University of Tartu

Faculty of Social Science

School of Economics and Business Administration

Elizaveta Lebedeva

SPILLOVERS BETWEEN CRYPTOCURRENCIES. NETWORK MAP OF CRYPTOCURRENCIES

Master's Thesis

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SPILLOVERS BETWEEN CRYPTOCURRENCIES. NETWORK MAP OF CRYPTOCURRENCIES

Elizaveta Lebedeva[1]

Abstract

The paper studies cryptocurrencies as financial assets. While most of the literature analyze Bitcoin and major altcoins, I investigate the large network of different cryptocurrencies (90 coins). The connectedness measures between their return and volatility are derived using the generalized variance decomposition methodology which allows constructing directional weighted network. Results (provided for different network specifications – various time period, time periodicity of data, size of the network) show that cryptocurrencies are highly connected to each other and connectedness increases more during shocks. Although Bitcoin is the largest cryptocurrency, there exist other coins (i.e. Ethereum, Monero, OmiseGo) that have more influence on the market. Besides that, the paper contains information useful for investors: there exist attractive cryptocurrencies less connected within the network and therefore, less affected by others' shocks.

JEL Classification: C32, C58, G15
Keywords: Cryptocurrency, Altcoins, Financial connectedness, Network effects

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[1] Master student, University of Tartu, Faculty of Social Sciences, School of Economics and Business Administration. Email: lebedeva.lizaveta@gmail.com
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1. Introduction

Cryptocurrencies as a subset of digital or virtual currencies become more and more popular nowadays. The number of existing cryptocoins have increased significantly since Bitcoin was first introduced in 2009, now we can observe more than 1500 different coins[2]. Their special feature is such that using cryptography, they allow secure transactions along with controlling of the creation every additional unit of cryptocurrencies (Chohan, 2017). But what we observe in present time is that they are mostly used not as a payment method, but as financial assets. People invest in cryptocurrencies expecting some return in changing prices. As with any financial return, it is rational to assume that there are interactions between cryptocurrencies in terms of their returns and volatilities.

Cryptocurrencies market is highly volatile and reacts quickly to different shocks. For example, after China announced that regulators will ban future ICOs (initial coin offering) on the 4th September 2017, the main cryptocurrencies dropped about 10-15% and some less popular coins lost over 30-40% of their value[3]. Another interesting example is a sharp increase of Bitcoin price in November-December 2017 (from 4000 to 19000 USD), accompanied by price growth of other cryptocurrencies.

Increasing popularity of the cryptocurrencies' trading forces Governments to introduce cryptocurrencies' regulation, which in turn influences the level of trading volume and price. On the one hand, there are successful examples of bitcoin regulation, for example, Japan, where the virtual currencies were recognized as a payment method for the first time in 2016. Currently, Japan regulators mainly induce more proper measures to safeguard citizens, responsible Bitcoin usage and implementation of 'Know your customer' procedure for exchanges. This country is becoming one of the biggest hubs of bitcoin trading. On the other hand, regulation of cryptocurrencies' market aimed to ban cryptocurrencies' exchanges and to limit trading (as in China or South Korea) increases volatility and is associated with shock periods and falling prices on the market. The first approach of the gradual adoption is more promising compared to examples of countries where cryptocurrencies regulation stands for 'anti-money laundering'. Knowing how the

[2] https://coinmarketcap.com/all/views/all/
[3] https://btcmanager.com/china-shocks-crypto-market-bans-icos/

cryptocurrencies market is connected may allow to estimate possible consequences of actions and prevent bad outcomes.

The field of cryptocurrencies connectedness and network is not well discovered since the topic itself is young. There exist a lot of papers on blockchain technology; in addition, the number of economical research on cryptocurrencies is growing (e.g., Iwamura et al. (2014), Chiu and Koeppl (2017)). Some papers investigate drivers of cryptocurrencies price, in particular, Bitcoin as a major one (Hayes (2016), Kim at al. (2016)). Overall, researchers investigate mostly Bitcoin, and there exist few papers dedicated to altcoins (e.g., Halaburda and Gandal (2016)). But information on how different coins influence each other, how the shock of one coin affect others is useful for investors and would help to make the investment decision. However, to the best of my knowledge, there are no articles that investigate the large cryptocurrencies' network. This paper is aimed to determine the interaction between different coins and construct network map of cryptocurrencies. It studies the following research questions: How strong is connectedness of cryptocurrencies' market? How does connectedness change over time? What are the most influential coins and what coins less affected by market shocks?

To achieve the goal and answer questions, I apply the approach of combining time series analysis and network theory proposed by Diebold and Yilmaz (2010, 2014). The authors develop methodology connecting financial econometrics and network theory based on the variance decomposition of Vector Autoregression modeling to study the banking network and global connectedness. Using the same methodology, I investigate connectedness of cryptocurrencies' return and volatility and analyze spillovers between different coins. Varying periodicity of data (hourly, daily), number of coins in the network, different periods of time allow examining how connectedness changes depending on initial setup. Application of this method is a new way to study cryptocurrencies from financial point of view and the findings will fill the gap in literature. Besides that, they are important for investors who would like to plan investments in cryptocurrencies wisely and diversify their portfolio. Results show that the cryptomarket is highly connected and its connectedness increases during shock period, but there exist coins less connected within the network, in other words – less affected by shocks of other cryptocurrencies.

The remainder of the paper is organized as follows. Section 2 reviews literature related to the topic of cryptocurrencies and financial connectedness. Section 3 presents data and preliminary analysis of cryptocurrencies' return and volatility. Section 4 describes the methodology. Section 5 provides with empirical results and Section 6 concludes.

2. Literature Review

2.1 Cryptocurrencies research

The term 'cryptocurrency' was initially put into practice when Bitcoin was created. In 2009, Satoshi Nakamoto published the white paper "Bitcoin: A Peer-to-Peer Electronic Cash System" where he described the process of a secure transaction based on cryptography. The main characteristics which distinguish cryptocurrencies from other types of money and make them popular are the decentralized control ensured by participants of a network through blockchain and the absence of the third party during payment process. Following Bitcoin, other cryptocurrencies (known as altcoins) have been invented and their number rises almost every day. Figure 1 shows exponential growth of coins during 2014-2017.

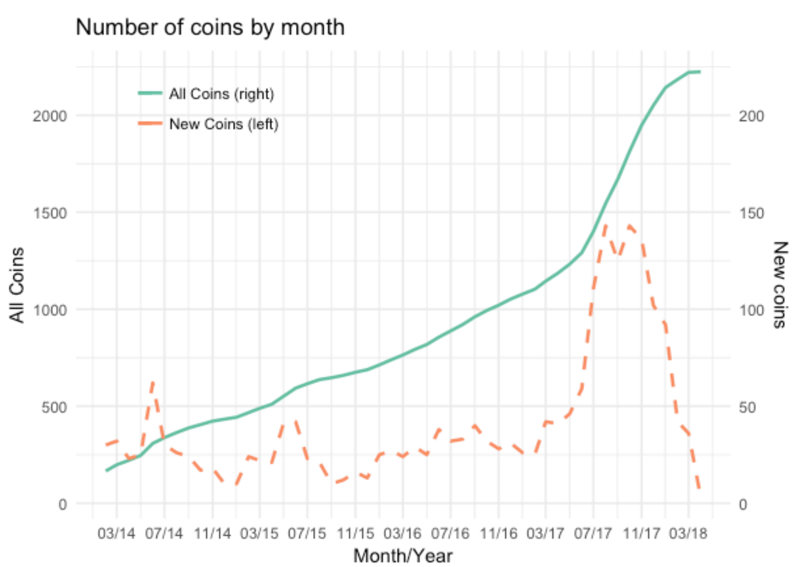


Figure 1 – Number of existing coins in 2014-2018[4]

Research dedicated to cryptocurrencies topic includes several directions:

- Technical literature,

[4] Based on cryptocompare.com

- Economics of cryptocurrencies,
- Cryptocurrencies market and price prediction.

There exist a lot of papers aimed to improve algorithms of cryptocurrencies, discuss their technical fundamentals, mining opportunities, blockchain technologies. Also, this group of literature discuss security and privacy areas. Authors agree on a point that the main subject for improvement is a prevention of cases where users' security is violated (e.g., hacking of wallets), such as precaution of DDoS attacks (Vasek (2014)) or 51% Attacks[5] (Beikverdi and Song (2015)).

The white papers that founders of cryptocurrencies usually publish before initial coin offering (ICO) have the large impact in this area. Such papers contain theoretical description of specific attributes, new features, as well as their practical implementation. The most influential among them were white papers of Ethereum which introduced a new possibility of launching smart contracts, Ripple with its strong connection to the banking system, Iota where the blockchain is replaced by directed acyclic graph ('Tangle'), etc.

As popularity and relevance of the field are growing, more papers summarizing the current situation of cryptocurrencies industry appear. Researchers from leading institutions conduct the studies including technical details about exchanges, mining, potential externalities (for example Global Cryptocurrency Benchmarking Study 2017 by University of Cambridge).

It is important to notice that, as Yli-Huumo et al. (2016) underline, the literature about cryptocurrency technology is mostly published in workshops and conferences rather than in scientific journals.

As for the next direction of research – the economics of cryptocurrencies, authors look from different points of view on how cryptocurrencies can be implemented into existing monetary system. On the one hand, Iwamura et al. (2014) show that many future cryptocoins will coexist in the common 'cryptocurrencies ecosystem' which will be stable with moderate fluctuations between competing cryptocurrencies. In contrast, Luther (2016) argues that cryptocurrencies cannot be widely used: the model of Dowd and Greenaway (1993) applied to currencies competition demonstrates that with existing network effect and switching cost agents will not affiliate alternative currencies. Based on the description of bitcoin and its network (Luther (2016)),

[5] 51% Attack means that network security can be violated by those who has more that 51% of computational power.

cryptocurrency appears not better than fiat currencies, and cost of switching to bitcoin is relatively high.

