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ARE DEMAND SHOCKS IN BITCOIN CONTAGIOUS?

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Are demand shocks in Bitcoin contagious?

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Abstract: The main aim of this paper is to examine interdependencies between prices of cryptocurrencies, with the special focus on Bitcoin. The analysis is conducted in two stages and results are compared between two consequent sub-periods. In order to analyze topological properties of cryptocurrency market, the Minimum-Spanning Tree technique is used. Results indicate that Bitcoin plays one of the most important roles in the cryptocurrency market, while other cryptocurrencies form clusters and such forming has a sensible economic interpretation. In the second stage, main cryptocurrencies from each of formed clusters are analyzed using the Vector Autoregression methodology. The results from VAR (1) indicate that demand shocks in Bitcoin price are not contagious to other cryptocurrencies, while some interdependencies within the formed clusters may be observed. Overall, results indicate that conclusions drawn from the analysis of Bitcoin shall not be generalized to the entire cryptocurrency market.

Keywords: cryptocurrency market, Bitcoin, Minimum-Spanning Tree, Vector Autoregression

JEL codes: C32, G11

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1. Introduction

Since its introduction in 2008 (Nakamoto 2008) up until 2011, Bitcoin has been the only application of blockchain technology. Then, new blockchain systems have started to be created, on the basis of Bitcoin's protocol, such as Namecoin, Litecoin, Peercoin, or Ripple. Within these applications, token serves only as a (crypto)currency in a decentralized peer-to-peer payment system, referred to as Blockchain 1.0. For a long time, Bitcoin has been the mostly used cryptocurrency, so the early history of Blockchain development is mainly connected with what was happening with Bitcoin. One of the most important events in early Bitcoin history was the bankruptcy of the biggest at that time Bitcoin exchange – Mt. Gox in February 2014. Few months before that, the price of Bitcoin was rapidly rising between November and December of 2013 reaching up to 1200 USD/BTC, and then started collapsing and stabilized around 200 USD/BTC in 2015. For the most part of 2015, Bitcoin price was relatively stable and started increasing again since September 2015.

Before 2017 prices of most of cryptocurrencies had been following their own (more or less similar) trends, but since the early 2017 almost all of them started simultaneously rising, reaching their all-time peaks on the turn of 2017 and 2018. The hype on blockchain technology throughout 2017 had been mostly related with the development of non-cryptocurrency tokens. It has now become possible to publicly issue a token, through a process called Initial Coin Offering (ICO – similar to Initial Public offering on stock market), in order to raise funds for financing further development of particular sub-platform. Therefore, a lot of people have started to seek investment opportunities, as such possibility is equally available to all people across the globe (depending on country's regulation). This resulted in major fluctuations of prices on the entire cryptocurrency market. Since 2017, the number of cryptocurrencies in the market has grown from ca. 600 at the beginning of the year to over 1.500 at the beginning of May 2018. Moreover, the cryptocurrency market capitalization has grown 24 times – from \$17 billion at the beginning of 2017 up to almost \$800 billion at the beginning of 2018. Such growth is especially striking, considering that between 2015 and 2017 the number of cryptocurrencies in the market had grown by only a hundred, while capitalization only tripled (from \$5.5 billion to \$17 billion).¹

¹ The data on the number of cryptocurrencies in circulation and their market capitalization comes from <https://coinmarketcap.com> database

The phenomenon of rapidly increasing size of cryptocurrency market, together with a common trend of almost all prices, brings the research question of whether such common movement of the entire market has been caused only by the proportional distribution of the demand among cryptocurrencies, or there exists an extra force pushing the market in the common direction. Therefore, it may be hypothesized whether Bitcoin has such a dominant role in the market that it affects, or is affected by, the common market trend. The main aim of this paper is to examine inter-dependencies between selected cryptocurrencies, with special focus on Bitcoin, due to the highest maturity of its infrastructure development. Namely, the study presents the evolution of the structure of cryptocurrency market and analysis of potential existence of shock transmission mechanism within the market. More specifically:

1. Whether the price of Bitcoin is considerably correlated with the price of other cryptocurrencies, so it is at the top of the hierarchical structure of the market in this regard?
2. Whether shocks in the price of Bitcoin are contagious to prices of other selected cryptocurrencies or the other way around?

The analysis is conducted with the use of two-stage analysis. First, an econophysics technique Minimum Spanning-Tree enables to determine the hierarchical structure in the cryptocurrency market, and therefore verify whether Bitcoin has the most important role in the market. Then, variables selected based on results from the first stage are analyzed with the use of Vector Autoregression Model, which enables to study the response of one variable to changes in values of another variable.

2. Literature review

The literature on the economic or financial aspects of cryptocurrencies is still in its early development. However, there are studies providing quite meaningful results, suggesting the interpretation of this phenomenon.

Kristoufek (2013) used VAR and VEC models in order to analyze the relationship between bitcoin's price and investors' sentiment (i.e. interest in bitcoin), which is represented by Google Trends and Wikipedia search queries. He finds that when bitcoin's price increases, so does the public interest in it, pushing the price to increase even more. While when the bitcoin's price decreases, the increasing interest in bitcoin makes the price decline even lower. These findings imply that there is a suitable environment for the emergence of a bubble. Glasser et al. (2014) studied whether bitcoin behaves more like a currency or rather like an asset, assessing two of three criteria of money: a medium of exchange and a store of value. Using

ARCH/GARCH methodology they analyze demand for bitcoin from two perspectives: intra-network volume and on-exchange volume of transactions. Their findings strongly suggest that bitcoin is mostly used for the purpose of speculation, rather than for the purpose of peer-to-peer intra-network exchange. Namely, users tend to hold bitcoin on their exchange wallets (statistically significant increase of on-exchange volume), instead of using it for buying goods or services (which would increase the intra-network transaction volume). In his later study, Kristoufek (2015) analyzed bitcoin's price determinants using the continuous wavelet framework. His findings indicate that bitcoin is a unique type of asset, with properties similar to both a standard and speculative type of financial asset. More importantly, he proves that even though bitcoin is widely considered as a speculative asset, its price is driven by standard fundamental factors (such as usage in trade, money supply and price level), which is in line with standard theory of monetary economics and quantity theory of money. Moreover, he finds that bitcoin's price is driven by the interest of users to become miners in the short-run, while in the long-run it is driven by investors' interest in gains from cryptocurrency market. Cheah & Fry (2015) used an econophysics technique, a so-called stochastic bubble model, which they used not only for determining if bitcoin is vulnerable to bubble creation but also to calculate its fundamental value. Based on their calculations they argue that bitcoin's fundamental value equals 0. Namely, their findings indicate that bitcoin's price is prone to speculative bubble, and that this bubble component is substantial. On the other hand, Garcia et al. (2014) argued that bitcoin's fundamental value is most likely higher than 0 and equals at least the cost of its production (cost of the energy and computing hardware used for producing bitcoins).

