic discounting), and under(over)reaction to news (Gabaix 2017; Sims 2003). Among the most relevant studies on attention, Merton (1987) article was one the most serious intents to pose the effect of information completeness, attention, investor behavior and their effect on equilibrium prices. More recently, Barber and Odean (2008) found that individual investors are net buyers of attention-grabbing stocks, namely, those that appear in news, unusual abnormal trading volume or extreme one-day returns. The authors argue that such lack of attention stems from their bounded rationality and the effort of searching problems given the thousands of alternative they can potentially acquire. Hirshleifer and Hong Teoh (2003) examined the consequences of firms' financial reporting narratives on investors perceptions and market price. Along the same lines of thought, Peng (2005) associates capacity constraints (attention) to delayed intertemporal consumption, finding that volatile assets attract more capacity allocation from investors, incorporating shocks more rapidly than it would be in the existence of true announcements. Another relevant article was provided by Hong and Stein (1999), they build a unified behavioral model based on the existence of two agents: *newswatchers* and *momentum traders*, being both of boundedly rational agents, that only differ in their ability to process available public information, the former rely only on news about the fundamentals, while the latter decide following past price changes.

It has been hypothesized that Bitcoin plays a dual role: firstly, it is, "as-is" a complex amalgam of currency and asset, and secondly, serves as a meta-informational input that conveys trust on the overall market of cryptocurrencies. Trust entails an underlying hope, loss-aversion, risk calculations, and a cue that shapes expectations on the future of cryptocurrencies. Trust, is also affected by noisy signals, that could be interpreted inconsistently both temporal and in magnitude dimensions across market participants. The spillovers of such cues spread over the entire market and reinforce attitudes, define beliefs, which manifests in posterior rounds of $cues - reaction - strategy - cues \ldots$ in a seemly endless feedback loop. To some extent, Bitcoin as meta-informational cue relates to the market-wide indicators (S&P500 or Dow Jones), that have been studied in depth by other authors.

The aim of this research is to integrate what has been argued in chapter 2 and chapter 3 about the main traits of cryptomarkets. This study contributes to the growing empirical literature on the effects of information on financial-like markets and demonstrating that in the particular case of crypto-markets the anomalies tend to be the rule and not the exception.

In this paper, it has been employed the Structural Vector AutoRegressive (SVAR) framework to analyze whether cryptomarkets markets and its underlying attitude to herd is affected by attention proxies. Attention has been measured with a similar fashion as Zhi Da, Engelberg, and Gao (2011), by creating a Search Volume Index of cryptocurrency news. Additionally, Bitcoins' returns act as a proxy for meta-informational indicator. Other proxies of market uncertainty are also included as GJR-GARCH estimates of Bitcoin's returns. Particularly, the SVAR model is suitable for the analysis of dynamic relationships among different salient traits of cryptomarkets, since it allows to identify the main channels of interactions and gather information about the impulse and responses of a given variable's innovations in other variables.

This research contributes to the existing empirical literature on attention effects on asset prices, and concisely, it applies the current framework to the cryptocurrency market. First, it expands and update the proxy for attention, while in chapter 2 it has been created a weekly index of "interest" of Bitcoin by finding such term in Google Trends, which was also disaggregated by country, in this study we cover a broader perspective, taking into account other terms related to other cryptocurrencies and created a Search Volume Index (SVI) as a proxy for attention, being also recomputed to show higher variance by being at a daily frequency. Second, it has been by employed a Time-Varying State Space Model to create a random walk index that captures the degreee of behavioral convergence (herding), the "hindex" unveils an underlying trait of cryptomarkets: a tendency to take decision according to the consensus. Third, the paper represents an improvement in relation to other similar studies that only look at correlations and causal relationships between attention proxies and aggregate market idiosyncrasies.

The results show that the proposed framework serves a conceptual system of the main aspects that define crypto-markets: herding behavior and attention based strategies. It has been discussed that Bitcoin's returns play a meta-informational role, since its dynamics are not only self-determined following a aggregate momentum strategy from market participants, but also triggers herding either on decreasing and increasing market states, and revealed attention. Shocks on attention on the other side, have no statistical effect on future returns, but it does affect positively the dispersion of Bitcoin returns. Regarding herding, it has been demostrated that shock on market consensus under increasing and decreasing market states are associated with significant instantenous increases in Bitcoin returns, that does not last for several days, however, shocks on herding reduces Bitcoins' returns volatility.

The structure of this chapter goes as follow: section two starts with a background section that relates the network effects of cryptomarkets and how information flows across this market. Section three provides an overview of the relevant literature related to this study. Section four describes the data, how it was extracted and computed. The fifth section presents the methodology focusing on the SVAR model. Section six discusses the empirical results of Granger and Wold causal estimates. Finally, section seven provides a brief summary and critique of the main findings.

4.2 Background

The invention of newspapers permitted a rapid spreading of salient and not relevant information. Moreover, it also provides as a ploy for the transmission of hypes with the purpose of capturing reader's attention towards different issues, being markets one of many of them.

Reflecting the growing recognition of the role of fads and endogenous market fluctuations, much of the research has focused in recent years on why large deviations of market values from fundamentals occur in the first place and how *"false"* information or fads can be disseminated in the market. Studying herd behavior[1] has been the object of considerable effort in recent years for its possible role in amplifying fads and lead market prices astray from fundamentals.

"A mania involves increases in the prices of real estate or stocks or a currency or a commodity in the present and near-future that are not consistent with the prices of the same real estate or stocks in the distant future" (Kindleberger and Aliber 2005).

Within this research it has been suggested that these patterns can be explained by the difficulty of evaluating a large number of available alternatives, and investors'

[1] for a survey, Devenow and Welch (1996) and Bikhchandani and Sharma (2000)

tendency to let their attention be directed by outside sources such as the financial media, by the disposition effect, and by investors' reluctance to sell short (Barber and Odean 2001).

A confrontation of different ideas has been playing an essential role in the development of society. The invention of the printing press is one of the most significant, if not the most dramatic event that yields to the conception of information as a near public good. There is evidence that the decline in the cost of dissemination of knowledge and ideas due to press accounted for 18 and 68 percent of European city growth between 1500 and 1600 (Dittmar 2011). Nowadays, in the digital economy, information is no longer a scarce commodity, conversely, there is an overload of data that demands the creation of mechanisms to discern which is relevant and which is not. On this matter, H. Simon accurately described the situation by saying *"wealth of information creates a poverty of attention"*. Furthermore, as humans, we have limited computation capabilities and an increasing number of constraints to develop a single activity, hence, the formation of *" rules of thumb"* usually takes place instead of coherent reasoning according to what each state demands. According to Barber and Odean (2013), the extension to financial markets stems to the limited devotion to investing mainly in two fashions: delayed reaction to salient information and overstated attention to stale information that can lead to overreaction. As a result, an active agent in the crypto marketplace may face uncertainty and not be able to assess probabilities of events, accuracy, well-timed choices, the degree of utility, and quality from some sort of heterogeneous information extracted from sources such as social media, newspaper, forums, and *prices*.

Social judgment is intrinsic to the cryptocurrency market since the valuation of any currency is contingent on the extension of the group that founds it valuable, that is, cryptocurrenct market exhibit network effects or network externalities, which is also particularly strong in communication platforms. Under these scenarios, the strategy is to achieve the interest of a critical mass of users/investors that yield a higher market capitalization. Those early adopters (*"Whales"* in cryptocurrencies' slang) can be positioned and exert market power by manipulating prices and making profits, this practice normally described as *"Pump and Dump"*. The objective of boosting prices has as a mechanism the exposition of exaggerated announcement about the future of any cryptocurrency, for instance, presumed cryptocurrency's experts anchor prospects by declaring future increases in prices, narrative stories of success, any Blockchain's innovative applications in social media, news, and forums. Once people receive this information, they have to discern if it is accurate or not, but prices often react faster, then, it is strategically rational to generate trading strategies according price dynamics. The practice of imitating behavior has been studied in extension in financial [2], it

[2]non-financial studies range from real state to wine tasting

has been named as positive feedback, informational cascades or herding.

To some extent, cryptomarkets can be explained in a small set of traits that define certain behavioral biases as explained above. Clearly, there is the limitation of capturing the biases directly from the investors, which is technically unfeasible. Nonetheless, with aggregated data, we can approximate these traits that capture momentum trading, herding, and attention.

4.3 Literature review

Over the past two decades, a large and growing body of literature has been mentioning the existing of anomalies from behavioral-based models, firstly applied to asset markets, then expanded to other similar instances such as exchange rate market. One of the firsts theoretical research was carried out in Merton (1987), who develop models of capital market equilibrium with incomplete information on the part of investors, with the assumption that these lack asymmetric state stemmed from searching problems in finding among thousand of securities available, which incentivized the attention on a minimal fractional sample of securities.

From Merton's seminal article, there has been an intensive and growing empirical research trying to unveil what is for several economists unambiguously true: people react in a non-rational consistent way when they face new information. Particularly, the "attention theory" coined by Barber and Odean (2008), states that investors are buyers of attention-grabber, henceforth defining selling and buying decisions. Several indirect attention-grabber proxies have been proposed in empirical studies: quality/price ratio (Bordalo, Gennaioli, and Shleifer 2013), past returns (Barber and Odean 2008; Cohen and Frazzini 2008; Hou and Moskowitz 2005), trading volume (Barber and Odean 2008), news stories (Barber and Odean 2008; Frank and Sanati 2018; Peress 2014; Zhang et al. 2016), industry/wide-market indicators (i.e. S&P500 or Dow-Jones) (Moskowitz and Grinblatt 1999; Joseph, Babajide Wintoki, and Zhang 2011; Peng, Xiong, and Bollerslev 2007), Google or Baidu search trends (Zhi Da, Engelberg, and Gao 2011; Joseph, Babajide Wintoki, and Zhang 2011; Takeda and Wakao 2014; Vlastakis and Markellos 2012; Vozlyublennaia 2014), day-of-the-week earnings announcements (DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009; Karlsson, Loewenstein, and Seppi 2009; Li and Yu 2012) and macroeconomic indicators (Kumar 2009).

We should be careful about attention-grabbing proxies (besides that the evident restriction being aggregate data (Coval and Shumway 2005), since they are not "created equal" (Barber and Odean 2008), mechanism that gave rise to it, for instance, someone who reads in the news that a given cryptocurrency is rising in value might be attracted to it, but it does not mean that it is taking action, conversely, search trends represent an explicit manifestation of such attention, or *revealed attention* (see Zhi Da, Engelberg, and Gao 2011).

Attention is closely related to other systematic behavioral biases (Gabaix 2017). One study from Hong and Stein (1999) posits on the puzzle of predictable returns based on publicly available information, more specifically, their model feature two rationally bounded agents: the *"newswatchers"* and the *"momentum traders"*. Newswatcher make a forecast on signals they observe about the fundamentals, therefore the diffusion of information flows slowly, whereas momentum traders rely exclusively on past price changes (typically faster reaction). According to Hirshleifer and Hong Teoh (2003), such difference in the speed of action can be explained through the limited attention of the investors. To some extent, crypto-investors in absence of fundamental can only form beliefs regarding the value of a given cryptocurrency based on what is being currently happening in the market. For instance, if Bitcoin is rising, it is interpreted as a signal conveying positive expectations to the $N-1$ cryptocurrencies, making Bitcoin sort of a "leading indicator". Having said that, this study, it has been hypothesized that Bitcoin plays a dual role: firstly, it is, "as-is" a complex amalgam of currency and asset, secondly, it serves as a meta-informational input that conveys trust on the overall market of cryptocurrencies.

The decision of investing in cryptomarkets does not rely only on a private calculation on the risk-return tradeoff, it also relates largely on the perception of market stability and resilience. A growing market is a positive cue, which presumable increases trust and reduces loss-aversion, and determines market participation, in regard of to the final uses of any cryptocurrency or token. Guiso, Sapienza, and Zingales (2008) have already noted the effects of trust on stock market participation; according to their conclusions, trust is partly rooted in an individual's idiosyncratic characteristics such as educational background, acquaintanceship, religion, and culture. More specifically, the authors outline that in the stock market, investors not only assess the risk-return trade-off, they also adjust their expected payoff by the faith that such reward will actually take place, that is, they also take into account the probability of been cheated. Other authors have studied trust and how it affects market participation, for instance, Ang, Bekaert, and Liu (2005) argues that trust is closely related to loss-aversion, while Barberis, Huang, and Thaler (2006) accounts also for narrow framing, both ideas were empirically proved by Dimmock and Kouwenberg (2010).

Trust or its counter part loss-aversion, entails an underlying hope, a cue of positive expectations and an increased likelihood on the future of the universe of potential that cryptocurrencies and tokens can provide. Trust, naturally is affected by noisy signals, that are interpreted inconsistently both temporal and in magnitude dimensions across market participants. The spillovers of such cues spread over the entire market (Altcoins) and reinforce attitudes, sentiment, which manifests in posterior rounds on Bitcoin price and continues in a seemly endless feedback loop. To some extent, Bitcoin as meta-informational cue relates to the market-wide indicators, namely, S&P500 or Dow Jones, that have been studied in-depth and concluding that they affect investors causing under and overreactions.

To some degree, one is tempted to believe that cryptocurrency is actually isolated from other markets, since there is the little relationship of them to foreign exchange markets, stock markets and macroeconomic conditions (chapter 3; Liu and Tsyvinski 2018). Crypto-markets are narrow-framed, and the rules that define its resilience are rooted in future expectation, that is at the same time conditioned by currently observed returns. Having said that, in this study, we use Bitcoin as a signaling indicator that entails trust.

Despite the growing trend in empirical studies on cryptocurrencies, there has been few of them that provide a theoretical framework to work on, and even more to focus on the most important traits that so far have undeniable importance: herding behavior, momentum trading, and attention-grabbing decision making. Moreover, establishing a causal path of across information dissemination, participants' reaction and market-wide outcomes in cryptocurrency environments are cumbersome. There is a vast amount of literature finding a correlation between news media and crypto-assets returns[3]. This association relates to the financial markets counterpart, however, is at least less fuzzy than cryptomarkets in the sense that the former has a confounder (fundamental announcements), that affects both, the coverage and the price of the stocks, whereas cryptomarkets lack such common factor. To the best of authors' knowledge, the closer research on this topic comes from Urquhart (2018) who examined the relationship between investors' attention and Bitcoin fundamentals.