The sources for successful cryptocurrencies' adoption are various. Iwamura et al. (2014) demonstrate that the characteristics of ideal qualified cryptocurrency which ensure steadiness of a system are no limit on supply, competitive and feasible pricing, relatively constant marginal cost, etc. But Luther (2016) shows that the only way for cryptocurrencies to have universal acceptance is to receive government support or in case of monetary instability. From his point of view, limited success of bitcoin is explained by the presence of Coordination Failure Equilibrium (when there are some agents who value bitcoin characteristics more than others).

Another approach to examining the conditions for cryptocurrency system based on blockchain technologies is to use general equilibrium monetary model as Chiu and Koeppl (2017) demonstrate. After conducting numerical analysis based on Bitcoin and calibrating parameters for benchmark model, authors conclude that the larger is transactions volume of cryptocurrency compared to individual transaction size, the better cryptocurrency functions. But one should not forget that the transactions based on blockchain allow the low cost of verification and networking. Catalini and Gans (2016) argue that this is the main factor leading to new emerging marketplaces rather than something else.

Some papers investigate cost of cryptocurrencies' production and drivers of their price (in particular, Bitcoin as a major one). For example, Hayes (2016), based on cross panel data for 66 coins, highlights such parameters as the mining difficulties, implemented crypto algorithm and the rate of unit production. But this point is arguable with regards to current cryptocurrencies' market. As on financial market, the prices of coins change over time as supply and demand rise and go down. The more popular view is that units of production do not matter and there exist other factors affecting Bitcoin price such as the user base growth and word-of-mouth social interaction (Garcia et al. (2014)), or pure evaluation by market (Hanley (2013)). Xie (2017) looks from a different perspective. He investigates the influence of social media networks and user comments on Bitcoin returns and finds that prediction and posts by more active users with high ranks in the cryptonetwork are less accurate and noisier compared to users with lower ranks. The similar sentiment analysis is presented by Kaminski (2016), but he applies it to twitter posts.

The next direction of research on cryptocurrencies considers coins as financial instruments and studies their returns and volatility. But, as previously, the majority of papers analysis Bitcoin. The literature presents that Bitcoin market is much more volatile compared to stock market (Baek and Elbeck (2015)). Some authors present GARCH modelling (Chu et al. (2017), Paraskevi (2017)), suggest arbitrage strategies for Bitcoin trading (Kokes and Bejcek (2016)), others consider adding cryptocurrencies to investment portfolio as a good alternative to benefit from diversification (Elendner et al. (2016)).

The volume of literature dedicated to Bitcoin is enormous and it explores broad directions. In contrast, there is only a few of them investigating altcoins. The reason for that is the topic of blockchain technology and, particularly, cryptocurrency is young and the most significant papers have appeared during last 3-4 years. Also, altcoins are introduced quite recently and started to play the more important role since 2016-2017. While growing interactions between different cryptocurrencies reveal the necessity of new research, this gap is still not covered by a few numbers of related papers available.

Elendner et al. (2016) partially discuss connectedness of coins although the main point of the paper is a comparison with financial assets. Based on cross-sectional data for 10 coins, authors present the low correlation between cryptocurrencies' return. But, at the same time, they show stronger correlation during negative movements of the market. The similar tendency is observed by Caporale and Plastun (2018).

Halaburda and Gandal (2016) examine competition between 7 coins. They distinguish three periods, where Bitcoin price was stable (in May–September 2013 and May – July 2014 it benefited from 'winner-take-all effect') and volatile (October 2013–April 2014 with reversed dynamics) and find out existing network effects between cryptocurrencies in the latter period. Firstly, authors explore correlations in daily closing prices and after they conduct Vector Autoregression analysis to see whether movements in the USD/BTC exchange rate 'predict' future changes in other digital currencies. But the size of used data is small, so results seem incomplete. In contrast, Ciaian et al. (2018) examine dependencies of 18 cryptocurrencies, using ARDL – Autoregressive Distributed Lag model. The particular interest of their paper is carried by a split of short- and long-run Bitcoin influence on altcoins. Their findings show that while analyzed coins are interdependent, short-run relationships are stronger that long-run ones.

2.2 Research on networks of financial markets

Since many authors consider cryptocurrencies as financial assets (e.g., Kokes and Bejcek (2016), Lee et al. (2018), Elendner et al. (2017)), and there is not much literature investigating connectedness of cryptomarket, it is reasonable to look at selected methodologies used in articles on connectedness of financial market that can be applied for cryptocurrencies.

The most commonly used approach to determine causal relationship in time series analysis (financial data is one of time series data types) is Granger causality test (Granger, 1969). It implies the following intuition: variable X changing over time Granger-causes variable Y (also changing over time) if prediction for Y based on past values of Y and X is better than prediction made using only past values of Y.

In case of multivariate time series, Vector Autoregressive analysis is used to define the presence of Granger causality. Billio et al. (2012) use Granger causality test and Principal Component Analysis (PCA) to measure connectedness between banks, insurance companies, hedge funds and broker/dealers. With PCA they detect a degree of commonality between stock returns and with Granger causality they capture direction of pairwise connectedness among financial firms. Authors conduct linear and nonlinear Granger causality test. The last one allows capturing the higher-order effects (in this case, volatility, or riskiness of financial institutions). In addition, they provide network map of largest companies to show how they are interconnected and how connectedness increases during crisis periods. Overall, the aim of this paper is to predict systemic risk in the finance sector and authors say that this kind of a risk is influenced by increasing connectedness of participants.

Granger causality is used also to present directed predictive relations between time series and contemporaneous undirected partial correlations in Barigozzi and Brownlees (2017). Their assumption on sparse inverse covariance matrix and implementation of LASSO (least absolute shrinkage and selection operator) method allow to estimate connectedness of ninety blue-chip stocks and improve forecasting.

But VAR gives incomplete connectedness measures because of its construction – it ignores the covariance matrix of disturbances (Demirer et al. (2017)). That is why another approach would be more preferable. Diebold and Yilmaz (2014) propose to measure connections between time series using variance decomposition. Their approach allows to define the strength of connections, as well as time-variation of connections and combines both network theory and time series analysis. Authors applied the model for biggest American financial firms' data. But the obstacle of this model is a difficult application for high dimensional datasets.

Demirer et al. (2017) develops an approach of variance decompositions for connectedness measurement and applies it for a higher dimensional network of 150 banks. Authors use LASSO method and depict static and dynamic network connectedness using full-sample and rolling-window estimation respectively. As a result, they found increasing connectedness between banks during crisis.

Another framework proposed by Barunik and Krehlik (2017) measures connectedness between financial time series using the spectral representation of variance decomposition. In contrast to Diebold and Yilmaz (2014) who focus on share of the forecast error variance of one series due to shock in another, Barunik and Krehlik examine how frequently responses to these shocks take place (i.e. spectrum of variance for a given frequency range) and apply the approach to measure systemic risk of the US financial firms.

To sum up, the literature studies cryptocurrencies from different perspectives, but most of them investigate Bitcoin. The field of cryptocurrencies connectedness is not well discovered and research gap on networks of cryptocurrencies exists. On the other hand, there are several research on connectedness of financial markets. Since cryptocurrencies are considered as financial assets, the same methods can be applied for cryptomarket.

As Chochan (2017) underlines: "given the recency of cryptocurrencies … the literature can be at best be described as emergent, and as an area of significant academic inquiry in the years to come".

3. Preliminary analysis of cryptocurrencies' returns and volatility

Before answering the research questions and starting to construct a network of cryptocurrencies, I conduct preliminary analysis to check if there are spillovers between cryptocurrencies' returns and volatilities applying VAR and GARCH models respectively. If there are the spillovers, I could later proceed studying the network itself.

3.1 VAR and GARCH analysis background

Linear dependencies among the returns of multiple time series are modeled by Vector Autoregression (VAR) which generalizes univariate AR models and allow two and more evolving variables.

The VAR(p) model is defined as follows:

$$\boldsymbol{Y}_t = c + \boldsymbol{\Pi}_1 \boldsymbol{Y}_{t-1} + \ldots + \boldsymbol{\Pi}_p \boldsymbol{Y}_{t-p} + \boldsymbol{\varepsilon}_t \, , t = 1, \ldots , T \qquad (1)$$

where $\boldsymbol{Y}_t$ is a set of *n* endogenous variables $y_{1t}, \ldots, y_{kt}, \ldots, y_{nt}$, Π_i is $n \times n$ coefficient matrix for $i = 1, \ldots, p$ and $\boldsymbol{\varepsilon}_t$ is *n*-dimensional process with $E(\boldsymbol{\varepsilon}_t) = 0$ and time invariant positive definite covariance matrix $\mathrm{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}^{\mathrm{T}}{}_t) = \Sigma$ (white noise).

VAR can be modeled with different lag *p*. To choose the best model, its lag *p* should minimize model selection criteria, such as Akaike Information Criterion (AIC), Schwarz-Bayesian Information Criterion (BIC) or Hannan-Quinn Information Criterion (HQ).

After VAR(p) has been estimated, diagnostic tests can be performed (tests for the absence of autocorrelation, heteroscedasticity or non-normality in the error process). Tests for heteroscedasticity are conducted with multivariate and univariate ARCH tests. Normality test uses the Jarque-Bera statistics (Bera and Jarque (1980)). Portmanteau test and Breusch-Godfrey LM are applied for testing the lack of serial correlation in the residuals[6].

Then, it is possible to investigate dynamic behavior of the model with impulse response functions and forecast error variance decomposition. They both are based on the Wold moving average decomposition for stable VAR(p)-processes which is defined as:

$$Y_t = \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \cdots \qquad (2)$$

where $\Psi_s = \sum_{j=1}^{p-1} \Psi_{s-j} \Pi_j \ with\ \Psi_0 = I_n \ and\ \Pi_j = 0 \ for\ j > p.$

The impulse response (or dynamic multiplier) is the *(i,j)-th* element of the matrix Ψ_s:

$$\psi_{ij}^{s} = \frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial y_{i,t}}{\partial \varepsilon_{j,t-s}}, i, j = 1, \ldots , n \quad (3)$$

and is interpreted as the expected response of variable $y_{i,t+s}$ to a unit change in variable $y_{j,t}$.