Dyhrberg (2015) used GARCH models to examine bitcoin's capabilities of being a financial asset. She found a significant relationship between bitcoin's price and federal funds rate, indicating bitcoin's currency-like behavior. Results from exponential and asymmetric GARCH model indicate similar behavior of bitcoin and gold, as both variables possess common hedging capabilities and react symmetrically to good and bad news. Overall, these findings imply that bitcoin is an asset with unique properties – between a currency and commodity. Polasik, et al. (2015) analyze the payment and investment features of bitcoin. Their results indicate that there is a significant relationship between bitcoin's price and its popularity, the sentiment expressed in the news, and the total number of transactions. They do not find any impact of USD/EUR exchange rate and other macroeconomic indicators. Moreover, their results imply that company features, use of other payment methods, customers' knowledge on bitcoin, and the size of overall and shadow economy in the country where the company is placed

are significant. Ciaian et al. (2016) study bitcoin's price formation in short- and long-run, using the applied gold standard model (Barro 1979). In line with Kristoufek (2015), their results indicate that bitcoin's price is strongly determined by supply and demand forces. Namely, as the supply of bitcoin is exogenous (predefined with publicly known and unchangeable algorithm), the discovered impact of demand-side may also be assumed to retain or even increase in the future. Similarly to Polasik et al. (2015), they do not find any relationship between bitcoin's price and macro-financial indicators (such as USD/EUR exchange rate, oil price and Dow Jones Index).

One of the most meaningful studies on the wider scope of the cryptocurrency market (as of yet) is provided by Hayes (2016), who conducts a regression model (OLS) to analyze cross-sectional data on 66 cryptocurrencies. His findings indicate that there are three main drivers of cryptocurrencies' price: the level of competition within the network of miners (producers), the rate of unit production, and the difficulty of algorithm to mine the cryptocurrency. Phillip et al. (2018) examine 224 digital currencies. Their results indicate that cryptocurrencies exhibit long memory, leverage effect, stochastic volatility and heavy tails. These results are in line with Catania et al. (2018), who provide GARCH model and the Score Driven-GHSKT model for Bitcoin, Litecoin, Ether, and Ripple, over the period from 2013 to 2017. They find that analyzed cryptocurrencies exhibit long memory in the volatility process and asymmetric reaction of the volatility process to the sign of past observations (leverage effect). Osterrieder et al. (2016) obtain similar results, as they provide both statistical analysis as well as univariate and multivariate analysis based on Extreme Value Theory. They find that cryptocurrencies exhibit strong non-normal characteristics, large tail dependencies, and heavy tails. It is worth mentioning that the results obtained in those studies present well-known stylized facts for a traditional time series.

Most of the studies on cryptocurrencies focus mainly on bitcoin, as it is the most mature and most widely known cryptocurrency. The main conclusion from the literature is that Bitcoin and other cryptocurrencies behave much more like the new type of asset class, rather than currencies or, speaking more broadly, the money. Moreover, as the supply of a cryptocurrency is pre-defined by the algorithm, the high volatility of the price is mainly caused by changes in investors' demand. However, the literature lacks studies on the wider scope of the cryptocurrency market. Often, based on their findings authors tend to generalize conclusion obtained from the analysis of Bitcoin to the entire cryptocurrency market. This study contributes to the literature with the analysis of the wide range of cryptocurrencies, attempting to prove that

the findings obtained from Bitcoin analysis shall be treated carefully, when drawing conclusions on the entire cryptocurrency market.

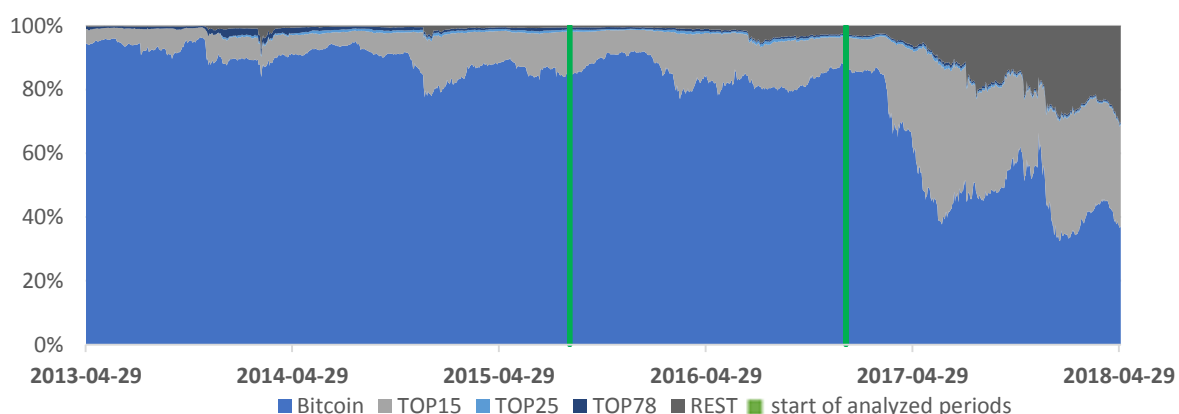
3. Novel approach for analysing the cryptocurrency market

The empirical analysis is conducted with the use of methods often used for studying inter-relationships between multiple time-series of log-returns in the particular stock market, i.e. Minimum-Spanning Tree and Vector Autoregression. Therefore, cryptocurrency market is treated analogically to the stock market. Such approach is based on the early theory on Blockchain-based tokens (not necessarily cryptocurrencies) and empirical studies on their nature, indicating that cryptocurrencies are more similar to traditional assets (e.g. stocks) rather than to traditional currencies.

3.1. Dataset description

The choice of analyzed time period is mainly based on the history of development of cryptocurrency market presented in the first chapter. Basically, at the starting point of the analysis (01.09.2015), only pure cryptocurrencies were available on the market, as it has not been yet possible to develop other types of tokens. This gives the consistency within the analysis, as we analyze relationship between the same types of variables. The research sample consists of cryptocurrencies with highest market capitalization, where the data is available throughout the entire analyzed period.

Figure 1: Cryptocurrency market capitalization – share of the sample in the entire cryptocurrency market, 28.04.2013 – 02.05.2018, green lines mark starts of the first and the second analyzed periods



Source: authors' own preparation based on coinmarketcap.com.

It is worth examining the transition of cryptocurrency market capitalization and how the share of particular cryptocurrencies changed over the time. Figure 1 present the data segregated into particular parts of analyzed research sample - the share of Bitcoin (blue area), the research

sample (TOP15, 25, 78), and all remaining cryptotokens in the cryptocurrency market capitalization (dark grey area). Green vertical lines are placed at the beginning of analyzed sub-periods.