Summarizing, the quest of disentangling the several elements that form the idiosyncrasy of any cryptocurrency only from the price a difficult task. In chapter 3 it has been stated that as financial markets, crypto investors have limited resources to process information, which jointly with their lack of attention tend to behave according to the market consensus. However, what remains to be explained is what is triggering such heuristic. This study is an empirical analysis of the causes and signals that orient decision makers to either behave to the consensus, momentum trading and awareness of the current trends.

[3] see chapter 2 for a review

4.4 Data description

As stated by Coval and Shumway (2005), an empirical test of behavioral models face a set of challenges, being the main one, possessing only aggregated data. It is quite difficult to unveil the factors that affect their behavior in the absence of granular information tracking signals and actions at an individual level. This paper uses daily data spanning the period between January 1st, 2014 and April 3rd, 2019 to examine the cross effects of the main traits of crypto-markets.

4.4.1 Measuring behavioral convergence

In chapter 3 it has been covered the characteristics of what is herding and the implications of highly biased decision-making processes within cryptocurrency markets. Taking the aforementioned study as a based, we propose the *herding index* (from now, hindex), which is a raw indicator of the magnitude of aggregate consensus within cryptomarkets under the existence of positive and negative extreme or abnormal average market returns. High frequency data exhibits changing dynamics that affect the relation between the parameters, in practice, such idiosyncracy is typically modeled as stochastic regimes, time-varying state space models or a combination of both. Since we are interested in the individual level of convergence over time as the information is included as "evidence", it is useful to work with state space approach to let the coefficients vary over time according to a random walk. For the sake of consistency, it will be used the same specification[4] as in chapter 3:

$$\begin{aligned} CSAD_t = &\gamma_0 + \gamma_1 D \times |R_{m,t}| + \gamma_2 (1-D) \times |R_{m,t}| + \\ &\gamma_3 D \times R^2_{m,t} + \gamma_4 (1-D) \times R^2_{m,t} + \\ &\gamma_5 D \times Vol_t^{R_{m,t}} + \gamma_6 (1-D) \times Vol_t^{R_{m,t}} + \\ &\gamma_7 CSAD_{t-1} + \gamma_8 CSAD_{t-2} + \gamma_9 CSAD_{t-3} \end{aligned} \tag{4.1}$$

Particularly, we are interested in coefficients γ_3 and γ_4 that according to their sign, it is either herding if ($\gamma_k < 0$) or adverse herding ($\gamma_k > 0$) behavior and their magnitude, under decreasing and increasing market returns $(R_{m,t})$ scenarios respectively. Since $\gamma_k\ for\ k = \{3, 4\}$ are just static indicator of an underlying market's participants behavior it is possible to expand the model and impose to $\gamma_k\ for\ k = 1, ..., k$ an innova-

[4] $|R_{m,t}|$ express absolute average market returns, $R^2_{m,t}$ squared average market returns, Vol_t^{CSAD}, $Vol_t^{R_{m,t}}$ the estimated volatilities from the Glosten-Jagannathan-Runkle GARCH(1,1) model and $CSAD_{t-k}$ autoregressive variables of order $k = 3$. Finally D that takes the value of 1 if $R_{m,t} \leq 0$ or 0 otherwise

tion parameter and treat each of them as a random walk ($\gamma_k + \varepsilon_{k,t}$). The resulting state space specification will look like[5]:

$$CSAD_t = \boldsymbol{Z_t}\alpha_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, H_t) \tag{4.2}$$

$$\alpha_t = \boldsymbol{T_t}\alpha_{t-1} + \boldsymbol{R_t}\eta_t \qquad \eta_t \sim N(0, Q_t) \tag{4.3}$$

State space models such as the representation above are composed by observation and state equations, respectively. The response variable is $CSAD_t$, $\boldsymbol{Z_t}$ and $\boldsymbol{T_t}$ are respectively known matrices of order $(K \times K)$ and $(M \times K)$, and α_t is a vector that contains all the dependent variables (γ_k), in which every variable except the constant and the lags of $CSAD$ are modeled as random walks. Parameters' attributes derive from innovations η_t, and $\boldsymbol{R_t}$ is an indicator matrix that determine the static or dynamic condition of the parameters α_t. Specifically, in the state equation, the coefficients associated to herding have the form $\gamma_k + \eta_k$ for $k = \{3, 4\}$, therefore HINU stands for herding under upward market states, and HIND (downward) behavioral convergence indexes are constructed given all the information Ω_t available at t.

$$HINU = \hat{\gamma_{3,t}}|\Omega_{t-1} \tag{4.4}$$

$$HIND = \hat{\gamma_{4,t}}|\Omega_{t-1} \tag{4.5}$$

As a measure for behavioral convergence, it has been proposed an empirical approach by estimating a state space time-varying model of asymmetric herding. The estimated herding index $\hat{hindex}_t$ indicates both the direction, that is, the herding condition (negative sign) and reverse herding (positive sign) and its magnitude.

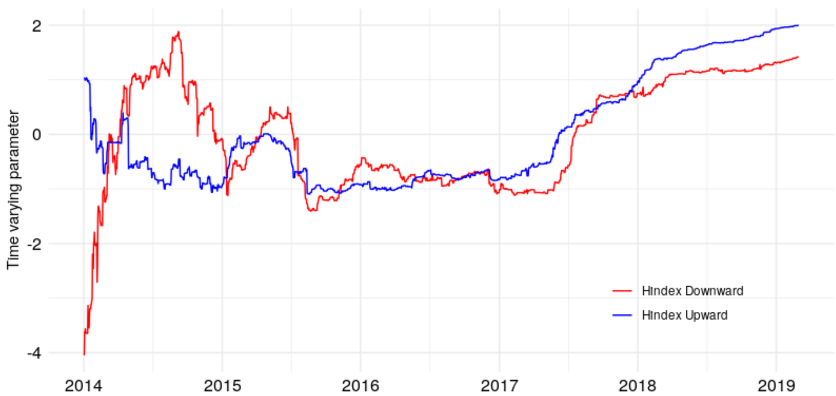


Figure 4.1. Herding index for asymmetric market conditions (standardized)

[5]For details about space state models applications to cryptocurrency markets see chapter 2.

Figure 4.1 describes the random walk coefficient, which has been stationary induced by differentiate the time-varying coefficient as $log(hindex_{(z)t}) - log(hindex_{(z)t-1})$, additionally, it has been standardized to standard score of it given the well-known formula: $hindex_{(z)t} = {}^{(hindex_t - \overline{hindex})}/_{\hat{\sigma}}$ without losing its purpose and facilitating the interpretation as well. Finally, it is important to highlight that this index is based on the top 100 cryptocurrencies, and is the same as specification was proposed by chapter 3, therefore, for a in-depth examination of the data sources, and treatment please refer to that research study.

4.4.2 Measuring attention

A measure of the surprise element of any specific change in the interest of the overall market can be derived from the change in the search volume index. Regarding the lasting, this case the returns of Bitcoin and search queries index on internet naming "bitcoin". It is relevant to mention that Google Trends API does not allow to query daily "hits" on time spans higher than 90 days, instead, it will create the weekly adjusted index. For instance, trying to get the score or "hit" for the period "2018-01-01" to "2018-04-01" will show as an output daily series, adjusted by the highest (highest=100) point within that range of dates. Whereas, querying for "2018-01-01" to "2018-05-01" will show a weekly index, which is also adjusted by the highest weekly point. To solve such problem it has been readjusted the index by querying recursively in three-months chunks (getting daily data), then reweight the series by their weekly weight within all the period of study. The result is a attention-grabbing index as in Figure 4.2:

Figure 4.2. Attention index

This score has been differetiated to induce stationarity as well as standardized.

4.4.3 Measuring uncertainty

Additionally, it has been taken into account Bitcoin's volatility as a proxy for uncertainty using a GJR-GARCH model. This model accounts for a skewed Generalized t-Student Distribution which is more suitable to approximate long-tail distributions of cryptocurrency's returns. A GJR-GARCH starts defining that returns r_t follow a random walk with mean μ and error terms (ε) expressed as $r_t = \mu + \varepsilon_t$. Particularly, the error term can expose a conditional heteroscedasticity behavior with the form $\varepsilon_t = \sigma_t z_t$ where z_t is a given distribution. The specification to model Bitcoins' uncertainty is described by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \epsilon_{t-i}^2 + \gamma_i I_{t-i} \epsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{4.6}$$

where the I_t indicator variable describe the bias stemming from the less than average returns described as:

$$I_{t-i} = \begin{cases} 1 & if\ r_{t-i} < \mu \\ 0 & if\ r_{t-i} \geq \mu \end{cases}$$

The best model according to its Akaike Information Criterion (AIC) is shown in Table 4.1. All parameters with exception of μ and γ_1 found to be significant at the 5% critical threshold, however, with the robust standard errors also ω fails to reject the null hypothesis with a p-value of 0.18.

The Figure 4.10 in the appendix shows the estimated volatility of Bitcoin returns following a GJR-GARCH(1,1). While its diagnostics can be checked in Figure 4.11.

Table 4.1. Volatility estimation for Bitcoin's return (GJR-GARCH(1,1))

Parameter	Estimate	Std.Error	t-value	p-value
μ	0.001	0.001	1.494	0.135
ω	0.000	0.000	2.490	0.013
α_1	0.163	0.024	6.881	0.000
β_1	0.850	0.020	42.656	0.000
γ_1	-0.028	0.027	-1.039	0.299
skew	0.952	0.025	37.740	0.000
shape	3.235	0.177	18.313	0.000
Robust Standard Errors				
μ	0.001	0.001	1.312	0.189
ω	0.000	0.000	1.353	0.176
α_1	0.163	0.025	6.433	0.000
β_1	0.850	0.032	26.451	0.000
γ_1	-0.028	0.034	-0.826	0.409
skew	0.952	0.026	36.797	0.000
shape	3.235	0.179	18.062	0.000
LogLikelihood		3923.026		
AIC		-4.162		
BIC		-4.141		

The table above describes the GJR-GARCH(1,1) model to get the estimated volatility of Bitcoin's returns. Additionaly, this table provides the parameters and their standard errors (SE) and robust version which produces asymptotically valid confidence intervals.

4.4.4 Descriptive statistics

The table below summarizes the statistics of the variables which are going to be part of the system.

As mentioned, variables were transformed to be as weakly stationary, the Table 4.3 describes the correlation matrix (only lower triangular entries only are printed) of the endogenous variables included in the model. It is clear that for most of the variables there is a little contemporaneous linear statistical relationship since the highest linear relationship are related to Bitcoin's return and the increasing state market returns herding (HINU) with 11.2% and decreasing state returns (HIND) with -9.5%.

Table 4.3 describes the pearson correlation coefficient between the variables within the system. At first sight, it is possible to conclude that there is little linear correlation between the terms, being the leading related to Bitcoin's returns, with 11.2% in herding under rising market conditions and 9.5% in the case of herding under decreasing status.

Table 4.2. Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
BTC	1885	0.001	0.039	−0.238	−0.012	0.002	0.017	0.225
ATT	1885	−0.000	1.000	−13.719	−0.094	−0.007	0.065	17.691
BTCv	1885	0.000	0.007	−0.063	−0.001	0.000	0.001	0.060
HINU	1885	−0.000	1.000	−18.903	−0.022	−0.010	0.049	8.443
HIND	1885	−0.000	1.000	−10.501	−0.065	−0.042	0.008	13.085

This table shows statistics for the variables that are relevant to the cryptocurrency system: Bitcoin's returns (BTC), Attention-grabbing index (ATT), Bitcoin's estimated volatility (BTCv), herding index for an increasing market state or upward herding (HINU) and finally the herding index for downward market states (HIND). All the variables except BTC and BTCv were standardized after the first differentiation, which is clearly visible just by looking at their first and second moments.

Table 4.3. Correlation between the endogenous variables

Variable	BTC	ATT	BTCv	HINU	HIND
BTC	1.000				
ATT	0.028	1.000			
BTCv	0.047	-0.037	1.000		
HINU	0.112	-0.008	0.019	1.000	
HIND	-0.095	0.001	-0.003	-0.009	1.000

4.5 Methodology

Empirical herding is typically measured as the impact of large returns on market's Cross-Sectional Absolute Deviations (CSAD) which is a contemporary index for market dispersion towards the mean. In chapter 2 we have employed a regime switching model to identify periods of high and low behavioral conformity. This study modes herding following a space state specification and using the estimated coefficient as an indicator of the intensity over time as mentioned earlier. Posteriorly, the estimated parameters were extracted and used as an endogenous variable in a structural vector autoregressive model (VAR) with the purpose of testing the effect of informational shocks of individual returns and news from the public.

4.5.1 Vector Autoregressive model

We are interested in modeling attention, underlying crypto-market consensus and uncertainty using a Vector Autoregressive (VAR) model. In such a setup VAR Sims (1980), is an appropriate tool since it very well consolidated in the empirical research literature given its property to unveil stochastic dependencies. More specifically, it was constructed to exhibit mathematical statistics properties of economic data instead of economic theory, which suits well in behavioral economics studies. Besides, in a VAR all variables are endogenous, that is, there is cross-temporal dependency among all the variables included in the left-hand side (LHS) and the lagged values of the set of endogenous variables. Finally, the impulse response and variance decomposition based on the unrestricted VAR can serve as an inspection the relationship between variables, and the possibility to identify causal relationships after maintaining the exogeneity of the right side (RHS) variable.