[6] For more details, see Hamilton (1994).

Responses can be accumulated through time and one can see expected response of y_i at the time *s* caused to one unit change in y_j. In addition, an alternative is to obtain orthogonal impulse responses when shocks are less likely to happen in isolation (i.e., there are contemporaneous correlations between the components of the error process ε_t).

To compute them, first, residual covariance matrix Σ is decomposed to $\Sigma = \boldsymbol{ADA'}$, where $\boldsymbol{A}$ is lower triangle invertible matrix with ones as diagonal elements and $\boldsymbol{D}$ is diagonal matrix with positive diagonal elements. Then, structural errors are represented as $\eta_t = \boldsymbol{A^{-1}}\varepsilon_t$. Having $var(\eta_t) = \boldsymbol{A^{-1}\Sigma A^{-1\prime}} \quad = \boldsymbol{A^{-1}ADA'A^{-1\prime}} = \boldsymbol{D}$, structural errors become orthogonal by construction and allow to represent Wold MA representation of VAR as

$$Y_t = A^{-1}\varepsilon_t + \Psi_1 AA^{-1}\varepsilon_{t-1} + \Psi_2 \varepsilon AA^{-1}{}_{t-2} \quad + \cdots = \mu + \Theta_0\eta_t + \Theta_1\eta_{t-1} + \Theta_2\eta_{t-2} + \cdots \quad (4)$$

where $\Theta_j = \Psi_j A$.

The orthogonal impulse response to orthogonal shock η_{jt} are the *(i,j)-th* element of the matrix Θ_s

$$\theta_{ij}^s = \frac{\partial y_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial y_{i,t}}{\partial \eta_{t_{j,t-s}}}, i,j = 1, \dots, n, s > 0 \quad (5)$$

What is important is that within standard VAR modeling, the different ordering of variables can produce different result (with *n* variables, there exist *n!* possible recursive orderings).

The orthogonal impulse responses are the basis for the forecast error variance decomposition. If one divides the element-wise squared orthogonal impulse responses by the variance of the forecast error, the result is the portion of the forecast error in predicting $y_{i,T+h}$which is due to the structural shock of variable y_j, in other words, the contribution of the variable *j's* shock to the h-step forecast error variance of variable *i* (in other words, to the mean squared forecast error of variable *i*).

$$FEVD_{i,j}(h) = \frac{\sigma_{\eta j}^2 \sum_{s=0}^{h-1}(\theta_{ij}^s)^2}{\sigma_{\eta 1}^2 \sum_{s=0}^{h-1}(\theta_{i1}^s)^2 + \cdots + \sigma_{\eta n}^2 \sum_{s=0}^{h-1}(\theta_{in}^s)^2} \qquad (6)$$

where $\sigma_{\eta j}^2 = var(\eta_{jt})$.

Generalized autoregressive conditional heteroscedasticity (GARCH) modeling can be applied to study the interaction between volatility of cryptocurrencies. GARCH models analyze the variance of the error term in the following form, introduced by Bollerslev (1986):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon^2{}_{t-i} + \sum_{i=1}^{p} \beta_i \sigma^2{}_{t-i} \qquad (7)$$

where σ_t^2 is conditional variance of the process $y_t = x_t'b + \epsilon_t$, p is the order of the GARCH component (σ_t^2), q is the order of the ARCH component (${\epsilon^2}_t$), α and β are model parameters, ω is the weighted long run variance.

Univariate GARCH can be extended to multivariate GARCH that allows the dependences in co-movements of many series. There is large number of different specification of multivariate GARCH models. They vary in assumptions on the distribution of error terms, conditional covariance matrix and trade-off between model complexity and dynamics. The richest models are fully parametrized, but it can be computationally expensive and unfeasible to apply them for more than 5 series.

The baseline VEC GARCH (Bollerslev, Engle, Wooldridge (1988)) parametrizes all lagged conditional variances, covariances, squared returns and cross-products of returns, providing with large number of coefficients and no restriction on positive definiteness of conditional covariance matrix H_t. The last issue is solved in BEKK specification by its model structure (Baba, Engle, Kraft and Kroner (1990)). But BEKK requires many matrix inversions and its estimation requires heavy computations in case of more than 2 series. To ease the estimation process, conditional covariance matrix can be decomposed in such a way that univariate and multivariate dynamics are separated as it is in constant conditional correlation (CCC) GARCH (Bollerslev (1990)). CCC GARCH models the volatility of time series by squared innovations and their own lagged volatility, i.e. there are no interactions between volatilities of different series (only contemporaneous dependencies of conditional correlation). Extended version of CCC (ECCC) GARCH (Jeantheau (1998)) overcomes this issue. The vector of conditional volatilities is given by

$$\boldsymbol{h}_t = \left[h_{1,t}, \dots, h_{N,t}\right]' = \boldsymbol{\omega} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} \boldsymbol{A_i \varepsilon_{t-i}^2} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{q}} \boldsymbol{B_i h_{t-i}} \qquad (8)$$

where $\boldsymbol{\omega}$ is $N \times 1$ vector, $\boldsymbol{\varepsilon_t^2} = (\varepsilon_{1,t}^2, \dots, \varepsilon_{N,t}^2)'$, $\boldsymbol{A_i}$ and $\boldsymbol{B_i}$ are $N \times N$ matrices. When off-diagonal elements of $\boldsymbol{A}$ and $\boldsymbol{B}$ are equal to zero, model reduces to CCC GARCH specification.

Conditional correlation matrix is constant over time and is defined as

$$\boldsymbol{H_t} = \boldsymbol{D_t R D_t} \quad (9)$$

where $\boldsymbol{D_t} = diag\left(\sqrt{h_{1,t}}, \dots, \sqrt{h_{N,t}}\right)$, R is time-invariant positive definite correlation matrix, $\boldsymbol{R} = [\rho_{ij}]$, where $\rho_{ij} = 1 \; for \; i = j$ and $|\rho_{ij}| < 1 \; for \; i \neq j$.

If there exist spillovers between volatilities, off-diagonal coefficients of matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ should be positive. To test this condition, Nakatani and Terasvirta propose a test of causality in conditional variance (Nakatani, Teräsvirta, 2009), where under *H0* $\boldsymbol{A}$ and $\boldsymbol{B}$ are jointly diagonal and alternative hypothesis states at least one non-zero off-diagonal elements of $\boldsymbol{A}$ and $\boldsymbol{B}$.

3.2 Data and Empirical Results

I apply VAR and GARCH for small dataset because at this stage it is just a general examination of cryptocurrencies' spillovers and more detailed analysis of network will be provided in the next chapter.

Data for analysis are obtained from platform https://www.cryptocompare.com/. It provides free API for getting historical prices and volume data for cryptocurrencies from multiple exchanges. It is possible to get daily, hourly and minute prices. As in literature (e.g., Ciaian et al. (2018), Halaburda and Gandal (2016)), I select the large players on the markets. To estimate VAR model, I choose TOP-23 cryptocurrencies based on 24 hours Sales Volume – major coins on cryptocurrencies' market (First 23 coins in Table of Appendix 1).

API allows to get open, high, low, close prices from many exchanges converted to different currencies (fiat as well). I use close prices of CryptoCompare Current Aggregate Index and obtain different datasets for analysis:

- Daily prices from 01.08.2017 to 18.01.2018 (171 observations),
- Hourly prices from 27.10.2017 to 18.01.2018 (2000 observations),
- 5-min prices from 17.01.2018 12:25 to 18.01.2018 21:45 (400 observations),
- Minute prices from 17.01.2018 11:46 to 18.01.2018 21:06 (2000 observations).

Prices of cryptocurrencies are crawled in USD. Descriptive statistics are presented in Appendix 2.

3.2.1 Returns of cryptocurrencies

Prices of coins are financial data and as with financial time series, they are unit root processes. Preliminary analysis (using Augmented Dickey-Fuller test for unit root) showed that time series data for cryptocurrencies' prices are not stationary. That is why all data is transformed to continuously compounded returns $r_t = p_t - p_{t-1} = logP_t - logP_{t-1}$, where P_t is close price[7]. Figures 2 and 3 present daily, and hourly returns for selected coins respectively.

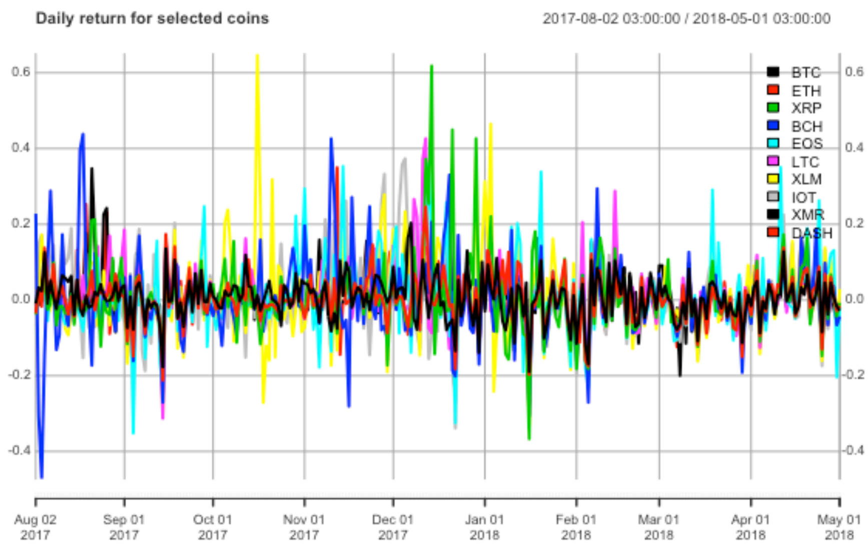


Figure 2 – Daily returns for major cryptocurrencies (August 2017 – May 2018)