The analysis of inter-dependencies between selected cryptocurrencies is conducted for the period between 01.09.2015 – 02.05.2018. The period is divided into two parts of the same length of 488 daily observations, so it enables the comparison of two subsequent sub-periods: 01.09.2015 – 31.12.2016 and 01.01.2017 – 02.05.2018. The source of the data is the database of coinmarketcap.com, which is the most comprehensive cryptocurrency database available. The data was gathered with the use of API provided in the package ‘crypto’ in R language. For the purpose of preliminary analysis, the threshold for market capitalization of USD 10 million was set, which gave the dataset of 537 cryptocurrencies (as of 11:30 a.m. on 2 May 2018). The actual analysis is conducted with the use of daily prices of all cryptocurrencies, denominated in USD, for which the data was available in 95% throughout 01.09.2015 – 02.05.2018. This approach provides 78 cryptocurrencies with non-missing data in this period. As the data on cryptocurrency prices is non-stationary, and there are differences in scale of the measured prices, logarithmic differences (returns) were calculated, which is the most frequent approach for analyzing the behavior of stock prices.

3.2. Research hypotheses

The final stage of the analysis, enabling to verify research hypotheses, is based on responses of Bitcoin’s price to changes in prices of other cryptocurrencies (and itself) as well as whether changes in Bitcoin’s price have any effect on future prices of other cryptocurrencies. As the mechanism of supply of all considered cryptocurrencies is predetermined and unexpected changes are impossible, all occurring shocks in prices come from the demand side. Therefore, following hypotheses are verified:

H1: Bitcoin’s price is affected by demand shocks in other cryptocurrencies

H2: Demand shocks in Bitcoin’s price affect prices of other cryptocurrencies

H3: Demand shocks in Bitcoin’s price affect its future price

The hypotheses are mainly formulated based on authors’ ongoing observations of the market (for 3 years) and on conversations with more and less experienced investors. The hypothesis **H1** is based on the fact, that especially during the first analyzed sub-period, only few cryptocurrencies can be bought directly for fiat money. It has been often necessary to purchase Bitcoin first, and then exchange it for another token. Moreover, particularly in the

second analyzed sub-period, cryptocurrency investors tend to hold Bitcoin together with other cryptocurrencies, so the shocks in one cryptocurrency can lead to changes in demand for Bitcoin (change in the share of Bitcoin in their portfolio) (**H1**). To follow up on this concept, the unexpected change in Bitcoin's price may also have an effect on demand for other cryptocurrencies (**H2**). It can be imagined, that if Bitcoin price increases, it brings the positive vibe in the market encouraging investors to purchase other cryptocurrencies as well. It is also worth analyzing if own shocks in Bitcoin's price affect its future demand (**H3**).

3.3. Methodology

The analysis is conducted in two stages. First, we use Minimum-Spanning Tree (MST) technique from the field of econophysics. This method allows for studying the hierarchical structure and topology of particular network, often used for studying relationships between stocks from the same market. We follow the methodology proposed by Mantegna (1999), further explained in Mantegna and Stanley (2001). Based on MST analysis, it is possible to determine the most influential cryptocurrencies in the market, and verify whether Bitcoin has the highest position in the hierarchy

Results from MST analysis enable to select potentially inter-related cryptocurrencies for further analysis of responses to shocks, with the use of Vector Autoregression (VAR) Model. Even though, VAR models are often used for the macroeconomic policy analysis (Sims, 1980) or with the purpose of forecasting, they are also helpful in discovering causal relationships between potentially inter-dependent variables, as explained in Lütkepohl (2005). Therefore, analysis of Granger Causality (Granger 1969) and, more importantly, Impulse Response Functions allows for verifying proposed hypotheses by examining directions of relationships between Bitcoin and other cryptocurrencies.

Minimum Spanning Tree (MST) methodology

The technique is more widely described in the book "An Introduction to Econophysics" written by Mantegna and Stanley (2001). Minimum Spanning Tree of an undirected, weighted graph is a tree that spans the graph while minimizing the total weight of the edges (their sum) in the tree. In the case of MST for stock market, weights are the correlations between the returns (usually daily logarithmic returns) of analyzed stocks. The MST is generated by the algorithm (e.g. Kruskal's or Prim's) which finds the most relevant connections between the set of variables. In order to apply correlations to the algorithm, it is necessary to calculate a symmetric distance

matrix D , where distances (weights) between stocks are the cross-correlations between them. The distance is usually calculated using a function:

$$d(i, j) = \sqrt{2(1 - \rho_{i,j})}, \quad (1)$$

where $\rho_{i,j}$ denotes the correlation between i th and j th variable.

Such function fulfills three axioms of a Euclidean metric:

1. $d(i, j) = 0 \Leftrightarrow i = j$;
2. $d(i, j) = d(j, i)$
3. $d(i, j) \leq d(i, k) + d(k, j)$.

The analysis of derived MST graph mainly contains:

- a) An analysis of distribution of vertex degrees, where each vertex represents each company (stock), and vertex degree is a number of edges connecting a given vertex, which simply indicates how many companies each company is (strongly) connected with (Mantegna & Stanley, 2001),
- b) An analysis of hierarchical structure, if such structure is observed within particular MST – as some of the stocks may be grouped in clusters indicating stronger connections within those clusters than with other stocks (Mantegna 1999); and then potential comparison between two separate periods in order to seek for topological properties (Sienkiewicz et al. 2013; Wiliński et al. 2013).

For the purpose of the analysis, first correlations between log-returns of 78 tokens are calculated, therefore obtaining distance matrix D and apply it into MST model. The distance between the variables is calculated according to Mantegna (1999) with the formula (1). Then, we examine the connections between tokens and compare the results between the MST containing all 78 tokens (TOP78 MST) and MSTs containing TOP25 and TOP15 tokens (in terms of capitalization). Such comparison enables to conduct a more in-depth analysis of obtained results, as the output graph of TOP78 MST does not provide clear results.

The reason for choosing MST containing TOP25 and TOP15 is based on the analysis of distribution of vertex (node) degrees, i.e. the distribution of connections among the variables. As every MST is constructed of $N - 1$ edges (connections), where N is the number of variables, MST for 78 tokens has 77 edges. The analysis shows that 11 (14%) of those edges are connecting TOP15 tokens, while another 30 edges (53% in total) connect TOP15 tokens with

other 63. Moreover, 16 of 77 edges (21%) are connecting TOP25 tokens, while another 35 connect TOP25 tokens with remaining 53 (65% in total).

Most importantly, we compare results between two analyzed sub-periods, so in fact **six MST models are compared – TOP78, TOP25, and TOP15 for 01.09.2015 – 31.12.2016, 01.01.2017 – 02.05.2018** (results from TOP78 MST, as well as precise statistics are available on reader's request).

The MST model visualized with R package outputs the number (index) of row/column in which the token is placed in the dataset. Tokens are sorted in the descending order, based on their current market capitalization on May 2, 2018 at 11:30. Thus, the connection between the number (1) and (4) always means it is the high correlation between *Bitcoin* (1) and *Litecoin* (4).