As stated by Nakamura and Steinsson (2018), it is an important task and challenge to identify plausibly exogenous variation in temporal aggregate variables, either by generating macroeconomic policies. No only in macroeconomic studies VAR models have solved some of the problems of identifying cross-temporal dependencies. A stationary reduced form model VAR of order p is specified as:

$$y_t = \alpha + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \epsilon_t, \qquad t = 0, 1, \ldots \tag{4.7}$$

where $y_t = (y_{it}, \ldots, y_{Pt})'$ is a $(K \times 1)$ random vector of stationary endogenous variables, the Φ_i are fixed $(K \times K)$ coefficient matrices $\forall\ i$, $\alpha = (\alpha_1, \ldots, \alpha_K)'$ is a fixed $(K \times 1)$ vector of constant terms, which tipically are zero $E(y_t) = 0$ when variables are stationary in mean. To conclude, $\epsilon_t = (u_1, \ldots, \epsilon_{Kt})'$ is a K-dimensional *i.i.d* innovation processes, with $E(\epsilon_t) = 0$, a given non-singular covariance $E(\epsilon_t \epsilon_t') = \sum_\epsilon$, and $E(\epsilon_t \epsilon_s') = 0$ for $t \neq s$. It has been employed five-variables VAR system, upward hindex (HINU), downward hindex (HIND), Bitcoin's returns (BTC), Bitcoin's volatility (BTCv) measured as a GJR-GARCH(1,1), attention-grabbing index (ATT), complying all of them as stationary.

Empirically, the optimal length of lags is unknown ex-ante, however, in some cases, it can be guided by a given economic theory. In this study we are not attached to established economic theory, conversely we are interested in the contemporaneous relationship between the endogenous variables and make an as good guess of the structure and dependencies. There are different statistical methods that serve as a rule to decide the number of lags we should include in the RHS of the VAR equations, the most common procedure for model order selection involves the selection of lags that minimizes one or more information criterion (IC) measures. Among the alternatives, Schwarz-Bayes (SC or BIC) Akaike (AIC) are undoubtedly the most known, being different by the weight they put on prediction error and number of parameters. Besides BIC and AIC, there is Akaike's Final Prediction Error (AFPE) and Hannan-Quinn Criterion (HQC), that vary in conformity to the magnitude they penalized big models (several estimated parameters). The formulas below describe the method we will compare:

$$AIC(n) = ln\ det(\hat{\Sigma}_u(k)) + \frac{2nK^2}{T} \tag{4.8}$$

$$HQ(n) = ln\ det(\hat{\Sigma}_u(k)) + 2nK^2 \frac{log(log(T))}{T} \tag{4.9}$$

$$SC/BIC(k) = ln\ det(\hat{\Sigma}_u(k)) + nK^2 \frac{log(T)}{T} \tag{4.10}$$

$$FPE(k) = \left(\frac{T+N}{T-N}\right)^K det(\hat{\Sigma}_u(k)) \tag{4.11}$$

where $\hat{\Sigma}_u(n) = T^{-1} \sum_{t_1}^{T} \hat{u}_t \hat{u}_t'$, N the total number of parameters per equation, n the lag order. Having said that, therefore, there is always on researchers' hand to choose the order according to the different IC options.

4.5.1.1 Structural analysis of cryptomarkets

It has been stated that crypto-markets can be expressed in a few traits: attention-grabbing, momentum trading and herding behavior. Since VAR models provide a framework to study cross-temporal correlations, they can also serve as a mean for the study of the directional effects, that is, what is the impact of one variable on the other *ceteris paribus*. Given that VAR models are essentially stacked univariate models that unveil cross-correlations among variables (everything affects everything), they are used to analyze specific aspects about regarding the relationships within the system. There are three methods that stem from VAR model estimation that serve as a tool to unveil dependencies: Granger-Causality test (GCT) and Impulse-Response Function (IRF).

The GCT (Granger 1969) is the predominant tool to provide causal-like interpretation to time series variables, in this case, whether a given trait of cryptomarket affects either a different trait or the overall system (except the variable which is "causing" the change). To formalize causality in Granger terms, we assume a system of one-two variables x_t and z_t. We begin considering all the information available Ω_t to explain what is happing within the system, and $z_t(h|\Omega_t)$ a loss function that determines how accurate Ω_t predicts observed values y_t, given h-step predictor process.

$$\Omega_t = (x_t, x_{t-1}, \ldots, x_{t-s}, z_t, z_{t-1}, \ldots, z_{t-s}, \ldots) \tag{4.12}$$

Then, it is considered that x_t causes z_t in Granger sense if:

$$loss_z(h|\Omega_t) < loss_z(h|\Omega_t \backslash x_t) \tag{4.13}$$

That is, given a loss function that minimizes the prediction error, x_t Granger-causes z_t if all the relevant information Ω_t except the past dynamics of x_t performs better than a model with all the information. The loss function can be expressed as Mean Squared Error (MSE) or Mean Absolute Error (MAE), however, in order to compare both models Granger-causal uses $F - statistic$ for the normal Wald test of restriction of coefficients expressed by:

$$F = \frac{(RSS_r - RSS_u)/m}{RSS_u/(n-k)} \tag{4.14}$$

where RSS stands for Residual Sum of Squares for the restricted r and unrestricted u models, with given m a k degrees of freedom. It is important to highlight that it is not a causal relationship per-se, because there is no structure defined.

Granger-causality proposition relies on the idea that if a event z is the "cause" of another event x, then the event z should precede the event "x". Granger-causality tests have been widely used in studying how shocks in the producer inflation rate are transmitted to the consumer inflation, interest rate on inflation or exchange rates. This research is interested in the effect of any given trait to rest of traits included in the conceptual system that represents cryptocurrency markets, hence, the following model specification is an example of three trait system:

$$\begin{aligned}
trait_t^A &= \gamma_{0,1} + \gamma_{1,1} trait_{t-1}^A + \cdots + \gamma_{n,1} trait_{t-n}^A + \\
&\qquad \phi_{1,1} trait_{t-1}^B + \cdots + \phi_{n,1} trait_{t-n}^B + \\
&\qquad \theta_{1,1} trait_{t-1}^C + \cdots + \theta_{n,1} trait_{t-n}^C + \varepsilon_{1,t} \\
trait_t^B &= \gamma_{0,2} + \gamma_{1,2} trait_{t-1}^A + \cdots + \gamma_{n,2} trait_{t-n}^A + \\
&\qquad \phi_{1,2} trait_{t-1}^B + \cdots + \phi_{n,2} trait_{t-n}^B + \\
&\qquad \theta_{1,2} trait_{t-1}^C + \cdots + \theta_{n,2} trait_{t-n}^C + \varepsilon_{2,t} \\
trait_t^C &= \gamma_{0,3} + \gamma_{1,3} trait_{t-1}^A + \cdots + \gamma_{n,3} trait_{t-n}^A + \\
&\qquad \phi_{1,3} trait_{t-1}^B + \cdots + \phi_{n,3} trait_{t-n}^B + \\
&\qquad \theta_{1,3} trait_{t-1}^C + \cdots + \theta_{n,3} trait_{t-n}^C + \varepsilon_{3,t}
\end{aligned} \tag{4.15}$$

for each equation we can test Granger-Causality by testing the null hypothesis of the leaving-one out trait, for instance, the effect of $trait^B$ on the system, for a given lag is tested by $(\phi_{1,1} = \cdots = \phi_{1,n} = 0)$, whereas for $trait^C$ it will be $(\theta_{1,1} = \cdots = \theta_{1,n} = 0)$ and so on.

Even though Granger-Causality is an interesting method to unveil structural relationships, it does not provide solutions to assess the cross-interactions within the system, since F-tests examine the Granger-causal within a VAR defines which of the variables within the model have statistically significant effects on the future values on the variables present in whole the system. The issues stem when we want to visualize the directionality, that is, GCT will never unveil if the effect is positive or negative, besides, it does not let us know of how long does this effect last to each variable and not the whole system. On the other hand, the IRF trace the responsiveness of a given endogenous variable specified in the LHS in front of a shock, or in other words, the effect of one unit in the innovation in a Vector Moving Average (MA) representation of a VAR model written as $\Phi_1^i = \Psi_i$, where i is the coefficient matrix of the MA representation of a VAR(1) process. Hence, if there are p variables in the system, there will be $p(1-p)$ impulse response functions, or p^2 including the self-induced shocks. IRF offers an intuitive solution based on forced shocks from one variable to each other present in the system, that is, the response of one variable to an impulse in another over time.

The Moving Average (MA) representation of the impulse response function is given by:

$$y_{t+n} \sum_{i=0}^{\infty} \Psi_i \epsilon_{t+n-1} \tag{4.16}$$

with:

$$\{\Psi_n\}_{i,j} = \frac{\partial y_{it+n}}{\partial \epsilon_{jt}} \tag{4.17}$$

hence, the equation above represents the response of variable i to a unit shock (namely, forecast an error) in another variable j present in the system for a given horizon in the future. If the shocks are correlated, it is expected the presence of multiplier effect from another variable in the impulse response function.

In this work, it has been decided to follow the Cholesky Decomposition (CD) to approximate a structure of the cryptocurrency system. The CD is a well-known method to orthogonalize the innovation within the covariance matrix by defining a lower triangular matrix of the MA representation of the Structural VAR model (SVAR). This "solution" has several side effects, for instance, the order of the variables matters, since the first equation in y_1t has an instantaneous effect on the $P-1$ variables in the system, the second equation y_2t on $P-2$, but not on y_1t and so on, this is often referred as Wold causality. The order affects in great extension the impulse response functions, and by extension the understanding of the cryptomarket system's mechanism.

As seen in Figure 4.3, in this research it is has been decided to set BTC as the first variable, based on the principle argued in chapter 2 that prices convey and transmit information at a faster pace than any other attention proxy within crypto-markets due to their momentum or trend is my friend idiosyncratic philosophy.

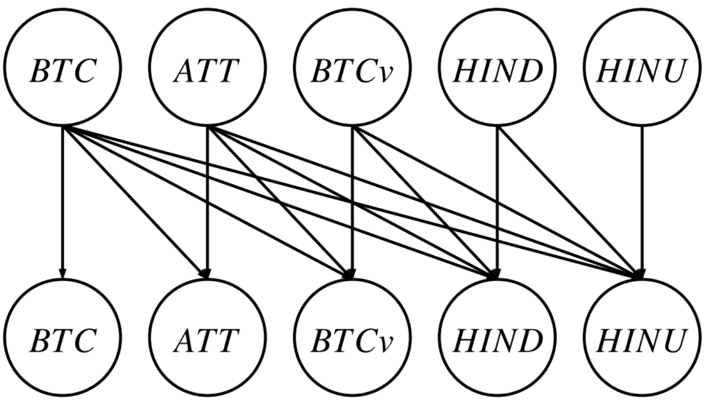


Figure 4.3. Ordering of the orthogonalized impulse-response function. The diagram defines the structure of the crypto-system transmission mechanisms from attention to behavioral convergence.

The order continues with the estimated volatility which is assumed to not affect returns instantaneously. The third equation is attention-grabbing indicators, this is assumed since individuals have uncertainty regarding a specific decision they might be facing, in this case, to buy or sell. And it not until they acquire information, and update/reinforce their priors, when they take an action, henceforth, it is natural to think of order between a fast attention-grabbing proxy (extreme returns in BTC), and the revealed attention of searching on the internet for such event. Lastly, it has been defined herding behavior under decreasing market states as the fourth in the order, since according to the prospect theory (Kahneman and Tversky 1979), when individuals face a decision under risk, the losses convey a larger value than gains, therefore, it is expected that when the market returns decrease, the individuals update their perspective and take less risk to increase market states, but not the other way.

4.6 Results

The current study aims to find the causal relationships between crypto-investors' attention proxies and behavioral convergence, this has been done using Granger Causality test and Structural Vector Autoregressive (SVAR) models impulse response functions. Following the literature we hypothesize that there is a delay in reaction, plus, investors' attention in form of prices (Bitcoin returns) is faster than the manifestation of interest expressed as searching the internet for a given cryptocurrency. In behavioral economic models typically rely on the concept that investors' beliefs and preferences to form decisions. The general idea is that information which comes with a diversity in noise to signal ratio, time frame and intensity (for instance, extreme returns, rumors or news) is revealed to the crypto investors, they assess the expectations and reach a consensus.

In this section, we study the cross effects of price pressure and information shocks on market dynamics. First, it has been shown the results of the reduced form SVAR, with its corresponding impulse response function.

4.6.1 Optimal lag length order

The most common approach for lag order selection is to inspect among different information criteria and choose the model that minimizes these indicators. There are several Information Criterion alternatives, and they vary on the weight they put on prediction error and parameters. For instance, Schwarz-Bayes (SC or BIC) over penalized big models (several estimated parameters) in comparison to Akaike (AIC).

Therefore, there is always on researchers' hand to choose the order according to the different IC options. But there is little "issue", different IC, have unequal units, therefore, they are not directly comparable, this is actually not a huge deal, it has been hypothesized that normalized IC provides comparable units to every method. To define the optimal lag length it has been created a comparative table as seen in Table 4.4 in the appendix showing the normalized values for each method, while the Figure 4.4 describes the differentiated normalized values. To find the most parsimonious lag length the rule is to choose the lowest the lag associated with the lowest the different IC: Akaike (AIC), Akaike's Final Prediction Error (FPE), Hannan-Quinn (HQ), and Schwarz/Bayes (SC) Information Criterion (IC). However, in the case when we consider several alternatives a good rule of thumb is to follow the "elbow" rule, that is, to visualize when the magnitude decrease significantly.

In this case, we can conclude that there is an important reduction in the IC from 5 lags for AIC, FPE, HQ and SC method, and stabilize around 8 to 10 lags. Since there is a

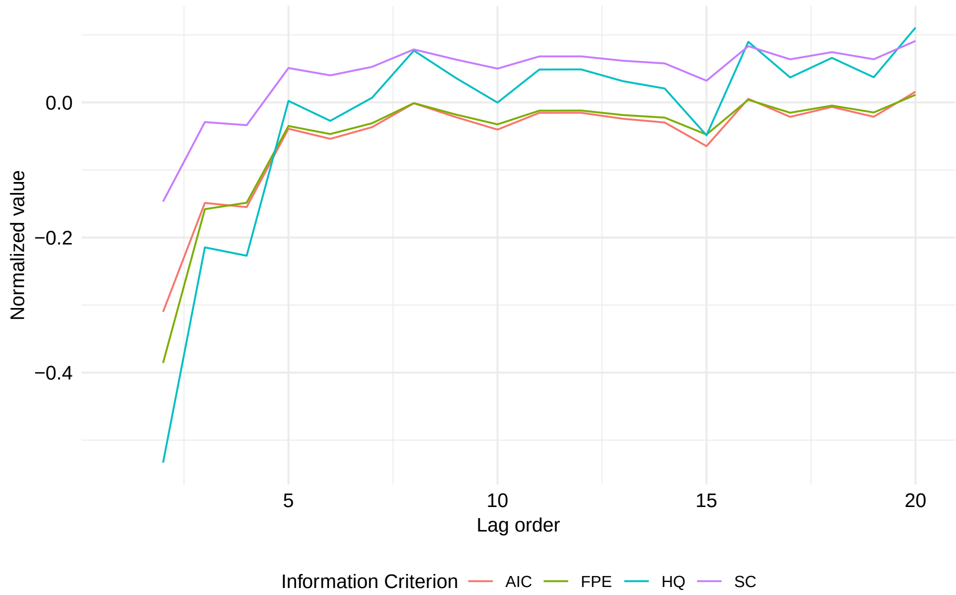


Figure 4.4. Optimal lag length estimates given information

relevant decrease in exactly 10 lags and the fact that losing degrees of freedom is not a problem, 10 lags have been selected.