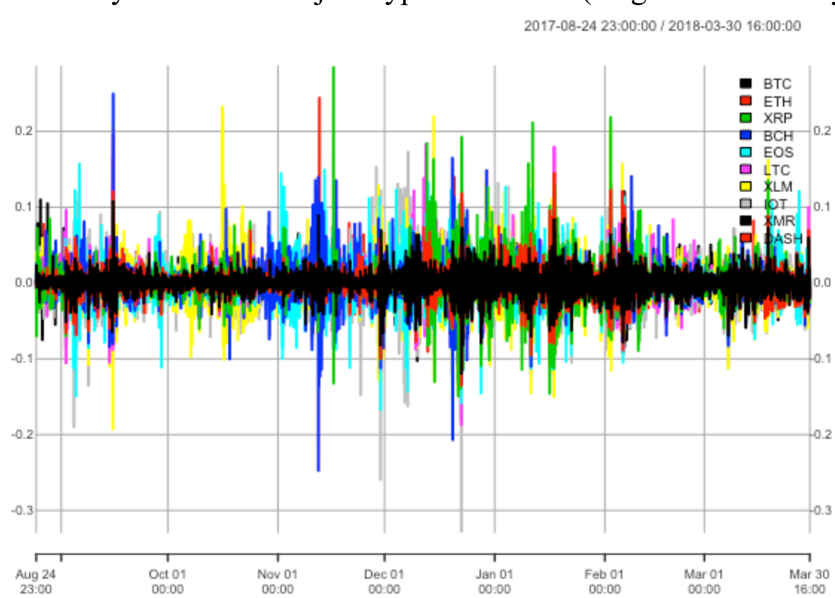


Figure 3 – Hourly returns for major cryptocurrencies (August 2017 – March 2018)

[7] Data are not seasonally adjusted (one of the reason is that not enough data for cryptocurrencies are available to study effects of seasonality (Haferkorn and Quintana (2015)).

Daily Data

I start VAR analysis with daily data. Based on minimized AIC, the best lag for VAR is 5, but considering its low degrees of freedom (48 compared to 144 for lag 1) and similar value of lag 1 coefficients in both models, I choose VAR(1) for analysis (AIC (lag 1) $= -1.139$ is greater only by 0.07 than AIC(lag 5) $= -1.209$). Results of estimated model are provided in Appendix 3.

What it can be observed is that lag 1 of Bitcoin price return is positively affected by other price returns (looking at statistically significant coefficients[8]). Ethereum has the positive lagged influence on BitcoinCash, negative on Veritaseum. Ripple negatively affects returns of other coins on average (Digital Cash, Ethereum Classic, ZeroCash, Siacoin).

Graphical analysis of residuals (diagram of fit and residuals, Normal Q-Q plot (as an example, Figures 4 and 5[9]), the autocorrelation of residuals suggests that most of them could be normally distributed.

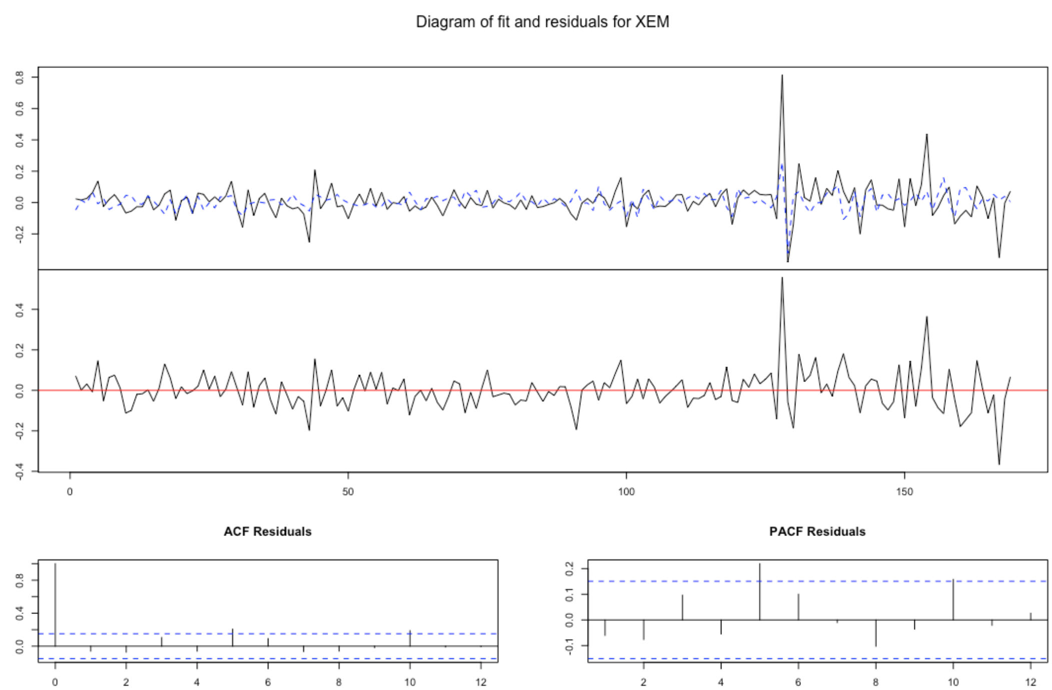


Figure 4 – Example of graphical analysis of NEM residuals for VAR(1) daily model

[8] Hereinafter, explanations are given for statistically significant coefficients at least at confidence level 90%.
[9] More graphs can be found at https://github.com/LizaLebedeva/cryptocurrencies-research (they are omitted here due to lack of space).

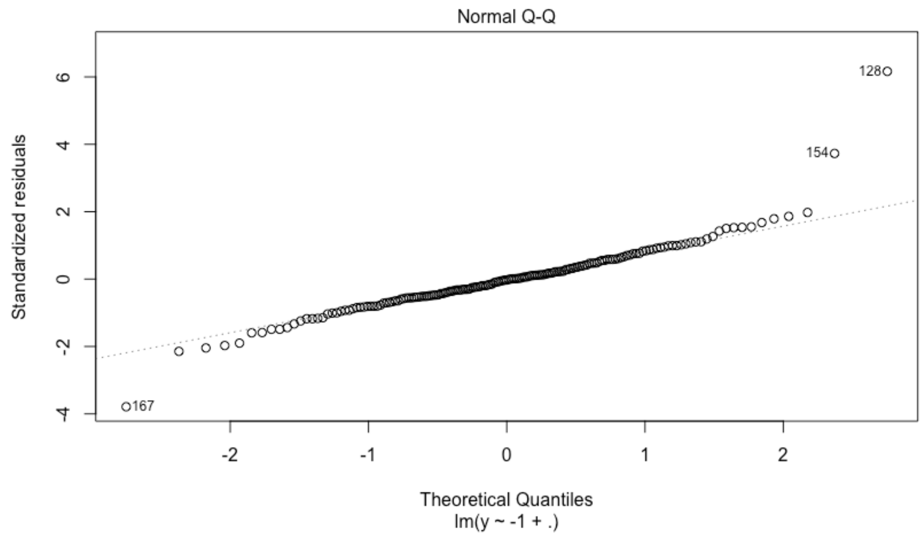


Figure 5 – Q-Q plot of standardized residuals for NEM series of VAR(1) daily model

Diagnostics tests present small p-value for ARCH test, Jarque–Bera test and show that multivariate time series is heteroskedastic, errors are not normally distributed. Also, Portmanteau Test for the lack of serial correlation in the residuals of a VAR has p-value = 0.0309. So, H0 of no serial correlation in the residuals is rejected on 5% significance level, but not at 1% significance level.

Hourly Data

Now let's look at VAR model for hourly data. I choose lag 2 for VAR model as it gives smallest AIC (-168.63). Results (Appendix 4) tell the following:

- Looking at lag 1: returns of Bitcoin, Lisk, BitShares have negative effect on returns of other cryptocurrencies on average, Ethereum has positive significant effect on Litecoin, Dash, Zcash, OmiseGO;
- As for lag 2: coefficients of Ethereum are negative in the equations for Bitcoin, Litecoin, NEM, Stellar, Iota, Monero, Lisk, Zcashs, Bitecoin, BitShares. Coefficients for Bitcoin are smaller and statistically significant in less number of equations. Among others, I would note VeChain with its negative effect on Ethereum, BitcoinCash, Litecoin, NEM, Stellar.

But graphical analysis of residuals shows that errors are correlated and probably not normally distributed (e.g., Q-Q plot of residuals has S-shape for most of the coins, rather than linear form. Multivariate LM ARCH, Jarque–Bera and Portmanteau test statistics used for model diagnostics are large, that confirm residuals are heteroskedastic, not normally distributed and correlated.

5 minutes data

Results of VAR model for 5 min data are presented in Appendix 5. I choose lag 2 because AIC is almost the same – for lag 1 (-219.853) and lag 2 (-219.16), but adjusted R^2 is higher for equations in VAR(2) and it is rational to assume more lags within high frequency data. The main things to notice are:

- While lag 1 of Bitcoin return has a positive effect on the return of other coins (statistically significant for Stellar, Monero, EthereumClassic, VeChain and EOS), lag 2 influences in opposite direction;
- Lag 1 and lag 2 of Ethereum are statistically significant only in Digital Cash equation (positive effect);
- Both lags of NEM provide negative influence on coins;
- Litecoin and Stellar lag 1 coefficients show negative effect on Bitcoin, BitcoinCash, Iota, Monero;
- Lag 1 of BitcoinCash return is not statistically significant in equations, but lag 2 has the negative significant coefficient in Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Monero, Bytecoin, BitShares equations.

Regarding model diagnostics, graphical analysis of residuals suggests some autocorrelation. According to ARCH test, H0 of homoscedastic time series is not rejected. But Jarque–Bera and Portmanteau tests suggest that errors are not normally distributed and serially correlated[10].