VAR Methodology used for analysis

We follow the methodology for VAR analysis described by Lütkepohl (2005) in his book "New Introduction to Multiple Time Series Analysis." He explains that VAR models can be either used for the forecasting purposes or for the structural analysis of dependencies between variables (not to be confused with Structural VAR (SVAR) model, where the structure is already known and restrictions are imposed from the beginning of the analysis). For the purpose of the analysis, we use the second approach, attempting to determine the potential direction of relationships only between selected cryptocurrencies.

The selection of variables is based on the previous stage of analysis with the use of Minimum-Spanning Tree technique, as it sheds light on the potential hierarchical structure in the market, while highlighting the potential group of variables to be studied further. Therefore, we select 4 groups of variables, conducting separate models for each group. Similar to the analysis conducted in the first stage, we compare the results between the first and second analyzed sub-periods, while referring to the results obtained from MST analysis. Following the conventional methodology of VAR analysis, using the stationary data of log-returns, following steps of analysis are performed:

1. Selection the VAR order based on the lag length criteria, especially Likelihood-ratio (LR) test
2. Analysis of roots, in order to confirm the dynamic stability of VAR, depending whether roots lie inside the unit circle
3. The autocorrelation test based on Lagrange multiplier test (also known as Breusch-Godfrey test)

4. The Wald Block Exogeneity test for Granger causality (joint and individual)
5. Analysis of visualized Impulse Response Functions between selected variables.

3.4. Econophysics approach for modelling hierarchy of the cryptocurrency market

The results obtained from analysis of MST in the first sub-period show that *Bitcoin (1)*² has the highest vertex degree of all variables, as it is connected with 18 other cryptocurrencies. *Bitcoin (1)* is, among others, connected with *Litecoin (4)*, which is further connected with *Dogecoin (14)*. *Dogecoin (14)* is the variable with second most connections (7). The results obtained from MST for the second sub-period are very similar to the ones obtained for the first sub-period, with one important exception. Even though, the hierarchy is constructed in the similar superhub-like structure, the cryptocurrency in the middle of TOP78 MST – *Dogecoin (14)* – does not have the highest vertex degree, as *MaidSafeCoin (21)* has the highest (6 and 16, respectively). However, *MaidSafeCoin (21)* is only connected with 4 tokens from TOP25 sample, i.a. *Monero (6)* and *NEM (8)*. In fact, *Dogecoin (14)* has only the third highest vertex degree, as *Bitcoin (1)* has 9 connections. The structure can be better observed in the case of TOP25 MST (Fig. 4), as *Dogecoin (14)* is in the middle of the graph and now has the highest equal vertex degree of 5, ex-aequo with *MaidSafeCoin (21)*. In fact, *MaidSafeCoin (21)* is a part of a cluster formed around *Monero (6)* (marked in yellow). In TOP25 MST *Bitcoin (1)* has the second highest vertex degree of 4 (Table 1).

Table 1: Vertex degree (number of connections) of most notable cryptocurrencies in MSTs

Name	First Period						Second Period					
	TOP 78		TOP 25		TOP 15		TOP 78		TOP 25		TOP 15	
	total	rank	total	rank	total	rank	total	rank	total	rank	total	rank
Bitcoin (1)	18	1	7	1	5	1	9	2	4	3	2	5
Litecoin (4)	3	6	2	7	2	4	1	32	1	12	1	8
Stellar (5)	3	6	3	2	3	2	2	16	2	7	2	5
Monero (6)	4	4	1	14	1	9	4	5	4	3	3	3
NEM (8)	2	16	3	2	3	2	2	16	1	12	1	8
Bitshares (13)	3	6	2	7	2	4	4	5	3	5	4	1
Dogecoin (14)	7	2	3	2	2	4	6	3	5	1	4	1
MaidSafeCoin (21)	1	38	n/a	n/a	n/a	n/a	16	1	5	1	n/a	n/a

Source: authors' own preparation in R.

Despite differences at the top of hierarchy between MSTs for the first and the second sub-period, cryptocurrencies form similar hubs in both sub-periods. This can be observed comparing TOP25 (Fig. 2,4) and TOP15 (Fig. 3,5) MSTs from both sub-periods, as corresponding hubs

² Bolded numbers in parentheses denote the corresponding number, which labels cryptocurrencies on the MST graph, in terms of the size of their market capitalization, e.g. **(1)** – Bitcoin (highest capitalization)

are circled with same colors. Circled in red, similarly to the first sub-period, *Bitcoin* (1), *Dogecoin* (14), and *Litecoin* (4) are placed in the middle of the graph, however there is no direct connection between *Bitcoin* (1) and *Litecoin* (4) in the second sub-period. This may result from the increased usage of Litecoin in the second sub-period, as in 2017 Bitcoin fees increased to very high level and it was less costly for people who use them as currencies.³