4.6.2 Granger-causality test

In order to assess differences over time, there has been estimated six different VAR models, each one assigned to a natural year within the whole period of study. The results of the subsamples regarding the Granger-Causality estimates when $P(Z < \alpha)$ with $\alpha = .01$ are shown in Figure 4.5, while the detailed results can be inspected in Table 4.5 located in the appendix.

From Figure 4.5 it is noticeable that in the subsample of the year 2014 there is little or no evidence in favor of Granger-Causality from attention-grabbing indicators, nonetheless, there is some evidence from herding behavior either in increasing and decreasing states at lags around 2 and 9, but this is likely that it derives from their own in-between prediction, since there is a negative correlation at long lags, that is, periods of high behavioral convergence are followed by periods of herding behavior in decreasing states. In 2015 it has been found that there is strong evidence ($P(F) < 0.05$ for all lags) in favor of Granger-causality from Bitcoin returns (BTC) to the system at all along with lags 1 to 10. Similarly, there is evidence of Granger-causality taken from attention (ATT) to the system at all lags included, however, there is a tendency that as lags increases, there is a lower probability of finding an extreme value given that the null hypothesis is true, however, all are below the 10% significant threshold.

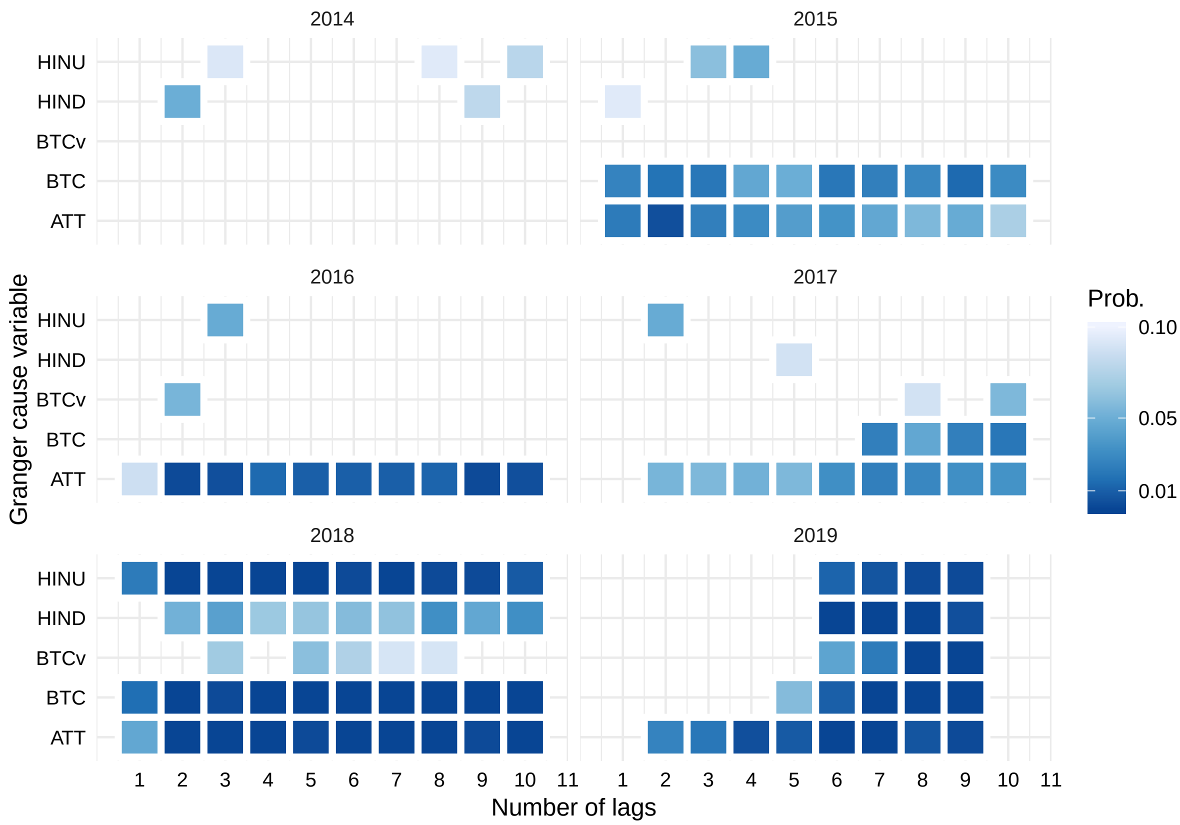


Figure 4.5. Granger-causality test for crypto-market system

The subsamples for years 2016 and 2017 exhibit similar results, for both years there is Granger-causality evidence coming from attention (ATT) to system, which is stronger at all lags in 2016 than 2017, but still below 10%. Regarding 2017, there is statistical evidence of Granger-causality from Bitcoin's returns at lags 7 to 10 with p-values of 4%, 5%, 4%, and 2% respectively. We have seen so far that there is evidence of Granger-causality from attention-grabbing traits, in turn, during 2018 it appears strong evidence coming from herding under upward and downward market conditions (stronger in the case of the former one) to the system, that is, previous underlying market consensus predicts traits related to attention in the future. To the same token, as the past subsamples ATT and BTC also present evidence in favor of Granger-causality to the rest of the traits at all lags analyzed. Finally, in 2019 there is evidence of ATT affecting the system from lag 2 up to 9, then after the fifth lag BTC seems to Granger-cause the dynamics of the systems, same to the rest of the traits from lag 6.

Concluding our tests for Granger causality reflects what hypothesized, in all of the subsamples (except 2014), there seems to be causality from attention indicators of short reaction term (BTC) and longer reaction (ATT), which is expected, since higher level of attention might generate price pressure dynamics, that also push people to follow the consensus given their own biases, and how they define value. Nonetheless, an inverse Granger-causality seems to be possible in the last two years, being the relationship stronger and lasting during 2018. Indeed this can be a product of constant feedback-loop between attention and reaction, however, given the nature of herding which is not directly observable, we need a deeper level of relationships, henceforth, a set of impulse response function had been estimated to test the impact of shocks in a one-to-one trait fashion.

4.6.3 Impulse response functions

In order to trace the response of behavioral convergence as a product of informational shocks in a SVAR, specific restrictions has been applied for identification purposes that define a forward-looking structure that goes along the chain from observation to a reaction. We are particularly interested to investigate the impulse response relationship between two variables included in the system. The method to identify the contemporaneous effects is important to unveil dependencies, in case of the reduced form SVAR, it is common to rely on orthogonalization of the error terms based on Cholesky decomposition in order to identify the system. The Cholesky decomposition is a traditional method to solve the problem of overidentification by orthogonalizing the terms in the innovation matrix.

4.6.3.1 Bitcoin as meta-informational indicator

It has been hypothesized that Bitcoin is an investment asset, but also conveys trust, and shape expectations on the future and robustness of the cryptocurrency market, this, in regard of the type of crypto investors, namely, the former users, advocate of free capital movement without financial system intermediation, blockchain technology advocates, etc: they all have benefit of the network economics. Moreover, it also serves as a signal that drives investors' attention and strategy to decide which position to take, in that sense it resembles the *momentum trader agent* as explained by Hong and Stein (1999). Having said that, it remains to define the directionality of the effect between the fast attention-grabbing component of Bitcoin's returns either on slower direct attention-grabbing (attention index), do prices rise because of larger attention or it occurs otherwise? Moreover, does a shock on BTC associated with an increasing tendency to follow the consensus? Figure 4.6 shows impulse response (black line) given an orthogonalized innovations matrix (Cholesky decomposition), while the shaded vignette describes the coefficients confidence intervals as two standard errors, and confidence interval intersecting the red dashed line means the lack of statistical evidence in favor of bidirectional effect from the shock.

Following the results of the dynamic multiplier as seen in Figure 4.6 we found one shock in Bitcoin's returns generates a short-term effect on the level of attention, which remains constant in the long run. This is an important finding, since in past studies there was no evidence of the directionality of the attention, in other words, people's revealed attention pushed demand of cryptocurrency, or any movement in cryptocurrency returns increase interest from the crypto investors generating in them the need to update their beliefs. As seen in the ATT grid, the effect of the shock starts to be significantly different from zero at a horizon of 2 days, hence, prices indeed react faster than revealed attention, which is in line with the arguments in chapter 2 about crypto

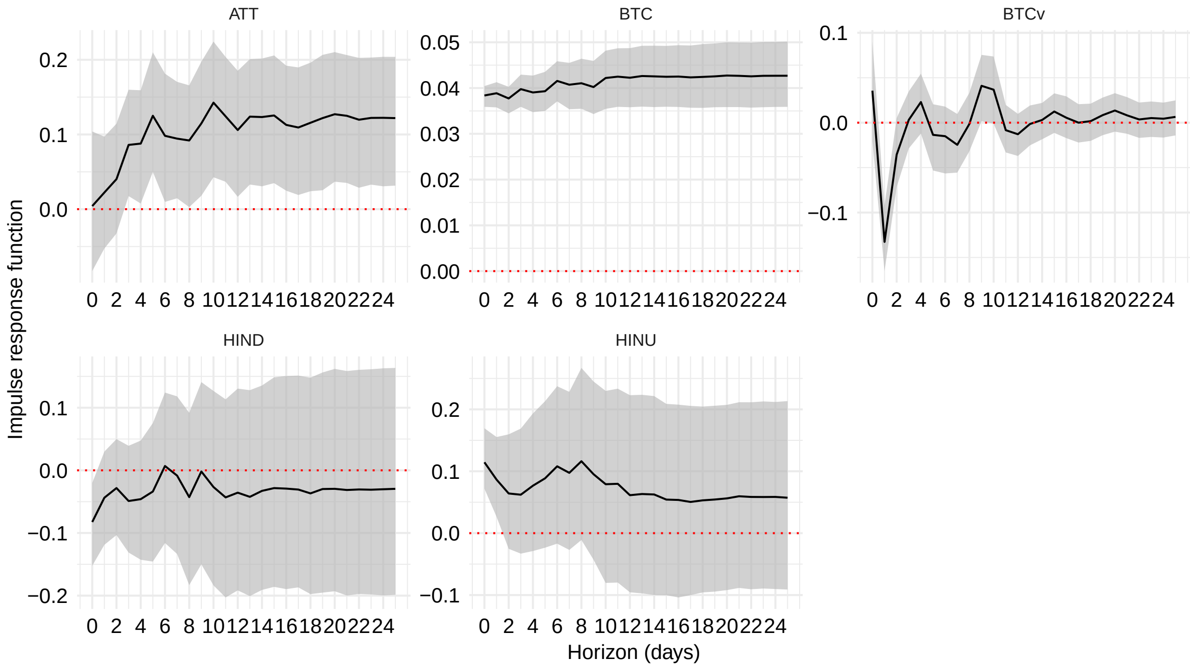


Figure 4.6. Cumulative impulse response function (IRF) for VAR of Bitcoin's returns (BTC) to the rest of the variables in the system

investors' heuristics. Considering the subsamples disaggregated by year (Figure 4.12 in appendix) it can be noted that a shock in BTC returns has a strong significant effect on attention during 2017, opposite to 2018 in which there is a significant negative response up to 8 days.

As expected, a shock in BTC returns generates an immediate and strong response in BTC that last for several periods. This result stems from the momentum trait of cryptocurrencies and a high level of predictability in Bitcoins' returns. Another interesting repercussion of shock in BTC returns is an instant negative effect of its own volatility, henceforth, product of a change in returns, the variance reduces drastically in the short-term at around -0.1 standard deviations, but the effect cancels out quickly at lag 3, presenting also an oscillating behavior for the next 10 days, however, non statistically significant from zero. Recall, that HIND and HINU is an underlying behavior of market participants towards coordinating their actions in light of extreme market returns, therefore it is not unlikely observable even for sophisticated participants. The hypotheses are that a shock of Bitcoin's returns sends a signal to the participants to follow a momentum strategy and increasing their demand for other cryptocurrencies expecting to capture profits in the short term. As seen in the two graphs in the lower part of Figure 4.6, an increasing in BTC generates a short-term response in the herding behavior under decreasing states, which is expected, since the sign is positive, however, the evidence in favor of such rapidly becomes null. Conversely, as a product of one impulse in BTC there is higher behavioral convergence under increasing market states, that is, BTC returns sends a signal to the participants, then they react by following the consensus by demanding more of the any of the 20 cryptocurrencies used to generate the index. It is important to highlight that this response is an effect of BTC at an average level, it is remaining to visualize what happens if the returns are located at the tails of the distribution.

4.6.3.2 Pressure from an attention-grabbing indicator

According to Barber and Odean (2008) attention-grabbing induces price pressure since investors respond to such shocks by demanding more of a small set of stock that "glitter" among all. In the last section we have proved that Bitcoin's returns cause people's revealed attention to increasing, in this section we test if there is a reverse directionality, that is, does attention affects future returns? Moreover, Hong and Stein (1999) insisted on the existence of two bounded rational agents, the *newswatchers* and *momentum traders* (as explained earlier), in this case, the former is a revealed attention of the newswatchers agent, since, even though a given person could be dazzled by any piece of information, it does not mean that this person will take an action product of the interest, in that sense, searching in Internet expose purpose and a higher responsiveness. Having said that, the equivalent of newswatchers in the crypto-markets framework will be called *"cues seekers"*.