I also estimate VAR model for minute data: it reflects the same results as for 5 minutes model. Since 5 min data consists of 5 times less number of observations, but provides with the same results, this specification should be enough to capture relations between cryptocurrencies for high-frequency periods.

All in all, analysis shows that there are spillovers between cryptocurrencies' returns.

[10] Diagnostics tests for presented models suggest that there may present omitted variables (it can be some external information that influences market, market regulations induced by Governments, blogs/posts/twits by users. At this stage, I check the presence of spillovers and look at VAR coefficients, rather than on the impulse response functions, to distortions in which the omitted variable bias leads.

3.2.2 Volatility of cryptocurrencies

To check if there are interactions between volatilities of cryptocurrencies I use Extended Constant Conditional Correlation (ECCC) GARCH(1,1) model applied for the return of coins. GARCH and ARCH components both are set to 1 based on Chu et al. (2017) (also it is driven by the amount of available data).

I analyze two datasets:

- Daily return for 10 coins (from January, 31 2016 to May, 1 2018 – 811 observations). The choice of 10 coins (Bitcoin, Ethereum, Ripple, Litecoin, Monero,DigitalCash, Siacoin, Verge, Bitshares, Dogecoin) is explained by the fact that only these 10 coins have enough daily data for ECCC-GARCH. Other coins have historical data less than one year.

- Hourly return for 23 coins (from October, 27 2017 to January, 18 2018 (2000 observations)) – the same as in the previous subsection.

The test of causality in conditional variance (Nakatani and Terasvirta (2009)) applied both for daily and hourly data suggests that at least one of non-diagonal elements of matrices ***A*** and ***B*** in the conditional volatility equation is non-zero. Applied test of stationarity (He and Terasvirta (2004)) shows that ECCC-GARCH process is stationary (applied both for daily and hourly specifications).

The main point of interest in ECCC-GARCH model for my analysis is matrix ***B***. Its non-zero off-diagonal element b_{ij} would say that volatility of i series affects volatility of j series. The ***B*** matrix of ECCC-GARCH model for daily data is presented in Appendix 6A. It shows that there are spillovers between volatilities of Bitcoin and DigitalCash, Ethereum and Siacoin, Monero and Siacoin, DigitalCash and Monero, etc. Appendix 6B presents ***B*** matrix of ECCC-GARCH model for hourly data, that consist of relatively more interaction between coins. For example, it exhibits spillovers between volatility of: Ethereum and Monero; Stellar and Litecoin; Miota and Monero, BitShares, Bitcoin and Siacoin, ZeroCash, etc.

To sum up the pre-analysis, there are spillovers between returns and volatilities of cryptocurrencies and I can proceed with modeling their connectedness.

4. Variance decomposition, connectedness measures and network theory

Following Diebold and Yilmaz (2014), I choose variance decomposition method to measure connectedness between cryptocurrencies. As it was mentioned earlier, variance decomposition allows answering a question: what is the contribution of variable *j's* shock to the h-step forecast error variance of variable *i*. Variance decomposition is based on VAR modeling and identified as:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma \Theta_h' e_i)^2} \qquad (10)$$

where e_j is a selection vector with *j-th* element unity and zeros elsewhere, Θ_h is the coefficient matrix multiplying the *h*-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR, and σ_{jj} is the *j-th* diagonal element of Σ. All $N*N$ d^{gH} elements constitute *H*-step generalized variance decomposition matrix D^{gH} that has the form as in Table 1.

Table 1 – Schematic representation of variance decomposition matrix (Diebold and Yilmaz (2014)).

	x_1	x_2	$\cdots$	x_N	***From others***
x_1	d_{11}^{gH}	d_{12}^{gH}	$\cdots$	d_{1N}^{gH}	$\sum_{j=1}^{N} d_{1j}^{gH}, i \neq 1$
x_2	d_{21}^{gH}	d_{22}^{gH}	$\cdots$	d_{2N}^{gH}	$\sum_{j=1}^{N} d_{2j}^{gH}, i \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^{gH}	d_{N2}^{gH}	$\cdots$	d_{NN}^{gH}	$\sum_{j=1}^{N} d_{Nj}^{gH}, i \neq N$
To others	$\sum_{i=1}^{N} d_{i1}^{gH}, i \neq 1$	$\sum_{i=1}^{N} d_{i2}^{gH}, i \neq 2$	$\cdots$	$\sum_{i=1}^{N} d_{iN}^{gH}, i \neq N$	$\frac{1}{N}\sum_{i,j=1}^{N} d_{1j}^{gH}, i \neq j$

In terms of network theory, Diebold and Yilmaz define d^{gH} as pairwise directional connectedness from *j* to *i* and denote as $C_{i\leftarrow j}^{H}$. Obviously, $C_{i\leftarrow j}^{H} \neq C_{j\leftarrow i}^{H}$.

Based on variance decomposition matrix, it is possible to calculate total directional connectedness. Taking its off-diagonal elements, row and column sums show "from" and "to" total directional connectedness measures respectively. Thus, total directional connectedness from others to *i* is

$$C_{i\leftarrow\star}^{H} = \sum_{j=1, j\neq i}^{N} d_{ij}^{gH} \quad (11)$$

and total directional connectedness from j to others is

$$C^H_{*\leftarrow j} = \sum_{i=1, j\neq i}^{N} d_{ij}^{gH} \quad (12)$$

And finally, total directional connectedness is defined as

$$C^H = \frac{1}{N}\sum_{i,j=1, j\neq i}^{N} d_{ij}^{gH} \ (13)$$

Thus, based on these measures, Diebold and Yilmaz (2014) define variance decomposition tables as weighted directed networks by analogy with network adjacency matrices that describe connectedness among components. Moreover, they define the directional connectedness from j to others and from others to i as from-degrees and to-degrees respectively (or alternatively "out-degrees" and "in-degrees") and total directional connectedness C^H as mean network degree.

Before analyzing network, one chooses the set of variable, the horizon for variance decomposition prediction and approximating model for variable dynamics (using vector autoregression).

In the framework of Diebold and Yilmaz, I identify the object, the choice and the frequency for my set of variables – cryptocurrencies.

- The object: return, volatility,
- Choice: list of major cryptocurrencies (Appendix 1),
- Frequency: hourly, daily.

Selecting different horizon H, one can examine short- or long-run connectedness measure. Literature underlines, that connectedness measurements are not robust to the choice of H, and there exists no reason to assume that.

But one should be careful with VAR identification. With Cholesky-factor VAR identifications (Sims (1980)), ordering of variables influences the results. To solve this problem, there are several possible ways. The first is to conduct robustness checks for Cholesky factorization VAR by computing variance decomposition for various variables' permutations (as done in Diebold and Yilmaz (2009)). But Klossner and Wagner (2013) argue that such approach doesn't give a precise estimation and propose a new algorithm of divide-and-conquer strategy for fast calculation of all possible remunerations of variable in a model. In addition, Diebold and Yilmaz (2014) propose instead to apply the generalized variance decomposition (GVD) framework of Koop et al. (1996) and Pesaran and Shin (1998) that gives variance decompositions invariant to ordering.

Another important point is high dimensionality of chosen data set. Following Diebold and Yilmaz (2017), I use Least absolute shrinkage and selection operator (LASSO) – the regularization applied for OLS methods which penalizes vector of coefficients and select 'most important', high-weighted coefficients shrinking the number of parameters in a model. In particular, the method is useful when the number of parameters exceed the number of observations in dataset (Tibshirani, 1996).

While standard OLS estimates

$$\hat{\beta} = arg \min_{\beta} \sum_{t=1}^{T} (y_t - \sum_i \beta_i x_{it})^2, \qquad (14)$$

LASSO transforms it to

$$\hat{\beta} = arg \min_{\beta} \left(\sum_{t=1}^{T} (y_t - \sum_i \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right) \qquad (15)$$

where $q = 1$[11]. With LASSO, VAR model becomes sparser, but it doesn't imply sparsity for variance decomposition.

Dynamical connectedness measures can be obtained with rolling window estimation: its idea is that model is estimated at each time point using a subset of the most recent observations – window; this window is swiped through the whole data producing $n - w$ models (where n is the length of data and w is the window size), for each model connectedness measures are calculated.

Return of cryptocurrencies are obtained as in previous part: $r_t = p_t - p_{t-1} = logP_t - logP_{t-1}$, where P_t is close price.

Volatility cannot be calculated directly and should be estimated. I use approach as in Garman and Klass (1980). They propose the best analytic scale-invariant estimator for volatility:

$$\begin{aligned} \tilde{\sigma}_{it}^2 = 0.511(logH_{it} - logL_{it})^2 \\ - 0.019[(logC_{it} - logO_{it})(logH_{it} + logL_{it} - 2logO_{it}) \\ - 2(logH_{it} - logO_{it})(logL_{it} - logO_{it})] - 0.383(logC_{it} - logO_{it})^2 \end{aligned}$$

[11] Value of λ is selected by 10-fold cross-validation

where $H_{it}, L_{it}, O_{it}, C_{it}$ are high, low, open, close prices of series *i* at time *t* respectively. In addition, I convert it to log volatility because volatility is asymmetrically distributed and log transformation induces normality required by generalized variance decomposition (Koop et al., 1996; Pesaran and Shin, 1998).

I use Gephi software[12] for network visualization and apply ForceAtlas2 algorithm (Jacomy et al. (2014)) to define nodes location (it finds a steady state where attracting and repealing forces of different nodes are balanced).

5. Empirical results

This section provides with results of cryptocurrencies' network analysis. I use different periodicity and time periods to compare how the connectedness of network is influenced by different settings. The data are obtained from cryptocompare.com as previously. Summary Statistics is presented in Appendix 2. The following datasets are used:

- Daily prices from 01.08.2017 to 01.05.2018, converted later to daily return and volatility (273 observations);
- Hourly prices, converted to hourly return:
  - From 15.09.2017 12:00 to 31.12.2017 22:00 (2554 observations),
  - From 01.01.2018 00:00 to 30.03.2018 16:00 (2128 observations).