Figure 2: MST for TOP 25 tokens in the 1st sub-period

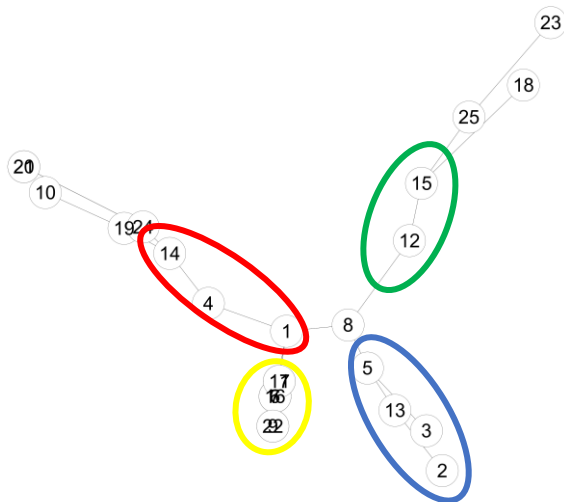


Figure 3: MST for TOP 15 tokens in the 1st sub-period

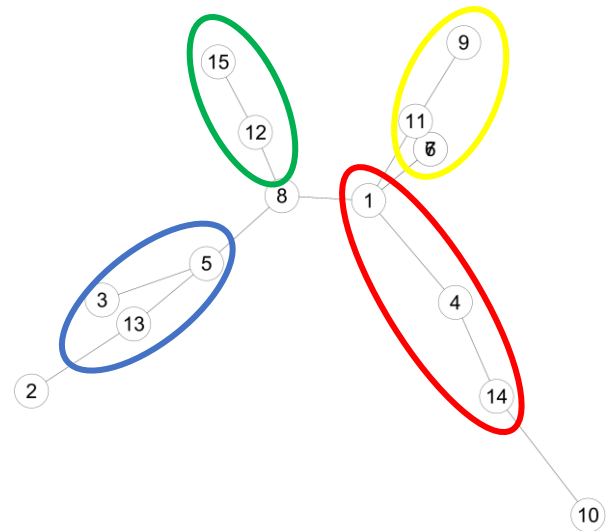


Figure 4: MST for TOP 25 tokens in the 2nd sub-period

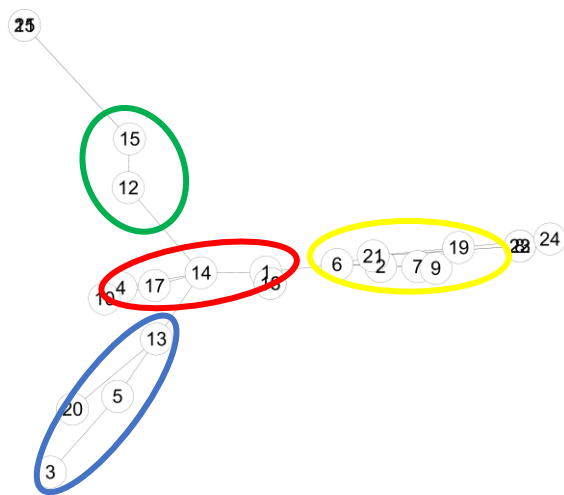
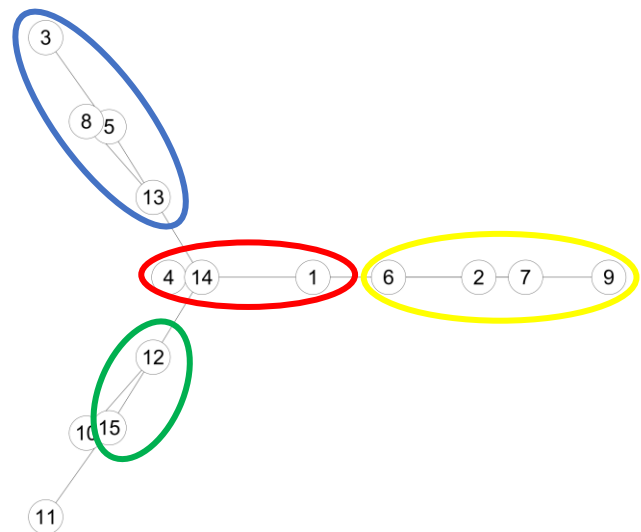


Figure 5: MST for TOP 15 tokens in the 2nd sub-period



Source: authors' own preparation in R.

³ <https://www.forbes.com/sites/jessedamiani/2017/12/13/5-reasons-why-the-litecoin-price-is-going-up-so-fast-will-the-ltc-surge-continue/>

Marked in blue, there is a cluster containing *Ripple* (3), *Stellar* (5), and *Bitshares* (13). In yellow, there is a hub consisting of *Monero* (6), *Dash* (7), and *Tether* (9). In green, there is a cluster formed around *Siacoin* (12) and *DigiByte* (15). These 11 tokens (all in TOP15) are forming similar clusters in both sub-periods. This is not the case for almost all other tokens included in the sample. For instance, *Ether* (2) is in the “blue” cluster in the first sub-period and in the “yellow” cluster in the second sub-period. Moreover, *NEM* (8) and *Verge* (11), in both sub-periods change clusters, depending on the size (TOP25 or TOP15) of the MST.

Similar to the results obtained by Mantegna (1999), there is a potential economic interpretation with respect to the cluster-grouping. The interesting fact about the branch formed by *Stellar* (5), *Bitshares* (13), *Ripple* (3), and *Ether* (2) (marked in blue) is that the first 3 of them (*Stellar*, *Ripple*, and *Bitshares*) belong directly to the financial sector. The blockchain behind *Stellar* and *Ripple* provides a wide variety of online-banking services (far beyond the simple transfer of coin between 2 parties), so they may easily be considered as competitors. In fact, both *Ripple* and *Stellar* were created by the same person - Jed McCaleb - who, due to the differences in ideologies, quitted *Ripple* and started *Stellar* based on his ideas. *Stellar* connects biggest banks in the world, and together with IBM they are developing platform enabling cheap and secure international transfers, as well as other financial services. On the other hand, *Ripple* is one of the oldest cryptocurrencies which is directly connected with financial sector. Moreover, the blockchain of *Bitshares* is a backbone of one of the biggest cryptocurrency exchanges in history (existing since 2013). There is an evidence that other branches are not created randomly either. The “yellow” branch contains *Monero* (6), *Bytecoin* (11), *Dash* (7), and *Tether* (9). *Monero* was created as a hard-fork of *Bytecoin*, which means that *Monero* is just a different version of *Bytecoin*, based on the same protocol (Proof-of-work – similar type to *Bitcoin*) but with some modifications. Moreover, they are both considered as completely anonymous cryptocurrencies. Similarly, *Dash* (7) is another cryptocurrency offering full privacy. *Tether* (9) is a cryptocurrency often used as a medium of exchange between two cryptocurrencies for whom there is no trading pair on the market, since there are many trading pairs involving *Tether* (9).

To summarize this part of analysis, the hierarchical structure in the cryptocurrency market as well as direct relationships between most important variables in formed clusters hold throughout both analyzed sub-periods. This proves that there are topological properties in the cryptocurrency market, similarly to the results obtained from studies on different stock markets (US, Poland, Germany). Specifically, *Bitcoin* (1) and *Dogecoin* (14) are the most important

variables in the system, as they have the highest vertex degrees (number of connections with other nodes) in both periods. Furthermore, they are always positioned in the middle of the tree, either through or very close to Litecoin **(4)**. This implies the highest importance of these three variables in the hierarchical structure of the market. Moreover, the other variables are grouped basically in three main clusters. It can be observed that there are variables which are formed within the same cluster in both analyzed sub-periods (“Blue” – *Ripple (3)*, *Stellar (5)*, *Bitshares (13)*; “Green” – *Siacoin (12)*, *DigiByte (15)*; “Yellow” – *Monero (6)*, *Dash (7)*).

3.5. Analysis of causal relationships between Bitcoin and other cryptocurrencies

The first stage of the analysis, with the use of MST technique, proved that cryptocurrency market forms clusters and the structure of these clusters is similar over two separate sub-periods. Therefore, following the standard methodology for VAR analysis (Lütkepohl 2005), the analysis focuses on 4 main clusters formed in MST graph, modelling each group separately. Results are compared between first (01.09.2015 – 31.12.2016) and second (01.01.2017 – 02.05.2018) sub-period. During the analysis following notation is used:

- Model I (“Red” cluster) – containing Bitcoin, Litecoin, and Dogecoin
- Model II (“Blue” cluster) – Model I + Ripple, Stellar, and Bitshares
- Model III (“Green” cluster) – Model I + Siacoin and DigiByte
- Model IV (“Yellow” cluster) – Model I + Dash and Monero

Variables from Model I are included in all three other models, as MST analysis indicates that Bitcoin, Litecoin, and Dogecoin appear to have the most important role in the hierarchy of the market (being positioned in the middle of the graph). Therefore, it allows for examining the potential direction of the relationship between variables from Model I (most importantly including Bitcoin) and three remaining groups. Because of the restrictions in the length of the article, results from conducted tests are briefly described, while exact results are available on reader’s request.