As seen in the first graph within the Figure 4.7, it can be concluded that there is a feedback of attention, since one shock in ATT generated an immediate and strong response on itself that last for several periods, and this relationship holds for every year as seen in Figure 4.12. From the past section it has been concluded that a shock in BTC returns leads to a quick reaction on attention that last for several periods, in this section we test if the directionality works backward as well. It has been found that a shock on attention-grabbing does generate a negative short term response on BTC, which is adjusted quickly and becoming positive effect, however, this relationship is not significant at 5% threshold. What it does affect in the short-term is the estimated volatility of Bitcoins' returns, henceforth, one standard deviation impulse from ATT increases the dispersion of BTC up to 0.2 standard deviations at a horizon of 2 days, then it is adjusted quickly and shows a positive long-lasting response around 0.05 over the rest of the periods analyzed.

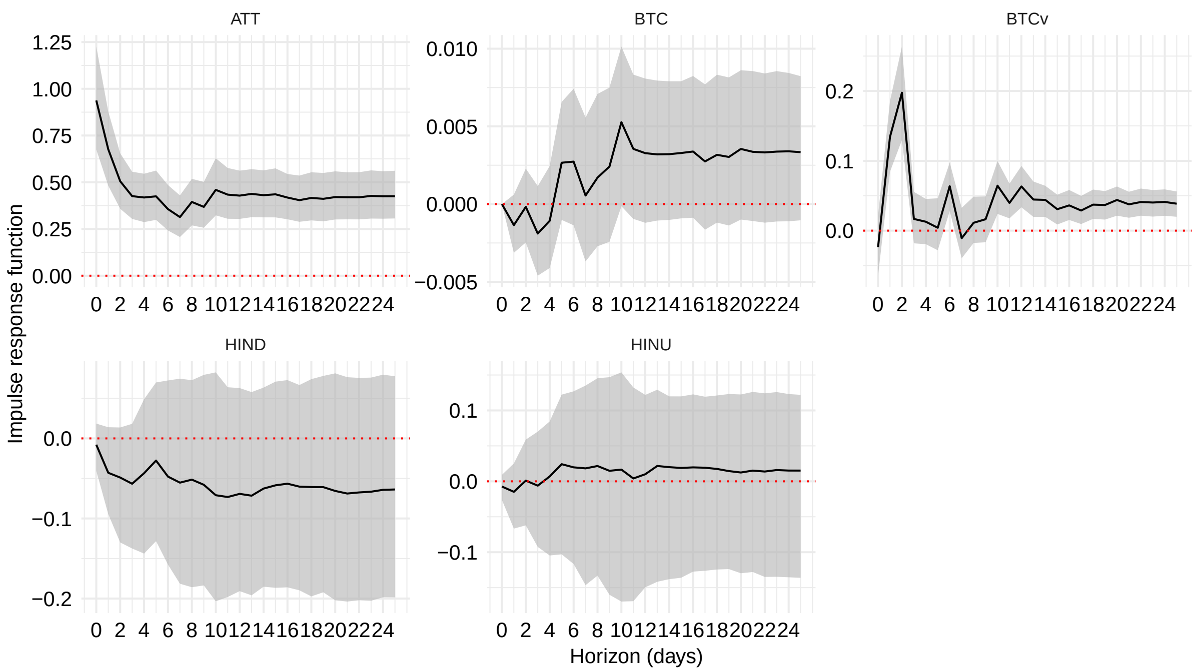


Figure 4.7. Cumulative impulse response function (IRF) for VAR of attention (ATT) to the rest of the variables in the system

Regarding the behavioral convergence, considering the whole sample, one shock in ATT is associated with a positive response in herding under decreasing and increasing market states, however, there is not enough statistical evidence in favor of such result. One look at the Figure 4.12 let us notice that during the 2016 and 2018 there is a negative and significant response to HIND, that is, a shock of ATT decreased the consensus in face of extreme low average market returns. One possible explanation is that revealed attention does generate a contrarian reaction, therefore not reacting according to the consensus in face of below negative market conditions. Conversely, one standard deviation shock on ATT was associated in 2018 with a positive effect of herding when the market had an upward market condition, in other words, crypto-investors might have reinforced their strategy of following the current market trend after updating their information from the Internet.

4.6.3.3 Behavioral convergence

The results so far indicate that attention either manifested from cues-seekers and momentum traders' agents, serve as drivers to decision-making, either to affect play a contrarian or herding role, and not otherwise. The reason is that herding is not explicitly observable by the agents, however, one possible scenario stem when investors' update their priors regarding their best strategy they could follow, hence, as a product of any unexpected event, the reaction undertook had a positive outcome, reinforcing in the previous strategy. For instance, a given crypto-investors after noticing that

$E[R_{z_{t+1}} > 0 | R_{x_t} > 0]$ and possibly $R_{z_{t+1}} \geq R_{x_{t+1}}$ for periods $t > 1$, it is own their benefit use x_t as signal. However, the opposite could also be possible (however, unlikely): since a product of observing a signal, investors' consensus might reinforce their current strategy and continuing buying more of $R_{x_{t+1}}$ expecting that the results will be similar in the future creating a feedback loop *cue* $\rightarrow$ *reaction* $\rightarrow$ *cue* ...

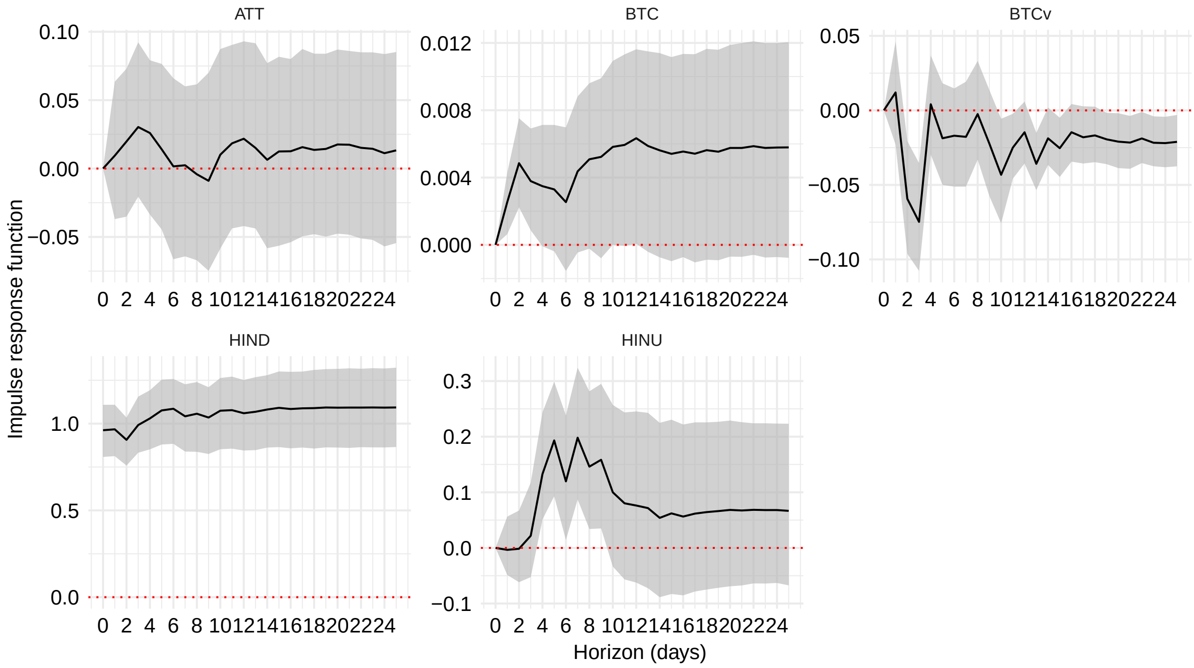


Figure 4.8. Cumulative impulse response function (IRF) for VAR of herding index under decreasing states (HIND) to the rest of the variables in the system

In this regard, the Figure 4.8 shows that an impulse in herding under decreasing market states has no effect on ATT, however, it does have a significant response on Bitcoins' returns, however, it is negligible around 0.004 standard deviations, and becoming non-significant from 4 days onwards. Returns' dispersion decreases when a shock occurs in HIND with a relatively strong negative short-term effect, respecting its own reaction it has been found that one shock in herding reinforces herding either under decreasing and increasing market conditions. This is expected since the definition itself of herding implies emulating past actions, in regard to the current states.

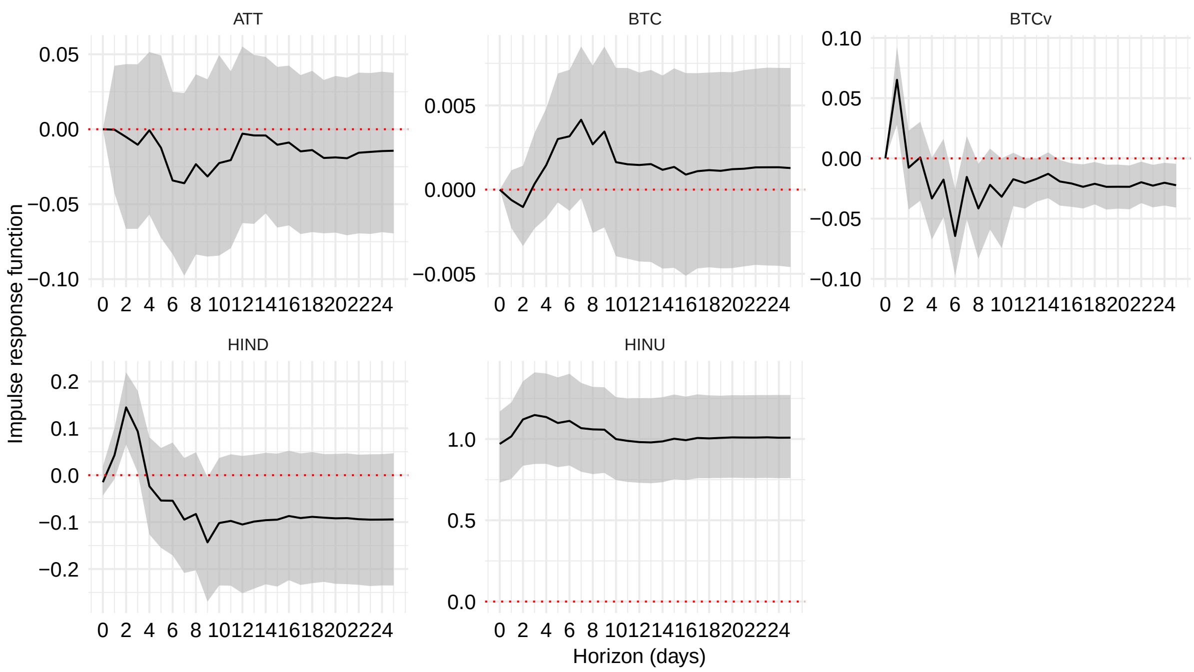


Figure 4.9. Cumulative impulse response function (IRF) for VAR of herding index under increasing states (HINU) to the rest of the variables in the system

Herding under increasing market states as seen in Figure 4.9 confirms raised hypotheses: HINU and HIND are underlying market behavior, hence there are not expected to affect the *cues-seekers* actions, by the same token, there is a positive response from BTC however non-significant at the 5% significance threshold. Then again, there is enough evidence in favor of negative response of uncertainty (similar results as argued by Peng (2005)) as a product of a shock in herding, whereas a HIND has positive short-term response becoming non-significant at a horizon of 4 days onwards, finally, it repeats the reinforcement behavior with itself on HINU.

4.7 Conclusion

In this study, it has been proposed a set of descriptors that conform to the main traits of crypto-markets structure and its dynamics. The results show that Bitcoin's returns play a meta-informational role, either by serving to momentum traders to shape their momentum strategies, and at the same time conveying information that shapes expectations on the future not only of the Bitcoin's returns but also on all other cryptocurrencies/assets existent within the market. Since prices react faster than any other element, it catches the investors' attention, who respond by showing more interest and increasing the search probability. However, the attention-grabbing index does not have an effect on returns, which means that the causality is unidirectional, that is, returns is associated with more interest, but there is no statistical evidence of the opposite. Also, it has been showed that Bitcoin's returns guides herding in the short run, however, the relation vanishes after a few days. Overall, these results show an interdependency of the whole market to Bitcoin's state.

How the information is created, interpreted, and forms trading strategies in crypto-market is a particular case, that exceeds what is has been studied in financial settings such as asymmetric information, bias-prone strategies and fuzzy decision-making. In the absence of cues on fundamentals, prices guides crypto-investors, therefore, there is little chance for the market to correct itself by the active participation of individuals if all form beliefs according to the positive feedback valuation only. As a result, the absence of reliable signals, there is strong evidence of crypto-investors to resort to ignore their private information and follow the consensus. Crypto-investors are highly adverse to losses, therefore they engage in trading strategies that emulate what the coordination mechanism conveys, generating a feedback loop represented by a strong probability of herding given that the previous state is herding as well, in other words, there is little chance of market correction, this is associated with unstable market conditions, failing to generate rational expectations, and prone to generate bubbles and fads as many other authors have expressed in other sectors.