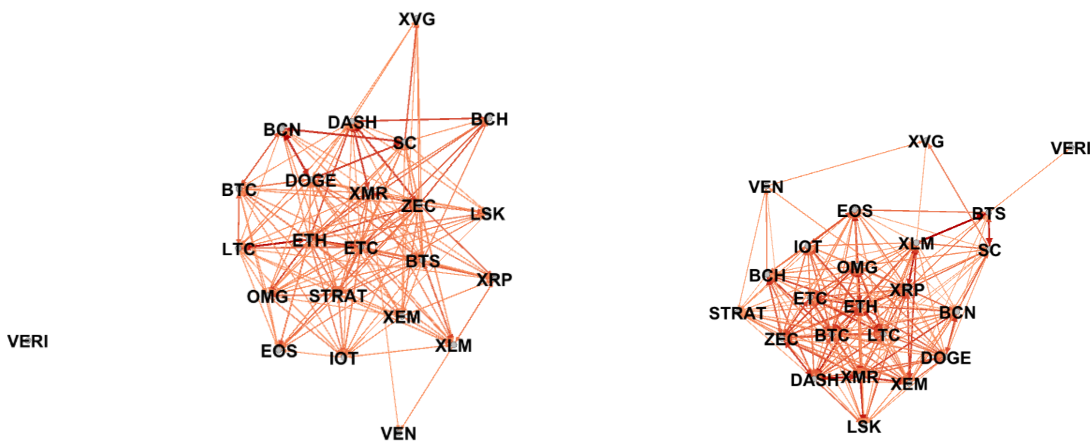
Identification model for variance decomposition is GVD VAR(1) with LASSO at horizon H=10.[13]

5.1 Analysis of daily data

I start analyzing daily data varying number of cryptocurrencies. Most of the cryptocurrencies become more popular in the second half of 2017, that is why historical prices are available for short period of time. Estimating VAR with LASSO helps to tackle the problem of small size of high-dimensional data (it selects the most important coefficients setting irrelevant ones to zero).

[12] https://gephi.org/
[13] As robustness assessment, models with lag 2,3,4 and horizon 5, 15, 20 were estimated, but the result showed that total connectedness is robust to the choice of VAR order and forecast horizon.

First, I model network of 23 major coins (they are the same as in Section 3). Total connectedness of return of 23 coins is very high – 80.05[14]. During this period – August 2017-May 2018 – the highest directional connectedness to other coins are observed from Ethereum, ZCash, Ethereum Classic. Bitcoin, Litecoin, Iota have middle values of 'from' connectedness, and Veritaseum, Verge, Vechain are less connected compared to others. It is clearly seen in Figure 6a, where Veritaseum is disconnected from others.



a - daily returns *b – daily volatility*

Figure 6 – Network of 23 cryptocurrencies, August 2017 – May 2018[15]

Total connectedness (Figure 7) significantly increased during last 4 months. At the beginning of December, it was around 65, but in March it jumped to the level of 90.

Dynamics of network shows increasing connectedness of Bitcoin, BitcoinCash, DigitalCash, while Ethereum, ZeroCash, Ethereum Classic, Monero became less connected (Figure 8).

[14] Appendix 7 presents the connectedness tables for different specification of network for 23 coins. Connectedness tables for bigger networks are not shown due to their large size.
[15] Network with filtered edges for better visualization – pairwise connectedness greater 0.04. Hereinafter, the higher connectedness is related to more intensive color of arrow.

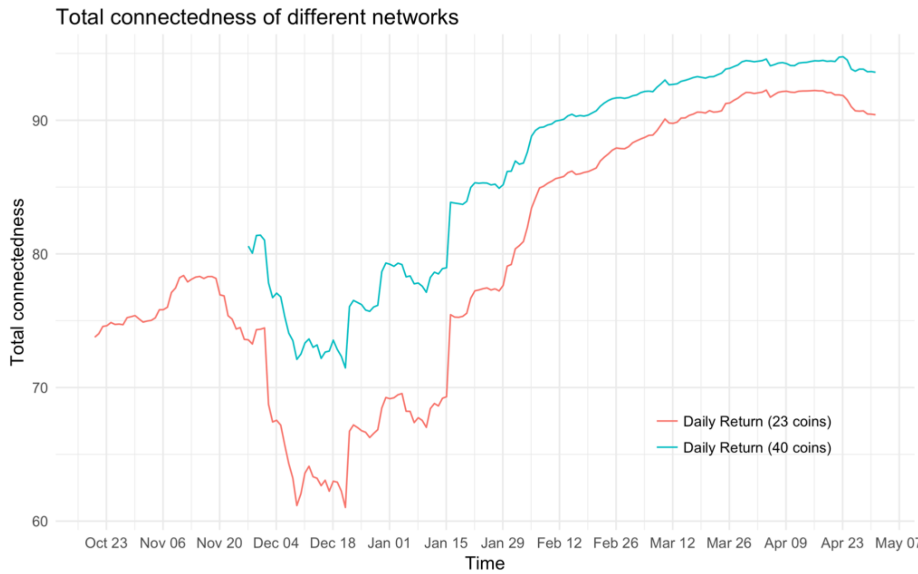


Figure 7 – Total connectedness of 23 and 40 cryptocurrencies' daily return networks, August 2017 - May 2017, rolling window estimation[16]

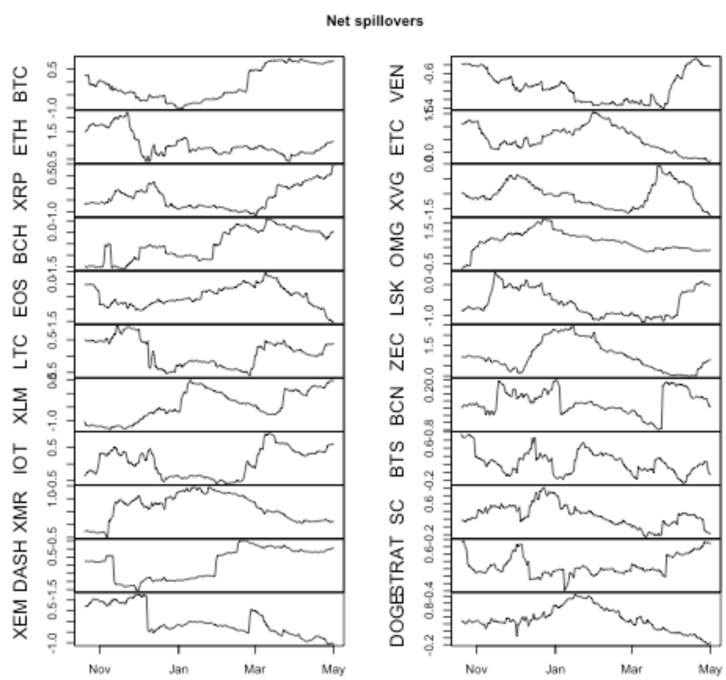


Figure 8 – Net Connectedness for selected coins, network of 23 cryptocurrencies' daily return, August 2017 - May, 2018, rolling window estimation

[16] For daily data, rolling window is set to 80.

Compared to return, models for volatilities (the same coins and the same period) of cryptocurrencies gives less connected network with total connectedness 75.36 (Appendix 7). Again, Ethereum, followed by Monero has the highest connectedness. Now, Bitcoin has stronger connectedness, Veritaseum, Verge, VeChain are the less connected coins as in return network (Figure 6b).

Dynamic connectedness of volatilities has the same trend as connectedness of returns (Figure 9), but slightly different slope. Even though volatilities connectedness is about 60-65 during beginning of December (less than return connectedness), both types are almost at the same level at the end of February-beginning of March.

Looking at volatilities connectedness of particular coins, its values are different to what is observed in return connectedness network. 'From' others connectedness increases for all coins, while 'to' others connectedness diminishes for Bitcoin, Monero, Bitshares, and increases for Iota, DigitalCash, Stellar (these three coins became more connected (Figure 10)).

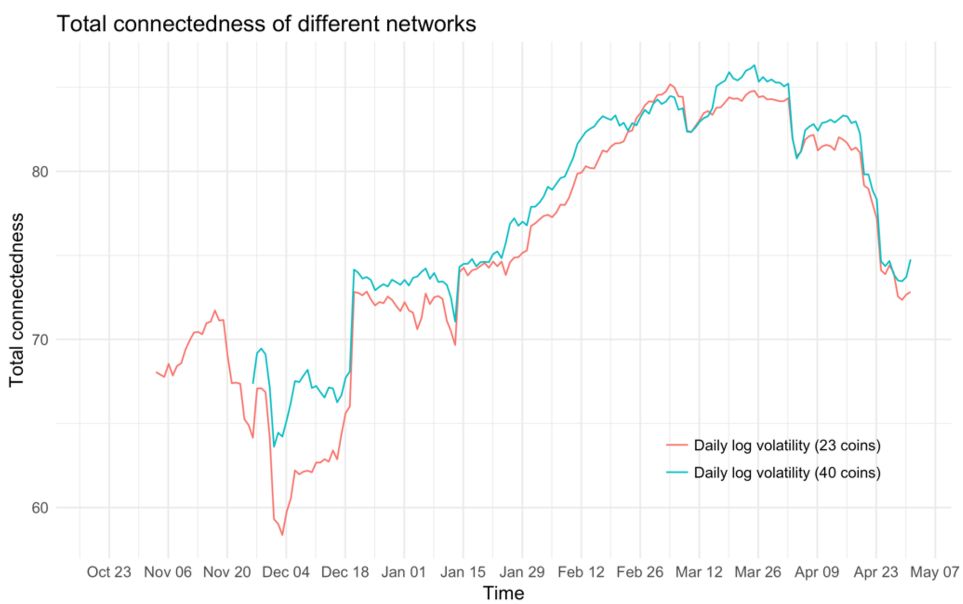


Figure 9 – Total connectedness of 23 and 40 cryptocurrencies' daily volatility networks, August 2017 - May 2017, rolling window estimation