VAR model identification

For the purpose of selecting the appropriate lag length, Likelihood Ratio (LR) test is used. Then, the stability of the model is verified by checking if all eigenvalues lie in the unit circle. Finally, test for autocorrelation of model residuals is conducted.

The results obtained from Likelihood Ratio test indicate that in most cases VAR (1) and VAR (6) is the most appropriate order (ANNEX 1). Due to the construction of this test, it always indicates using the highest possible order (at 5% significance level). However, it can be observed that models with one lag length, i.e. VAR (1) also have very low p-values compared to other models. Moreover, other information criteria (AIC, BIC, HQ) also indicate that in most cases VAR (1) is the most appropriate. Lutkepohl (2005) suggests that VAR models tend to produce worse results (e.g. in terms of precision of impulse response estimates), if selected order is unnecessarily too large (overfitting). Therefore, only VAR (1) model is analyzed. Nevertheless, Lütkepohl (2005) also suggests that the choice of the appropriate lag length should be based on results from multiple tests, especially Likelihood Ratio test, and that there might be more than one appropriate order for a particular model. Therefore, the results from VAR (6) will be possible to find in another article, which is currently in the preparation.

Wald block exogeneity test for Granger causality

The Wald test for Block Exogeneity/Granger Causality shows not only significance of direct Granger causality between all variables but also shows the significance of joint causality of all other variables on each variable. Precise results contain p-values for joint causality for each variable as well as all discovered statistically significant (at least at 10% level) causal relationships between variables.

VAR (1)

The analysis of Wald test for Granger causality shows that Bitcoin's price is not significantly affected by neither set of variables. Bitcoin is only affected by Dash in the first period (at the border of 5% level), but it does not translate to joint effect of all variables in this cluster (Model IV). This is against the **H1** hypothesis. The results are also not in favor of hypothesis **H2**. Bitcoin only affects Bitshares (Model II) at 10% level, and the joint effect appears to be related with the highly significant effect from Dogecoin (Table 2).

It is also worth noting that there are significant relationships between variables within particular clusters. Ripple, Stellar, and Bitshares (Model II) are all jointly affected by the set of variables in both analyzed sub-periods (all at 5% significance level). In the first period, the most influential variable is Dogecoin, while in the second period there is a bi-directional relationship between Stellar and Ripple. This is in line with the results obtained in the first stage of analysis, with the use of MST technique.

Table 2: Granger Causality (Wald block exogeneity test) for VAR (1)

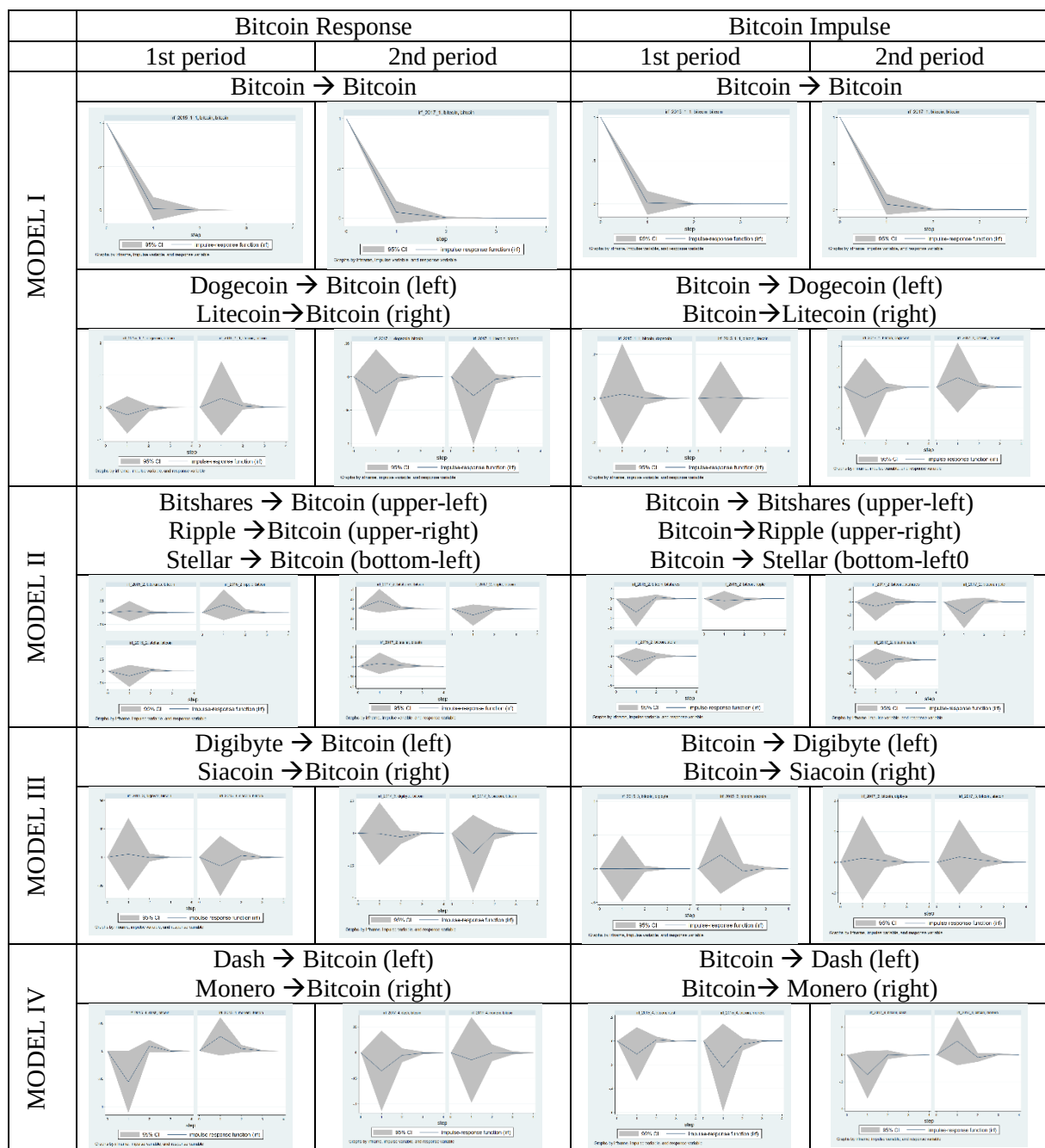
Model	Dependent variable	Independent variables			
		First Period		Second Period	
		Variable	p-value	Variable	p-value
I	Bitcoin	ALL	0.686	ALL	0.418
	Dogecoin	ALL	0.158	ALL	0.726
	Litecoin	ALL	0.967	ALL	0.777
II	Bitcoin	ALL	0.816	ALL	0.442
	Dogecoin	ALL	0.233	ALL	0.384
	Litecoin	ALL	0.829	ALL	0.773
	Ripple	ALL	0.028**	ALL	0.022**
		Dogecoin	0.026**	Litecoin	0.004***
				Stellar	0.052*
	Stellar	ALL	0.021**	ALL	0.031**
		Dogecoin	0.007***	Ripple	0.006***
	Bitshares	ALL	0.040**	ALL	0.016**
		Dogecoin	0.012**	Dogecoin	0.018**
		Bitcoin	0.071*	Stellar	0.004***
III	Bitcoin	ALL	0.895	ALL	0.529
	Dogecoin	ALL	0.358	ALL	0.022**
				Digibyte	0.022**
	Litecoin	ALL	0.789	ALL	0.971
	Siacoin	ALL	0.604	ALL	0.022**
				Digibyte	0.001***
IV	Digibyte	ALL	0.484	ALL	0.311
	Bitcoin	ALL	0.163	ALL	0.535
		Dash	0.049**		
	Dogecoin	ALL	0.112	ALL	0.448
		Dash	0.053*	Dash	0.094*
	Litecoin	ALL	0.043**	ALL	0.910
		Monero	0.005***		
	Monero	ALL	0.386	ALL	0.539
		Dash	0.087*		
	Dash	ALL	0.811	ALL	0.552