4.8 Appendix

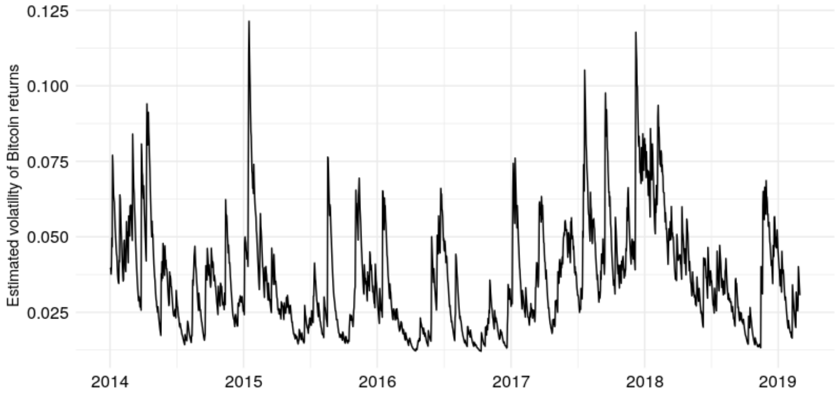


Figure 4.10. Estimated volatility of Bitcoin returns

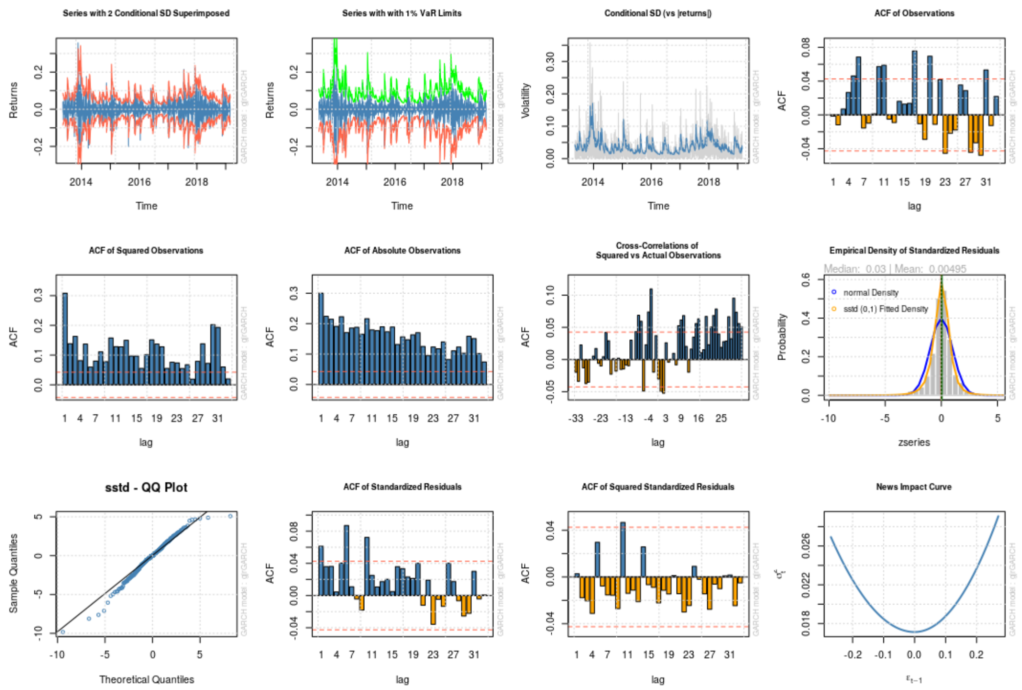


Figure 4.11. Conditional standard deviations of BTC returns

Table 4.4. Method comparison for optimal lag length (normalized values)

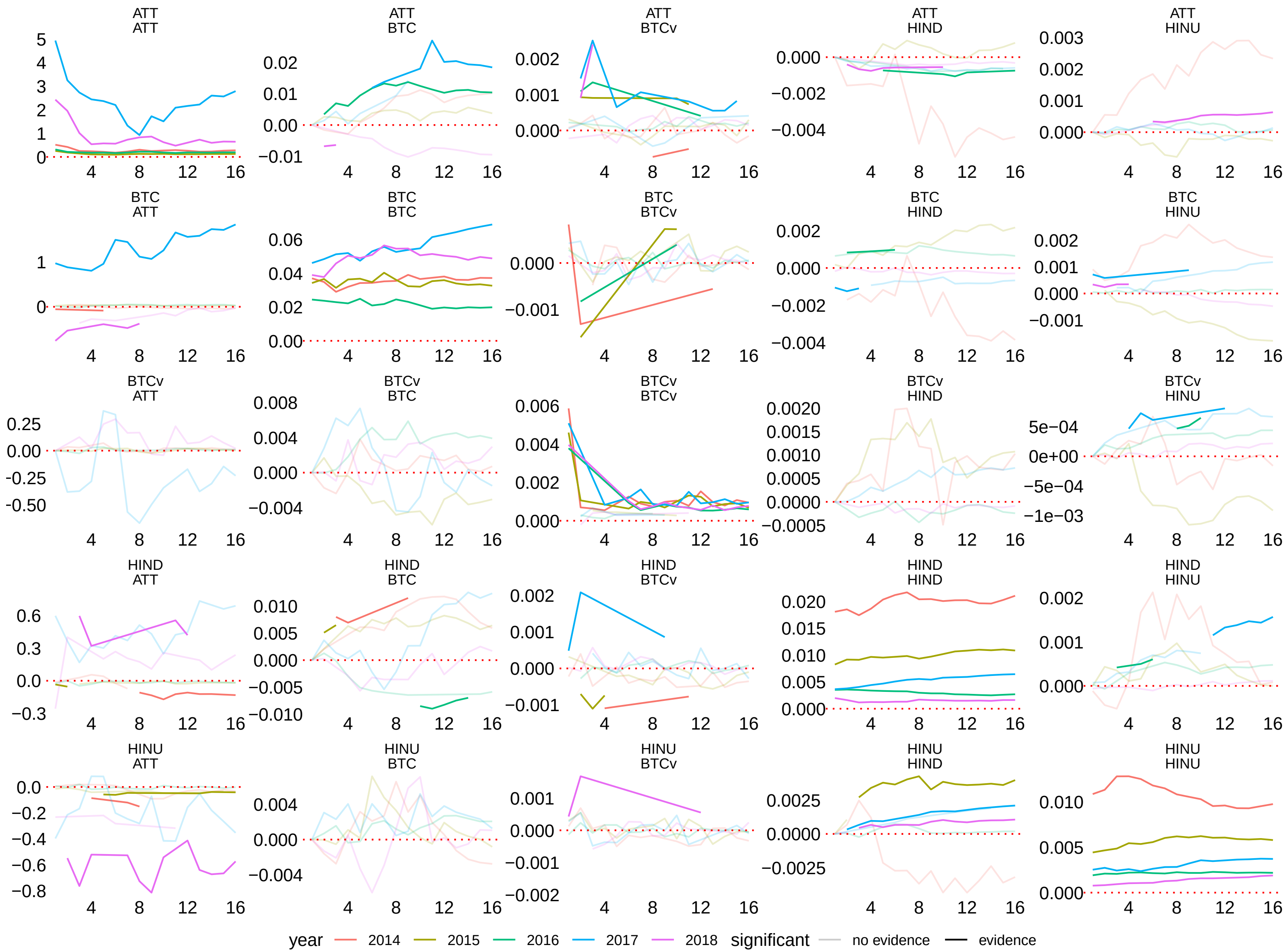
Lag	AIC	HQ	SC	FPE
1	-0.677	-0.631	-0.553	0.508
2	-0.901	-0.822	-0.689	0.406
3	-1.001	-0.889	-0.700	0.368
4	-1.063	-0.918	-0.673	0.345
5	-1.109	-0.931	-0.631	0.330
6	-1.156	-0.945	-0.589	0.315
7	-1.175	-0.931	-0.520	0.309
8	-1.176	-0.899	-0.432	0.308
9	-1.183	-0.873	-0.351	0.306
10	-1.189	-0.846	-0.268	0.304
11	-1.196	-0.820	-0.187	0.302
12	-1.195	-0.786	-0.097	0.303
13	-1.191	-0.749	-0.005	0.304
14	-1.185	-0.710	0.090	0.306
15	-1.230	-0.722	0.134	0.292

The table above describes the results for the optimal lag length given the method and lag order. The measures were normalized in order to have a direct comparison across the alternatives.

Table 4.5. Granger causality test for the cryptomarket system

Cause	Lag order	2014		2015		2016		2017		2018		2019	
		F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.
BTC	1	8.86	0.11	20.91	0.02	3.67	0.39	0.65	0.89	9.22	0.02	0.42	0.85
	2	4.08	0.21	11.09	0.02	3.25	0.40	1.06	0.76	9.14	0.00	0.18	0.97
	3	2.94	0.22	7.74	0.02	2.56	0.40	1.40	0.54	6.14	0.00	0.41	0.82
	4	3.49	0.15	5.81	0.04	2.21	0.39	1.33	0.47	5.89	0.00	0.49	0.67
	5	2.86	0.14	4.90	0.05	1.72	0.46	1.52	0.35	5.25	0.00	1.21	0.06
	6	2.65	0.11	3.67	0.01	1.49	0.57	1.90	0.13	4.85	0.00	1.38	0.02
	7	1.86	0.25	3.10	0.03	1.52	0.49	2.33	0.04	4.98	0.00	1.51	0.00
	8	1.77	0.26	3.01	0.02	1.52	0.44	2.13	0.05	4.33	0.00	2.56	0.00
	9	1.57	0.28	2.86	0.01	1.45	0.43	2.04	0.04	4.12	0.00	1.57	0.00
	10	1.59	0.24	2.71	0.01	1.32	0.43	2.06	0.02	3.93	0.00		
HIND	1	0.99	0.62	5.44	0.09	0.96	0.37	3.09	0.35	10.22	0.12	1.95	0.30
	2	2.94	0.08	2.99	0.11	3.19	0.30	4.36	0.17	6.04	0.05	1.04	0.43
	3	1.86	0.17	2.19	0.16	2.75	0.26	3.76	0.13	3.65	0.07	1.18	0.21
	4	1.70	0.36	1.77	0.15	2.89	0.23	3.51	0.09	3.40	0.08	1.03	0.29
	5	1.69	0.28	1.56	0.33	2.46	0.26	3.10	0.08	2.82	0.08	1.17	0.14
	6	1.73	0.20	1.53	0.28	2.13	0.22	2.40	0.17	2.79	0.05	1.49	0.00
	7	1.79	0.23	1.30	0.34	1.93	0.24	2.42	0.16	2.44	0.07	1.50	0.00
	8	1.89	0.10	1.33	0.26	1.75	0.29	2.30	0.15	2.43	0.05	2.87	0.00
	9	1.96	0.11	1.23	0.24	1.74	0.21	2.10	0.16	2.10	0.05	2.05	0.00
	10	1.87	0.12	1.18	0.25	1.67	0.23	2.15	0.14	2.21	0.02		
HINU	1	0.85	0.46	1.41	0.17	0.15	0.81	1.55	0.30	5.69	0.02	1.62	0.42
	2	1.12	0.40	1.71	0.11	0.94	0.24	2.50	0.05	11.92	0.00	1.32	0.45
	3	2.40	0.13	1.53	0.04	1.55	0.06	2.00	0.15	7.86	0.00	1.07	0.34
	4	2.77	0.16	1.40	0.04	1.32	0.12	1.56	0.26	6.67	0.00	0.91	0.39
	5	2.34	0.13	1.80	0.27	1.09	0.21	1.77	0.18	5.19	0.00	1.22	0.11
	6	2.60	0.12	3.73	0.26	0.88	0.31	1.79	0.16	4.15	0.00	1.80	0.01
	7	2.15	0.12	3.35	0.24	0.95	0.26	1.52	0.19	4.54	0.00	2.08	0.00
	8	2.05	0.11	3.13	0.25	0.94	0.22	1.23	0.29	3.85	0.00	1.48	0.00
	9	2.01	0.10	2.88	0.24	0.92	0.24	1.21	0.28	3.63	0.00	3.14	0.00
	10	2.07	0.07	2.93	0.21	0.91	0.24	1.30	0.13	3.71	0.01		
ATT	1	0.95	0.56	3.47	0.01	3.22	0.07	4.34	0.46	21.42	0.04	0.44	0.85
	2	1.16	0.54	4.03	0.01	8.36	0.00	11.75	0.05	17.58	0.00	3.15	0.02
	3	1.01	0.73	2.76	0.01	5.85	0.00	8.77	0.04	13.85	0.00	2.17	0.02
	4	0.79	0.82	2.17	0.03	4.87	0.01	7.17	0.05	9.79	0.00	2.04	0.02
	5	1.08	0.66	1.82	0.05	4.05	0.00	6.29	0.05	8.40	0.00	2.51	0.00
	6	1.13	0.61	1.70	0.03	3.38	0.02	6.62	0.02	6.89	0.00	3.53	0.00
	7	1.42	0.53	1.56	0.04	2.93	0.01	6.07	0.02	6.16	0.00	3.12	0.00
	8	1.68	0.35	1.69	0.06	2.77	0.02	5.46	0.04	5.69	0.00	1.85	0.00
	9	2.03	0.23	1.54	0.05	2.48	0.01	4.97	0.03	5.02	0.00	4.06	0.00
	10	1.71	0.23	1.48	0.09	2.48	0.01	5.14	0.04	4.78	0.00		
BTCv	1	0.03	1.00	2.14	0.23	0.42	0.71	2.12	0.14	0.64	0.71	0.99	0.21
	2	1.23	0.65	0.82	0.47	1.76	0.08	1.29	0.32	2.76	0.12	0.54	0.51
	3	1.66	0.50	0.97	0.41	1.17	0.44	0.71	0.55	2.73	0.08	0.41	0.63
	4	1.35	0.55	0.79	0.57	1.04	0.51	1.20	0.14	1.56	0.29	0.65	0.33
	5	1.31	0.45	0.97	0.45	1.00	0.50	0.85	0.50	2.47	0.05	0.97	0.15
	6	1.30	0.33	1.14	0.26	0.91	0.62	1.28	0.14	1.85	0.08	1.50	0.04
	7	1.18	0.42	1.09	0.19	0.82	0.62	1.43	0.08	1.75	0.11	1.46	0.02
	8	0.97	0.53	1.15	0.24	0.98	0.44	1.47	0.08	1.68	0.08	2.83	0.00
	9	0.96	0.62	1.19	0.22	1.29	0.35	1.34	0.08	1.40	0.18	1.90	0.00
	10	0.93	0.53	1.39	0.13	1.26	0.20	1.62	0.06	1.47	0.13		

* The table above describes the results for the optimal lag length given the method and lag order. The measures were normalized in order to have a direct comparison across the alternatives.



Within the elements grid, the title in the upper part in each square represents the impulse, while the response variable is described below.
Confidence intervals are not shown, however transparent lines represent non−signficant difference from zero, gizen the horizon and per year.