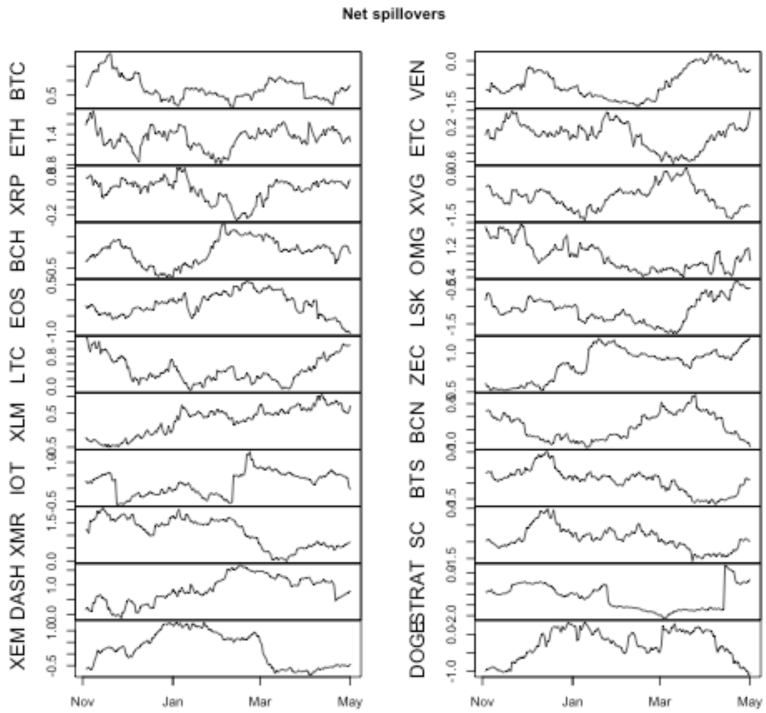
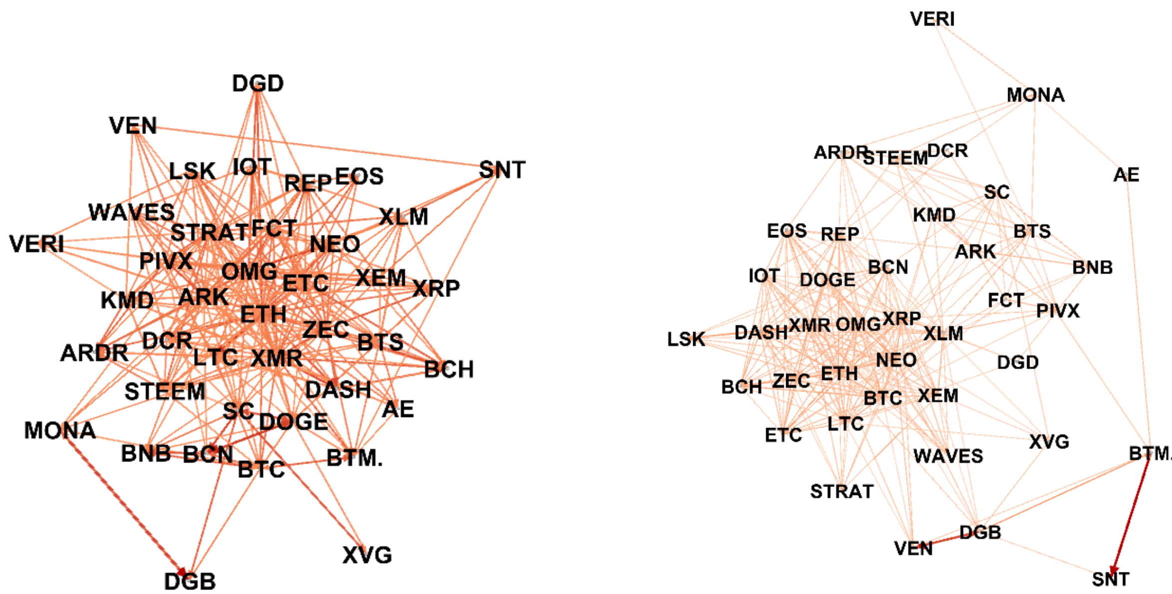


Figure 10 – Net Connectedness of selected coins, network of 23 cryptocurrencies' daily volatility, August 2017 - May, 2018, rolling window estimation

Then, I increase the number of cryptocurrencies in analyzed network for the same period of time (take 40 major coins that has historical data more than 240 days). Total network connectedness of return is also high, as with 23 coins, – 88.27. The more connected coins are Ethereum, OmiseGo, Monero, ZeroCash (Figure 11a), followed by Ark, EthereumClassic, and less connected – Status Network Token (SNT), DigiByte and Verge. One important aspect is that half of the coins have negative net connectedness, meaning that connectedness 'to others' are less than connectedness 'from others'.

Dynamic connectedness reflects the same tendency as the network of 23 coins (Figure 7): it starts at level 80 in November, then decreases to level 70 at the beginning of December and later exceeds 90 in February-April.

Analysis of net spillovers for cryptocurrencies (Figure 12) shows that there is no common pattern for all coins: whereas some coins become more connected (as Bitcoin, BitcoinCash, EOS, DigitalCash), net connectedness for others decreases (Ethereum, Litecoin, Lisk, NEM). But 'from others' connectedness (Figure 13) mostly follows the same increasing trajectory after declining in December. Therefore, the difference comes from 'to others' measurement. It shows that during market 'up' and market 'down' period of time, different coins have higher influence on others. Thus, depending on the market situation, investors should consider this fact and modify portfolio.



a - daily returns *b – daily volatility*

Figure 11 – Network of 40 cryptocurrencies, August 2017 – May 2018[17]

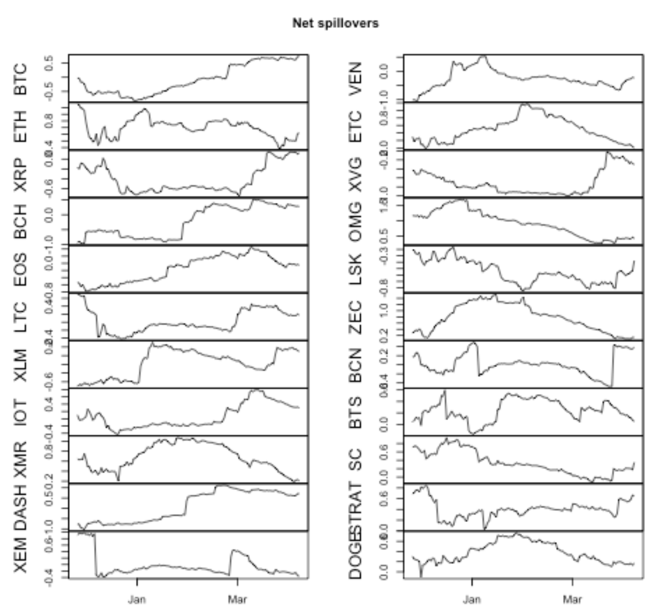


Figure 12 – Net Connectedness of selected coins, network of 40 cryptocurrencies' daily return, August 2017 - May, 2018, rolling window estimation

[17] Network with filtered edges – pairwise connectedness greater 0.03.

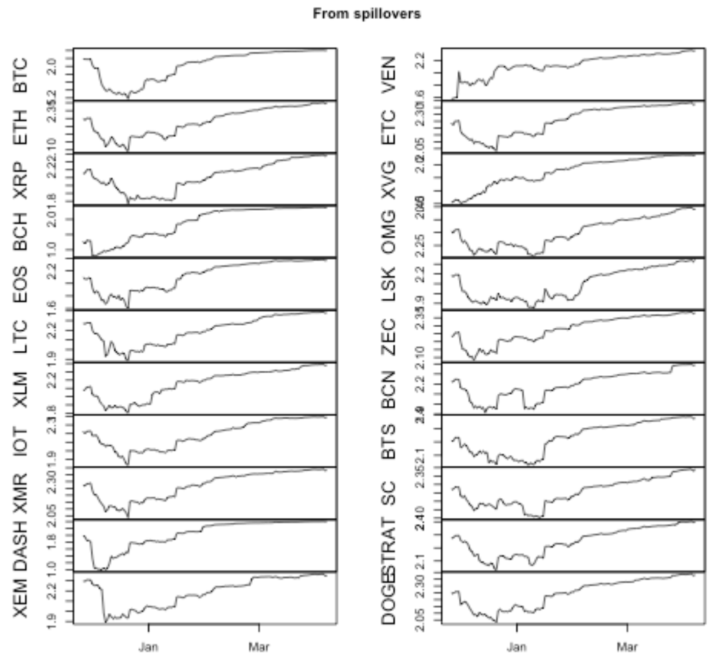


Figure 13 – From Connectedness of selected coins, network of 40 cryptocurrencies' daily return, August 2017 - May, 2018, rolling window estimation

Total connectedness of volatility network (40 coins) is 76.86 with most connected Ethereum, OmiseGo, Monero, Ripple, followed by NEO, Bitcoin, and less connected Private Instant Verified Transaction, Status, Veritaseum (Figure 11b). As in the return network, half of the coins have negative net connectedness.

Dynamic connectedness (Figure 9) of 40 coins' volatility network is similar to the network of 23 coins: it has small decrease in the end of November, but then goes up to more than 80 in March (it starts growing earlier that return connectedness does).

As for connectedness of individual coins, 'from others' measure increases from the end of December, while dynamics of net connectedness varies across different coins (Figure 14). Bitcoin becomes less connected in the network, as Siacoin, Monero (because of decreased 'to others' connectedness). But Lisk, ZeroCash, Stellar, Litecoin have higher net connectedness at the end of analyzed period.

I don't increase the number of coins in network for daily data, since it would be small amount of available data, not enough for analysis.