Source: authors' own preparation based on calculations in STATA ver. 15.

Analysis of Impulse Response Functions from Bitcoin perspective

The analysis of generalized IRFs from VAR (1) models shows that neither shocks in Bitcoin affect the price of other cryptocurrencies, nor the shocks in other cryptocurrencies affect Bitcoin in any of analyzed periods at 5% significance level (Figure 6). Moreover, shocks in Bitcoin also do not appear to have further impact of the price of Bitcoin itself. These results are mainly in line with results obtained from Granger Causality test, and furthermore against the hypotheses **H1**, **H2**, and **H3**.

The further analysis shows, contrary to the findings obtained for Bitcoin, that shocks in other tokens tend to affect their own future price (ANNEX 2). The most notable example is Stellar, where the response to its own shock can be observed in both analyzed periods, especially in the second period. Such relationship may also be observed in the case of Dogecoin, Bishares, Ripple, Dash, Siacoin, and Monero, however only in one of two periods. Moreover, in the case of VAR (1) there are also other inter-relationships between variables, and most of them can be also observed in the case of VAR (6) which will be further analyzed in the forthcoming article.

Figure 6. VAR (1) Impulse Response Functions – Bitcoin's response

Source: authors' own preparation based on calculations in STATA ver. 15.

3.6. Summary of empirical analysis

The first stage of analysis proved that bitcoin is dominant on the cryptocurrency market not only in terms of its total market capitalization but has also been correlated with the highest number of other cryptocurrencies throughout two consequent sub-periods. Furthermore, the cryptocurrency market forms clusters which are consistent over those two periods. More importantly, the grouping of cryptocurrencies in such clusters has a sensible economic interpretation. The central cluster ('red') includes the most mature cryptocurrencies, i.e.

Bitcoin, Litecoin, and Dogecoin, who are to some extent competing with one another. Another cluster ('blue') contains cryptocurrencies related with the financial market, i.e. Ripple, Stellar, and Bitshares. Interestingly, Ripple and Stellar have been developed by the same person, which may be the reason for the mutual relationship between them. The 'yellow' cluster consists of cryptocurrencies advertised as offering full privacy within conducted transactions, i.e. Monero and Dash. It is difficult to explain the relationship between cryptocurrencies in the last cluster ('green'), however it may be observed on the forums that investors have recognized the high correlation between Siacoin and Digibyte.

The second part of the analysis shows that the changes in price of Bitcoin are neither affecting nor affected by the changes in prices of other cryptocurrencies. However, the contagion effect may be observed in the case of other variables, especially between Ripple and Stellar. Moreover, the analysis shows that Dogecoin may potentially be the cryptocurrency whose shocks in prices are contagious to other cryptocurrencies. Such phenomenon may be even better observed in the case of analysis of VAR (6) model, which is the main focus of the other article (in the process of submission and review).

4. Conclusion

The evidence from the empirical literature suggests that bitcoin and other cryptocurrencies share basic stylized facts with traditional asset classes, such as currencies, stocks, or commodities. However, some studies prove that bitcoin is mainly used as a speculative investment and users tend to hold their amount of bitcoin on the cryptocurrency exchanges rather than use it for intra-network transactions to exchange goods or services. Therefore, in this study cryptocurrency market is treated similarly to the stock market, in order to use an appropriate approach to the methodology of empirical analysis.

The results from econophysics analysis suggest that cryptocurrencies form hierarchical clusters and that there is a sensible economic interpretation for such grouping. This may imply that investors tend to hold similar groups of cryptocurrencies in their portfolio. Topological properties, i.e. similar market structure throughout two consequent (however different in terms of the level of volatility in prices and market size) periods indicate that inter-relationships between some cryptocurrencies are consistent over the long period of time. Such results are in favor of the assumption that cryptocurrencies are used rather as an investment than as a medium of exchange.

More importantly, final results indicate that there is no mechanism of contagion effect between changes in prices in Bitcoin to prices of other cryptocurrencies. This finding indicates that Bitcoin is separate from the rest of the market and the discovery of its price has its own rules. This may result from the substantial difference in the development of Bitcoin infrastructure (due to the highest maturity), in comparison to the infrastructure around other cryptocurrencies.

However, the potential contagion effect among prices of cryptocurrencies may be especially observed in the case of ‘blue’ cluster (Model II), containing cryptocurrencies closely related with the financial sector. Namely, there is a strong relationship between Ripple and Stellar – observed both in the case of Wald Block Exogeneity test for Granger Causality as well as in the case of Impulse Response Functions. In the case of this cluster, also Dogecoin exhibits the potential for shocks in its price being contagious to other cryptocurrencies. The results considering the inter-relationships between other cryptocurrencies than Bitcoin are further explained in the forthcoming article. All in all, it may be concluded that findings discovered from the analysis of Bitcoin shall not always be generalized to the entire cryptocurrency market.

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ANNEX 1. Diagnostic tests for VAR model – stability and autocorrelation

The test for stability of VAR model indicates that all roots lie inside the unit circle for all considered models in both analyzed periods. This means that all considered models are stable and may therefore be interpreted.

For the purpose of testing the serial correlation of residuals in considered models, the Lagrange multiplier test (often called Breusch – Godfrey test) is conducted. The results indicate that, in general, as the VAR order increases, the serial correlation among residuals decreases.