Figure 4.12. Impulse response function by year

Chapter 5

References

Abad, Carlos, and Garud Iyengar. 2015. "Are Trump and Bitcoin Good Partners?" France: University of Pau. http://epubs.siam.org/doi/10.1137/140967635.

Alpert, Marc, and Howard Raiffa. 1982. "A progress report on the training of probability assessors." In *Judgment Under Uncertainty: Heuristics and Biases*, edited by Amos Tversky, Daniel Kahneman, and Paul Slovic, 294–305. Cambridge: Cambridge University Press. https://doi.org/DOI: 10.1017/CBO9780511809477.022.

Ang, Andrew, Geert Bekaert, and Jun Liu. 2005. "Why stocks may disappoint." *Journal of Financial Economics* 76 (3): 471–508. https://doi.org/10.1016/j.jfineco.2004.03.009.

Antonopoulos, Andreas M. 2014. *Mastering Bitcoin: unlocking digital cryptocurrencies*. O'Reilly Media, Inc.

Arjoon, Vaalmikki, and Chandra Shekhar. 2017. "Dynamic herding analysis in a frontier market." *Research in International Business and Finance* 42: 496–508. https://doi.org/10.1016/j.ribaf.2017.01.006.

Athey, Susan, Ivo Parashkevov, Vishnu Sarukkai, and Jing Xia. 2016. "Bitcoin Pricing , Adoption , and Usage : Theory and Evidence."

Bachelier, L. 1900. "Théorie de la spéculation." *Annales Scientifiques de L'École Normale Supérieure* 17: 21–86. https://doi.org/10.24033/asens.476.

Baek, C, and M Elbeck. 2014. "Bitcoins as an investment or speculative vehicle? A first look." *Applied Economics Letters* 22 (1). Routledge: 30–34. https://doi.org/10.1080/13504851.2014.916379.

Balcilar, Mehmet, Riza Demirer, and Shawkat Hammoudeh. 2013. "Investor herds and regime-switching: Evidence from Gulf Arab stock markets." *Journal of International Financial Markets, Institutions and Money* 23 (1): 295–321. https://doi.org/10.1016/j.intfin.2012.09.007.

Banerjee, A. V. 1992. "A Simple Model of Herd Behavior." *The Quarterly Journal of Economics* 107 (3): 797–817. https://doi.org/10.2307/2118364.

Barber, Brad M, and Terrance Odean. 2013. "The Behavior of Individual Investors." In *Handbook of the Economics of Finance*. California: Elsevier. https://doi.org/http://dx.doi.org/10.2139/ssrn.1872211.

Barber, Brad M., and Terrance Odean. 2001. "Boys Will be Boys : Gender , Overconfidence , and Common Stock Investment." *The Quarterly Journal of Economics* 116 (1): 261–92. https://doi.org/10.1093/rfs/hhm079.

———. 2008. "All that Glitters: The effect of Attention and news on the Buying Behavior of Individual and Institutional Investors." *The Review of Financial Studies* 21 (2): 785–818. https://doi.org/10.1002/9781118467411.ch7.

Barberis, Nicholas, Ming Huang, and Richard H Thaler. 2006. "Individual Preferences , Monetary Gambles , and Stock Market Participation: A Case for Narrow Framing." *The American Economic Review* 96 (4): 1069–90.

Barberis, Nicholas, and Richard H. Thaler. 2005. "A Survey of Behavioral Finance." In *Advances in Behavioral Finance, Volume Ii*, 1–76. Princeton University Press. https://doi.org/10.1515/9781400829125-004.

Baur, Dirk G, and Brian M Lucey. 2010. "Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold." *Financial Review* 45 (2): 217–29. https://doi.org/10.1111/j.1540-6288.2010.00244.x.

Baur, Dirk G, and Thomas K McDermott. 2010. "Is gold a safe haven? International evidence." *Journal of Banking & Finance* 34 (8): 1886–98.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy* 100 (5): 992–1026. https://doi.org/10.1086/261849.

Bikhchandani, Sushil, and Sunil Sharma. 2000. "Herd Behavior in Financial Markets: A Review." IMF Institute.

Bjerg, Ole. 2016. "How is Bitcoin Money?" *Theory, Culture {&} Society* 33 (1): 53–72. https://doi.org/10.1177/0263276415619015.

Black, Fischer. 1986. "Noise." *Journal of Finance* 41 (3): 529–43. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2013. "Salience and Consumer Choice." *Journal of Political Economy* 121 (5): 803–43. https://doi.org/10.1086/673885.

Bouoiyour, Jamal, and Refk Selmi. 2016. "Bitcoin: a beginning of a new phase?" *Economics Bulletin* 36 (3).

Bouri, Elie, Rangan Gupta, Aviral Kumar Tiwari, and David Roubaud. 2017. "Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions." *Finance Research Letters* 23: 87–95. https://doi.org/10.1016/j.frl.2017.02.009.

Böhme, Rainer, Nicolas Christin, Benjamin Edelman, and Tyler Moore. 2015. "Bitcoin: Economics, Technology, and Governance." *Journal of Economic Perspectives* 29 (2): 213–38. https://doi.org/10.1257/jep.29.2.213.

Brodersen, Kay H, Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L Scott. 2015. "Inferring causal impact using bayesian structural time-series models." *Annals of Applied Statistics* 9 (1): 247–74. https://doi.org/10.1214/14-AOAS788.

Brunnermeier, Markus K., and Martin Oehmke. 2013. "Bubbles, Financial Crises, and Systemic Risk." In *Handbook of the Economics of Finance*, 1221–88. Elsevier. https://doi.org/10.1016/B978-0-44-459406-8.00018-4.

Chang, Eric C., Joseph W. Cheng, and Ajay Khorana. 2000. "An examination of herd behavior in equity markets: An international perspective." *Journal of Banking and Finance* 24 (10): 1651–79. https://doi.org/10.1016/S0378-4266(99)00096-5.

Cheah, Eng Tuck, and John Fry. 2015. "Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin." *Economics Letters* 130 (May): 32–36. https://doi.org/10.1016/j.econlet.2015.02.029.

Chiang, Thomas C., and Dazhi Zheng. 2010. "An empirical analysis of herd behavior in global stock markets." *Journal of Banking and Finance* 34 (8): 1911–21. https://doi.org/10.1016/j.jbankfin.2009.12.014.

Chipman, Hugh, Edward I. George, and Robert E. McCulloch. 2001. "The Practical Implementation of Bayesian Model Selection." In *Institute of Mathematical Statistics Lecture Notes - Monograph Series*, 65–116. Institute of Mathematical Statistics. https://doi.org/10.1214/lnms/1215540964.

Christie, William G, and Roger D Huang. 1995. "Following the Pied Piper: Do Individual Returns Herd around the Market?" *Financial Analysts Journal* 51 (4): 31–37.

Ciaian, Pavel, Miroslava Rajcaniova, and D'Artis Kancs. 2016a. "The digital agenda of virtual currencies: Can BitCoin become a global currency?" *Information Systems and E-Business Management* 14 (4): 883–919. https://doi.org/10.1007/s10257-016-0304-0.

———. 2016b. "The economics of BitCoin price formation." *Applied Economics* 48 (19): 1799–1815. https://doi.org/10.1080/00036846.2015.1109038.

Ciner, Cetin, Constantin Gurdgiev, and Brian M Lucey. 2013. "Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates." *International Review of Financial Analysis* 29: 202–11.

Cohen, Lauren, and Andrea Frazzini. 2008. “Economic Links and Predictable Returns.” *The Journal of Finance* 63 (4): 1977–2011.

Coval, Joshua D, and TYler Shumway. 2005. “Do Behavioral Biases Affect Prices?” *The Journal of Finance* 60 (1): 1–34. https://doi.org/10.1111/j.1540-6261.2005.00723.x.

da Gama Silva, Paulo Vitor Jordão, Marcelo Cabus Klotzle, Antonio Carlos Figueiredo Pinto, and Leonardo Lima Gomes. 2019. “Herding behavior and contagion in the cryptocurrency market.” *Journal of Behavioral and Experimental Finance* 22. Elsevier B.V.: 41–50. https://doi.org/10.1016/j.jbef.2019.01.006.

Daniel, Kent, and David Hirshleifer. 2015. “Overconfident Investors, Predictable Returns, and Excessive Trading.” *The Journal of Economic Perspectives* 29: 61–87. https://doi.org/10.2307/43611011.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. “Investor Psychology and Security Market under- and Overreactions.” *The Journal of Finance* 53 (6): 1839–85.

De Bondt, Werner, and Richard H Thaler. 1985. “Does the Stock Market Overreact?” *The Journal of Finance* 40 (3): 793–805.

DellaVigna, Stefano, and Joshua M Pollet. 2009. “Investor Inattention and Friday Earnings Announcements.” *The Journal of Finance* 64 (2): 709–49.

De Long, J Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann. 1990. “Positive Feedback Investment Strategies and Destabilizing Rational Speculation.” *The Journal of Finance* 45 (2): 379–95.

Demirer, Riza, and Ali M. Kutan. 2006. “Does herding behavior exist in Chinese stock markets?” *Journal of International Financial Markets, Institutions and Money* 16 (2): 123–42. https://doi.org/10.1016/j.intfin.2005.01.002.

Demirer, Riza, Hsiang Tai Lee, and Donald Lien. 2015. “Does the stock market drive herd behavior in commodity futures markets?” *International Review of Financial Analysis* 39 (May 2008): 32–44. https://doi.org/10.1016/j.irfa.2015.02.006.

Devenow, Andrea, and Ivo Welch. 1996. “Rational herding in financial economics.” *European Economic Review* 40 (3-5): 603–15. https://doi.org/10.1016/0014-2921(95)00073-9.

Dimmock, Stephen G, and Roy Kouwenberg. 2010. “Loss-aversion and household portfolio choice.” *Journal of Empirical Finance* 17 (3): 441–59. https://doi.org/10.1016/j.jempfin.2009.11.005.

Dittmar, Jeremiah E. 2011. "Information Technology and Economic Change: The impact of the printing press." *The Quarterly Journal of Economics* 126 (3): 1133–72. http://www.jstor.org/stable/23015698.

Durbin, James, and Siem Jan Koopman. 2012. *Time Series Analysis by State Space Methods*. Vol. 7. 11. https://doi.org/10.1017/CBO9781107415324.004.

Dwyer, Gerald P. 2015. "The economics of Bitcoin and similar private digital currencies." *Journal of Financial Stability* 17: 81–91. https://doi.org/10.1016/j.jfs.2014.11.006.

Dyhrberg, Anne Haubo. 2016. "Bitcoin, gold and the dollar – A GARCH volatility analysis." *Finance Research Letters* 16: 85–92. https://doi.org/10.1016/j.frl.2015.10.008.

Economou, Fotini, Epameinondas Katsikas, and Gregory Vickers. 2016. "Testing for herding in the Athens Stock Exchange during the crisis period." *Finance Research Letters* 18: 334–41. https://doi.org/10.1016/j.frl.2016.05.011.

Fama, Eugene F. 1965. "Random Walks in Stock Market Prices." *Financial Analysts Journal* 21 (5): 55–59.

Franco, Pedro. 2014. *Understanding Bitcoin: Cryptography, engineering and economics*. John Wiley & Sons.

Frank, Murray Z, and Ali Sanati. 2018. "How does the stock market absorb shocks?" *Journal of Financial Economics* 129 (1): 136–53. https://doi.org/10.1016/j.jfineco.2018.04.002.

Gabaix, Xavier. 2017. "Behavioral inattention." In *Handbook of Behavioral Economics*, edited by B Douglas Bernheim, Stefano DellaVigna, and David Laibson. North Holland. https://doi.org/10.1016/bs.hesbe.2018.11.001.

Garcia, David, Claudio J Tessone, Pavlin Mavrodiev, and Nicolas Perony. 2014. "The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy." *Journal of the Royal Society, Interface* 11 (99): 16. https://doi.org/10.1098/rsif.2014.0623.

Gebka, Bartosz, and Mark E. Wohar. 2013. "International herding: Does it differ across sectors?" *Journal of International Financial Markets, Institutions and Money* 23 (1): 55–84. https://doi.org/10.1016/j.intfin.2012.09.003.

Geoffrey Smith. 2017. "How a China Crackdown Caused Bitcoin's Price to Plunge." http://fortune.com/2017/01/05/bitcoin-plunge-china-currency/.

George, Edward I, and Robert E McCulloch. 1993. "Variable Selection via Gibbs Sampling." *Journal of the American Statistical Association* 88 (423): 881–89. https://doi.org/10.1080/01621459.1993.10476353.

Georgoula, Ifigeneia, Demitrios Pournarakis, Christos Bilanakos, Dionysios Sotiropoulos, and George Giaglis. 2015. "Using Time-Series and Sentiment Analysis to Detect the Determinants of Bitcoin Prices." https://doi.org/10.2139/ssrn.2607167.

Glaser, Florian, Kai Zimmermann, Martin Haferkorn, Moritz Christian Weber, and Michael Siering. 2014. "Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions." *ECIS*, 1–14.

Graham, John R. 1999. "Herding among Investment Newsletters : Theory and Evidence." *The Journal of Finance* 54 (1): 237–68.

Granger, C W J. 1969. "Investigating Causal Relations by Econometric Models and Cross-spectral Methods." *Econometrica* 37 (3): 424–38.

Greenland, S, M Maclure, J J Schlesselman, C Poole, and H Morgenstern. 1991. "Standardized regression coefficients: a further critique and review of some alternatives." *Epidemiology* 2 (5): 387–92. https://doi.org/10.1097/00001648-199109000-00015.

Grossman, Sanford J, and Joseph E Stiglitz. 1976. "Information and Competitive Price Systems." *The American Economic Review* 66 (2): 246–53.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2008. "Trusting the Stock Market." *The Journal of Finance* 63 (6): 2557–2600.

Halaburda, Hanna. 2016. "Beyond Bitcoin. The Economics of Digital Currencies." New York University. https://doi.org/10.1057/9781137506429.

Harvey, A C. 1990. *Forecasting, structural time series models and the Kalman filter*. Cambridge University Press London.