Lagrange-multiplier test for serial autocorrelation - lag number with autocorrelation (p-value below 10% significance level)

Period	01.09.2015 – 31.12.2016				01.01.2017 – 02.05.2018			
model	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
VAR (1)	1,3,4,5	1,2,4	1,5,6	1,2,4,5,6	3,5,6	1,2,3,5	1 – 7	1,2,3,5,6
VAR (2)	1,2,4,5,6	2,4	5,6	2,4,5,6	1,2,3,5,6	1,2,3,5	1 – 7	1,2,3,5,6
VAR (3)	1,3,4,5,6	1,2,4	5,6	1,2,3,5,6	1,2,3,5	2,3,5,6	1,2,4,5,6,7	1,2,3,5,6
VAR (4)	1,5,6	-	1,2,3,4,6	1,2,4,5,6	1,3,5	1,5	1,2,3,4,5,7	1,2,3,5,6
VAR (5)	1,4,6	5,6	1 – 6	1,4,5,6	5	6	3,5,7	1,5,6
VAR (6)	6	5	1,4,5	5,6	-	4	1,3,4,5,7	-

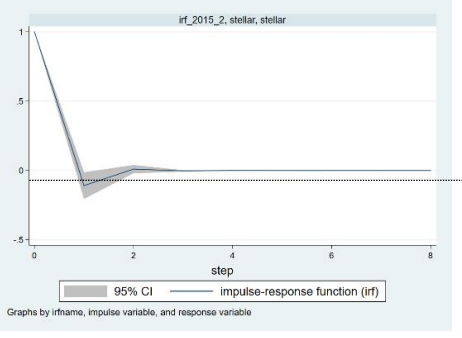
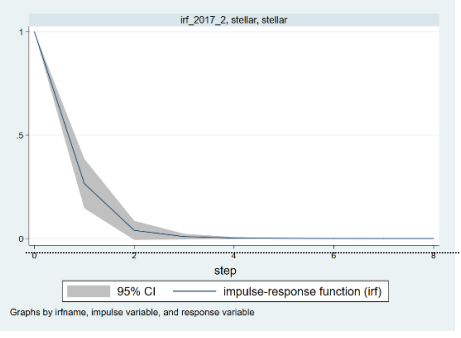
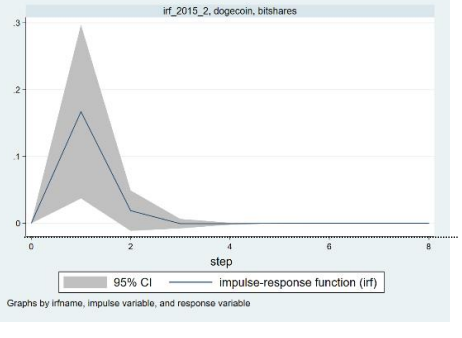
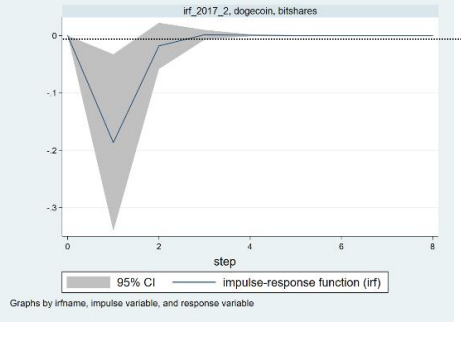
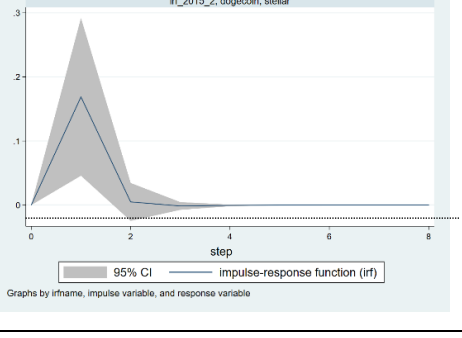
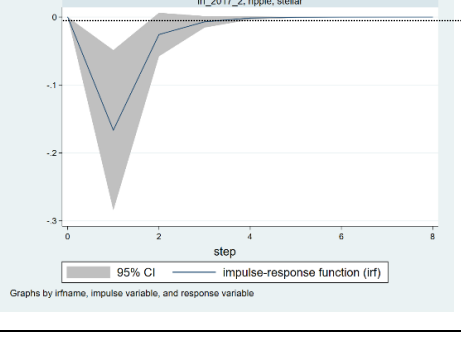
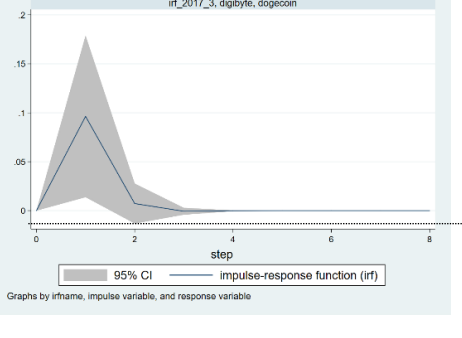
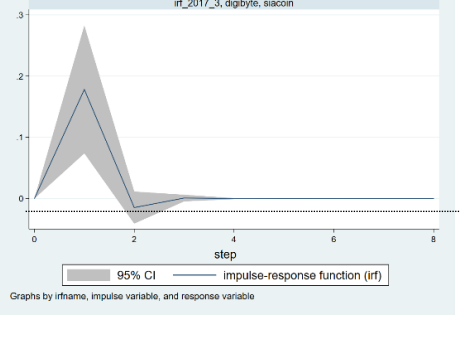
Source: authors' own preparation in STATA 15.

Lag length selection - p-values from Likelihood Ratio (LR) test

Period	01.09.2015 – 31 .12.2016				01.01.2017 – 02.05.2018			
model	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
VAR (1)	0.168	0.000***	0.005***	0.016**	0.542	0.000***	0.001***	0.011**
VAR (2)	0.076*	0.048**	0.046**	0.020**	0.106	0.000***	0.000***	0.004***
VAR (3)	0.069*	0.208	0.569	0.159	0.061*	0.000***	0.000***	0.004***
VAR (4)	0.009***	0.013**	0.280	0.070**	0.039**	0.123	0.012*	0.202
VAR (5)	0.051*	0.196	0.034**	0.005***	0.056*	0.000***	0.000***	0.093*
VAR (6)	0.017**	0.060*	0.008***	0.004***	0.078*	0.027**	0.077*	0.002***
VAR (7)	0.556	0.494	0.698	0.722	0.299	0.631	0.000***	0.464
VAR (8)	0.424	0.352	0.609	0.127	0.782	0.096	0.259	0.338

Source: authors' own calculations in STATA 15.

ANNEX 2. IRFs of other variables in VAR (1) – selected significant relationships

	Relation	First Period	Second Period
MODEL II	Stellar → Stellar		
	Dogecoin → Bitshares		
	Dogecoin → Stellar (left) Ripple → Stellar (right)		
MODEL III		Second Period	
	Digibyte → Dogecoin (left) Digibyte → Siacoin (right)		

Source: authors' own preparation based on calculations in STATA ver. 15.



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