Hirshleifer, David, and Siew Hong Teoh. 2003. "Herd behaviour and cascading in capital markets: A review and synthesis." *European Financial Management* 9 (1): 25–66. https://doi.org/10.1111/1468-036X.00207.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh. 2009. "Driven to Distraction : Extraneous Events and Underreaction to Earnings News." *Journal of Finance* 64 (5): 2289–2325. https://doi.org/10.1111/j.1540-6261.2009.01501.x.

Hoerl, Arthur E, and Robert W Kennard. 1970. "Ridge Regression: Biased Estimation for Nonorthogonal Problems." *Technometrics* 12 (1): 55–67. https://doi.org/10.1080/00401706.1970.10488634.

Hong, Harrison, and Jeremy C Stein. 1999. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *The Journal of Finance* 54 (6): 2143–84. http;//www.jstor.org/stable/2325364.

Hou, Kewei, and Tobias J Moskowitz. 2005. "Market frictions, price delay, and the cross-section of expected returns." *Review of Financial Studies* 18 (3): 981–1020. https://doi.org/10.1093/rfs/hhi023.

Ishwaran, Hemant, and J Sunil Rao. 2005. "Spike and slab variable selection: Frequentist and Bayesian strategies." *The Annals of Statistics* 33 (2): 730–73. https://doi.org/10.1214/009053604000001147.

Joseph, Kissan, M Babajide Wintoki, and Zelin Zhang. 2011. "Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search." *International Journal of Forecasting* 27 (4): 1116–27. https://doi.org/10.1016/j.ijforecast.2010.11.001.

Kabir, M Humayun, and Shamim Shakur. 2018. "Regime-dependent herding behavior in Asian and Latin American stock markets." *Pacific-Basin Finance Journal* 47 (November 2017): 60–78. https://doi.org/10.1016/j.pacfin.2017.12.002.

Kahneman, Daniel. 1973. *Attention and effort*. Vol. 1063. Englewood Cliffs, NJ: Prentice-Hall.

Kahneman, Daniel, and Mark W Riepe. 1998. "Aspects of Investor Psychology." *The Journal of Portfolio Management* 24 (4): 52–65. https://doi.org/10.3905/jpm.1998.409643.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47 (2): 263. https://doi.org/10.2307/1914185.

Kaminski, Jermain. 2014. "Nowcasting the Bitcoin Market with Twitter Signals," no. September 2014: 1–8. http://arxiv.org/abs/1406.7577.

Karlsson, Niklas, George Loewenstein, and Duane Seppi. 2009. "The ostrich effect: Selective attention to information." *Journal of Risk and Uncertainty* 38 (2): 95–115. https://doi.org/10.1007/s11166-009-9060-6.

Kate, Rohit J. 2016. "Using dynamic time warping distances as features for improved time series classification." *Data Mining and Knowledge Discovery* 30 (2): 283–312. https://doi.org/10.1007/s10618-015-0418-x.

Keynes, John Maynard. 1936. *General theory of employment, interest and money*. Atlantic Publishers & Dist.

Kim, Young Bin, Jun Gi Kim, Wook Kim, Jae Ho Im, Tae Hyeong Kim, Shin Jin Kang, and Chang Hun Kim. 2016. "Predicting fluctuations in cryptocurrency transactions based on user comments and replies." *PLoS ONE* 11 (8): 1–18. https://doi.org/10.1371/journal.pone.0161197.

Kindleberger, Charles P, and Robert Z. Aliber. 2005. *Manias, Panics, and Crashes*. Palgrave Macmillan UK. https://doi.org/10.1057/9780230628045.

Koop, Gary., Dale J Poirier, and Justin L Tobias. 2007. *Bayesian econometric methods*. Cambridge University Press.

Kristoufek, Ladislav. 2015. "What are the main drivers of the bitcoin price? Evidence from wavelet coherence analysis." *PLoS ONE* 10 (4): 1–19. https://doi.org/10.1371/journal.pone.0123923.

Kumar, Alok. 2009. "Who Gambles in the Stock Market?" *The Journal of Finance* 64 (4): 1889–1933.

Kumar, Satish, and Nisha Goyal. 2015. "Behavioural biases in investment decision making – a systematic literature review." *Qualitative Research in Financial Markets* 7 (1): 88–108. https://doi.org/10.1108/QRFM-07-2014-0022.

Li, Jun, and Jianfeng Yu. 2012. "Investor attention, psychological anchors, and stock return predictability." *Journal of Financial Economics* 104 (2): 401–19. https://doi.org/10.1016/j.jfineco.2011.04.003.

Liu, Yukun, and Aleh Tsyvinski. 2018. "Risks and returns of cryptocrrency." NBER. http://www.nber.org/papers/w24877.

Luther, William J. 2016. "Bitcoin and the future of digital payments." *Independent Review* 20 (3): 397–404. https://doi.org/10.2139/ssrn.2631314.

Lux, Thomas. 1995. "Herd Behaviour, Bubbles and Crashes." *The Economic Journal* 105 (431): 881–96.

Mackay, Charles. 1852. *Extraordinary popular delusions and the madness of crowds*. Library of Economics; Liberty.

Merlise, A. 1999. "Bayesian model averaging and model search strategies." *Bayesian Statistics* 6: 157.

Merton, Robert C. 1948. "The self-fulfilling prophecy." *The Antioch Review* 8 (2): 193–210.

———. 1987. "A Simple Model of Capital Market Equilibrium with Incomplete Information." *The Journal of Finance* 42 (3): 483–510.

Mitchell, T J, and J J Beauchamp. 1988. "Bayesian Variable Selection in Linear Regression." *Journal of the American Statistical Association* 83 (404): 1023. https://doi.org/10.2307/2290129.

Moskowitz, Tobias J, and Mark Grinblatt. 1999. "Do Industries Explain Momentum?" *The Journal of Finance* 54 (4): 1249–90. https://doi.org/10.1111/0022-1082.00146.

Nakamoto, Satoshi. 2008. "Bitcoin: A Peer-to-Peer Electronic Cash System." *Www.Bitcoin.Org*, 9. https://doi.org/10.1007/s10838-008-9062-0.

Nakamura, Emi, and Jón Steinsson. 2018. "Identification in macroeconomics." *The Journal of Economic Perspectives* 32 (3): 59–86. https://doi.org/10.22201/fq.18708404e.2004.3.66178.

Newey, Whitney K., and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3): 703. https://doi.org/10.2307/1913610.

Nimon, Kim F, and Frederick L Oswald. 2013. "Understanding the Results of Multiple Linear Regression." *Organizational Research Methods* 16 (4): 650–74. https://doi.org/10.1177/1094428113493929.

Ofek, Eli, and Matthew P. Richardson. 2001. "Dotcom Mania: A Survey of Market Efficiency in the Internet Sector." *Ssrn*. https://doi.org/10.2139/ssrn.268311.

Owusu, Richard A, Crispin M Mutshinda, Imoh Antai, Kofi Q Dadzie, and Evelyn M Winston. 2016. "Which UGC features drive web purchase intent? A spike-and-slab Bayesian Variable Selection Approach." *Internet Research* 26 (1): 22–37. https://doi.org/10.1108/IntR-06-2014-0166.

Parmigiani, Giovanni, Sonia Petrone, and Patrizia Campagnoli. 2009. *Dynamic Linear Models with R*.

Peng, Lin. 2005. "Learning with Information Capacity Constraints." *Journal of Financial and Quantitative Analysis* 40 (2): 307–29. https://doi.org/10.1017/s0022109000002325.

Peng, Lin, Wei Xiong, and Tim Bollerslev. 2007. "Investor attention and time-varying comovements." *European Financial Management* 13 (3): 394–422. https://doi.org/10.1111/j.1468-036X.2007.00366.x.

Peress, Joel. 2014. "The media and the diffusion of information in financial markets: Evidence from newspaper strikes." *Journal of Finance* 69 (5): 2007–43. https://doi.org/10.1111/jofi.12179.

Psaradakis, Zacharias, and Nicola Spagnolo. 2003. "On the determination of the number of regimes in Markov-switching autoregressive models." *Journal of Time Series Analysis* 24 (2): 237–52. https://doi.org/10.1111/1467-9892.00305.

Raskin, Max, and David Yermack. 2016. "Digital currencies, descentralized ledgers, and the future of central banking."

Read, Colin. 2012. *The Efficient Market Hypothesists*. https://doi.org/10.1057/9781137292216.

Ročková, Veronika, and Edward I George. 2014. "Negotiating Multicollinearity with Spike-and-Slab Priors." *Metron* 72 (2): 217–29. https://doi.org/10.1007/s40300-014-0047-y.

Rogojanu, Angela, and Liana Badea. 2014. "The Issue of competing Currencies. Case Study – Bitcoin." *Theoretical and Applied Economics* 21 (1): 103–14. http://store.ectap.ro/articole/946.pdf.

Scharfstein, David, and Jeremy Stein. 1990. "Herd Behavior and Investment." *The American Economic Review* 80 (3): 465–79.

Scott, Steven L, and Hal Varian. 2013. "Bayesian Variable Selection for Nowcasting Economic Time Series." *Working Paper*, no. January: 1–19.

Shapiro, Carl, and Hal R Varian. 1999. *Information rules*. Vol. 32. 2. https://doi.org/10.1145/776985.776997.

Shiller, Robert J. 1987. "Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence." *NBER Working Paper*, no. October. https://doi.org/10.3386/w2446.

———. 1999. "Chapter 20 Human behavior and the efficiency of the financial system." *Handbook of Macroeconomics* 1 (PART C). Elsevier: 1305–40. https://doi.org/10.1016/S1574-0048(99)10033-8.

———. 2015. *Irrational Exuberance*.

Shleifer, Andrei. 2004. *An Introduction to Behavioral Finance*. Oxford: Oxford University Press.

Shumway, Robert H, and David S Stoffer. 2010. *Time series analysis and its applications: with R examples*. Springer Science & Business Media.

Simon, Herbert Alexander. 1982. *Models of bounded rationality: Empirically grounded economic reason*. Vol. 3. MIT press.

Sims, Christopher A. 1980. "Macroeconomics and reality." *Econometrica* 48 (1): 1–48.

———. 2003. "Implications of rational inattention." *Journal of Monetary Economics* 50 (3): 665–90. https://doi.org/10.1016/S0304-3932(03)00029-1.

Simser, Jeffrey. 2015. "Bitcoin and modern alchemy: in code we trust." *Journal of Financial Crime* 22 (1): 155–69. https://doi.org/10.1108/JFC-11-2013-0067.

Sornette, Didier. 2017. *Why Stock Markets Crash*. Vol. 41. 0. Princeton: Princeton University Press. https://doi.org/10.23943/princeton/9780691175959.001.0001.

Stavroyiannis, Stavros, and Vassilios Babalos. 2019. "Herding behavior in cryptocurrencies revisited: Novel evidence from a TVP model." *Journal of Behavioral and Experimental Finance* 22: 57–63. https://doi.org/10.1016/j.jbef.2019.02.007.

Stracca, Livio. 2004. "Behavioral finance and asset prices: Where do we stand?" *Journal of Economic Psychology* 25 (3): 373–405. https://doi.org/10.1016/S0167-4870(03)00055-2.

Subrahmanyam, Avanidhar. 2008. "Behavioural finance: A review and synthesis." *European Financial Management* 14 (1): 12–29. https://doi.org/10.1111/j.1468-036X.2007.00415.x.

Svenson, Ola. 1981. "Are we all less risky and more skillful than our fellow drivers?" *Acta Psychologica* 47 (2): 143–48. https://doi.org/10.1016/0001-6918(81)90005-6.

Takeda, Fumiko, and Takumi Wakao. 2014. "Google search intensity and its relationship with returns and trading volume of Japanese stocks." *Pacific Basin Finance Journal* 27 (1): 1–18. https://doi.org/10.1016/j.pacfin.2014.01.003.

Tibshirani, Robert. 1996. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society: Series B (Methodological)* 58: 267–88. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x.

Urquhart, Andrew. 2018. "What causes the attention of Bitcoin?" *Economics Letters* 166 (August 2010). Elsevier B.V.: 40–44. https://doi.org/10.1016/j.econlet.2018.02.017.

Vaughan, Neil. 2016. "Comparing and Combining Time Series Trajectories Using Dynamic Time Warping." *Procedia Computer Science* 96: 465–74. https://doi.org/10.1016/J.PROCS.2016.08.106.

Vlastakis, Nikolaos, and Raphael N Markellos. 2012. "Information demand and stock market volatility." *Journal of Banking and Finance* 36 (6): 1808–21. https://doi.org/10.1016/j.jbankfin.2012.02.007.

Vozlyublennaia, Nadia. 2014. "Investor attention, index performance, and return predictability." *Journal of Banking and Finance* 41 (1). Elsevier B.V.: 17–35. https://doi.org/10.1016/j.jbankfin.2013.12.010.

Welch, Ivo. 1992. "Sequential Sales, Learning, and Cascades." *The Journal of Finance* 47 (2): 427–65.

———. 2000. "Herding among security analysts." *Journal of Financial Economics* 58 (3): 369–96. https://doi.org/10.1016/S0304-405X(00)00076-3.

West, Mike, and Jeff Harrison. 2006. *Bayesian forecasting and dynamic models*. Springer Science & Business Media.

Xi, Ruibin, Yunxiao Li, Yiming Hu, and Others. 2016. "Bayesian quantile regression based on the empirical likelihood with spike and slab priors." *Bayesian Analysis* 11 (3): 821–55. https://doi.org/10.1214/15-ba975.

Yelowitz, Aaron, and Matthew Wilson. 2015. "Characteristics of Bitcoin users: an analysis of Google search data." *Applied Economics Letters* 22 (13): 1030—–1036. https://doi.org/10.1080/13504851.2014.995359.

Yermack, David. 2013. "Is Bitcoin a real currency? An economic appraisal." National Bureau of Economic Research.

Zhang, Yongjie, Weixin Song, Dehua Shen, and Wei Zhang. 2016. "Market reaction to internet news: Information diffusion and price pressure." *Economic Modelling* 56: 43–49. https://doi.org/10.1016/j.econmod.2016.03.020.

Zhi Da, Joseph Engelberg, and Pengjie Gao. 2011. "In Search for Attention." *The Journal of Finance* 66 (5): 1461–99.