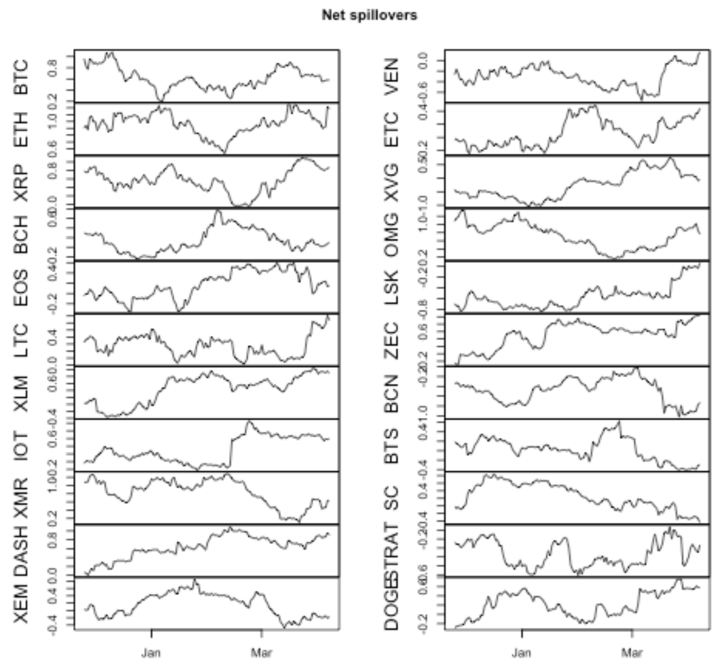


Figure 14 – Net Connectedness of selected coins, network of 40 cryptocurrencies' daily volatility, August 2017 - April, 2018, rolling window estimation

Summarizing analysis of daily data:

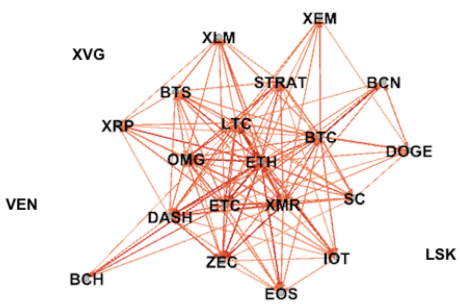
- Connectedness of return is higher than connectedness of volatility;
- Networks of 23 and 40 coins are similar to each other in terms of connectedness measure and strongest/weakest coins;
- During growing market period (November-December), connectedness is less compared to decreasing period (January-March);
- Bitcoin is not the most connected node in the network. The most connected coins in terms of daily return are Ethereum, ZeroCash, in terms of daily volatility – Ethereum, OmiseGo, Monero. The less connected nodes are VeChain, Veritaseum, Verge and Ripple. One would expect that the larger coin is (it terms of market share, market capitalization, popularity), the higher it should be connected within the network. But result shows that TOP-10 cryptocurrencies (Ripple, EOS, VeChain) have less connectedness. This fact will be discussed in Section 6.

5.2 Analysis of hourly data

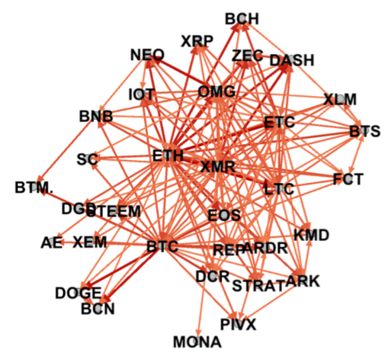
As the next step, I analyze networks of hourly return of 23, 40 and 90 coins. I divided data into 2 periods to compare results during different market situation:

1. October – December 2017 – 'hype' period, most of coins' prices increased;
2. January – March 2018 – shock period, most of coins' prices dropped.
    1. October – December 2017

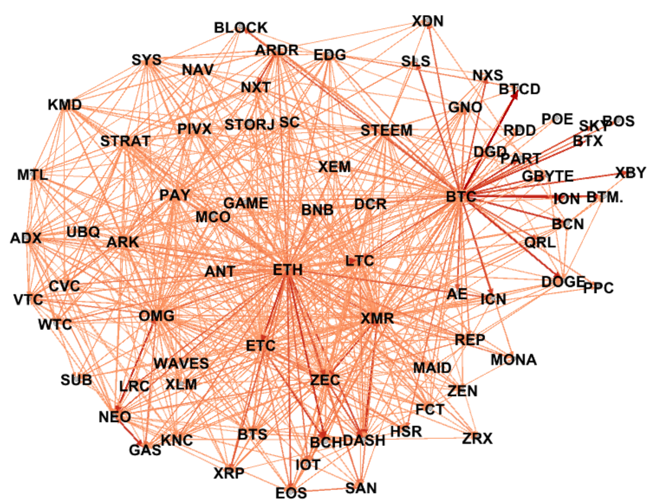
Analyzing networks for more stable period of time October – December 2017, results show smaller total connectedness 64.68. In that period of time the more connected coins are Ethereum, Monero followed by Bitcoin and Ethereum Classic (Figure 15a). The network is less connected and more coins have negative net connectedness (15 out of 23).



a – 23 coins



b – 40 coins



c – 90 coins

Figure 15 – Network of cryptocurrencies hourly returns, October – December 2017[18]

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[18] Network with filtered edges – pairwise connectedness greater 0.04 for 23 coins, 0.035 for 40 coins, 0.017 for 90 coins.

Dynamics of the network (Figure 16) varies during time. Starting at level 45 in the end of October, it has an overall increasing trend, but with three falls: start and end of November, middle of December. It can be related to the fluctuation of Bitcoin price that attracted high public attention. On the 13th November, its price reverted back to 5800$ after being 7500$ (lost 23% within a week). On the 28th November, it broke an important boundary of 10 000$, and on the 17th December, it reached maximum historical price (19800$).

During October-December, net connectedness for some coins goes down (Lisk, Verge, VeChain): they are least connected in the network till the end of December (close to zero 'to' and 'from' connectedness) when their 'from others' connectedness quickly increases (Figure 17).

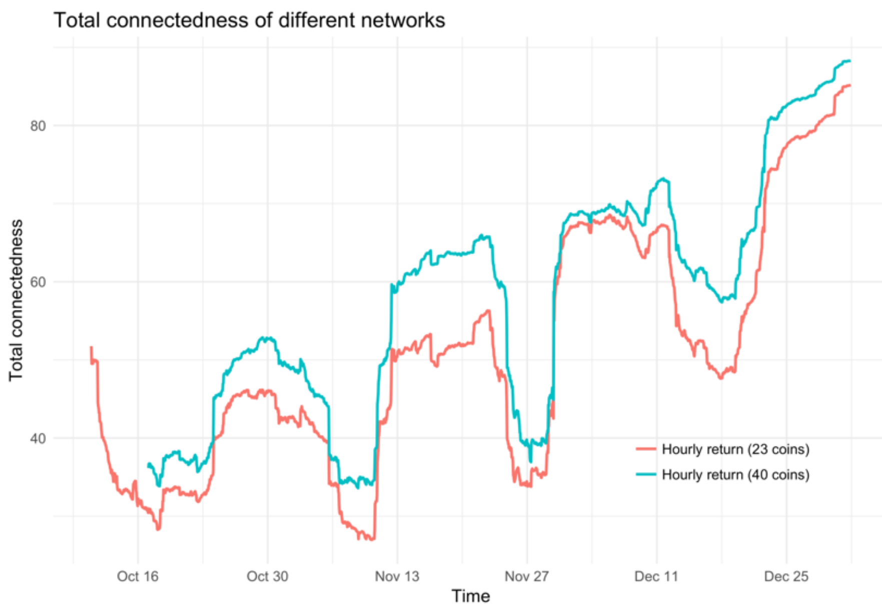


Figure 16 – Total connectedness of 23 and 40 cryptocurrencies' hourly return networks, October – December 2017, rolling window estimation

With 40 coins in return network, total connectedness increases – to 69.4, but again: Ethereum and Monero are the most connected compared to others (Figure 15b) and dynamics follow a similar trend (Figure 16).

Dynamic connectedness of individual coins is similar to what is observed in 23 coins network. Their 'From others' connectedness resembles total connectedness of network (Figure 18) – overall increasing trend with three cavities, except for Verge, Lisk, Veritaseum, Stratis – their total connectedness starts to increase only in the end of December. ‘To others’ connectedness increases for Iot, Eos, OmiseGo.

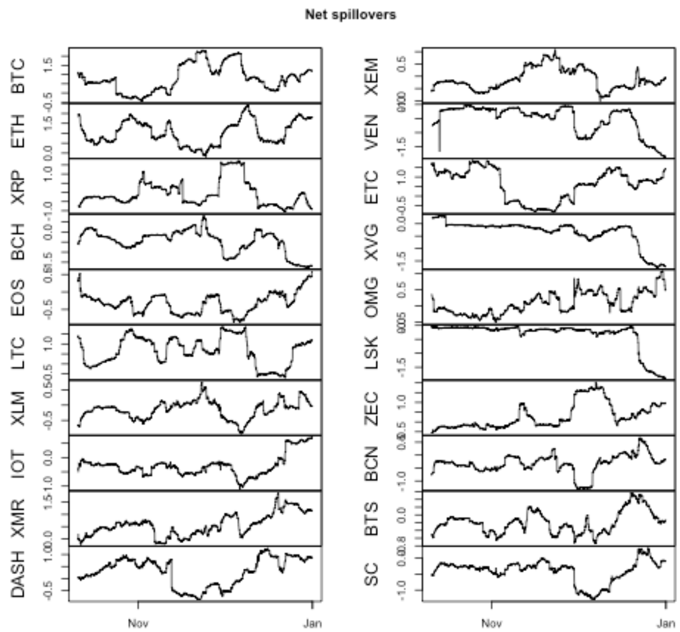


Figure 17 – Net Connectedness for selected coins, network of 23 cryptocurrencies’ hourly return, October – December 2017, rolling window estimation

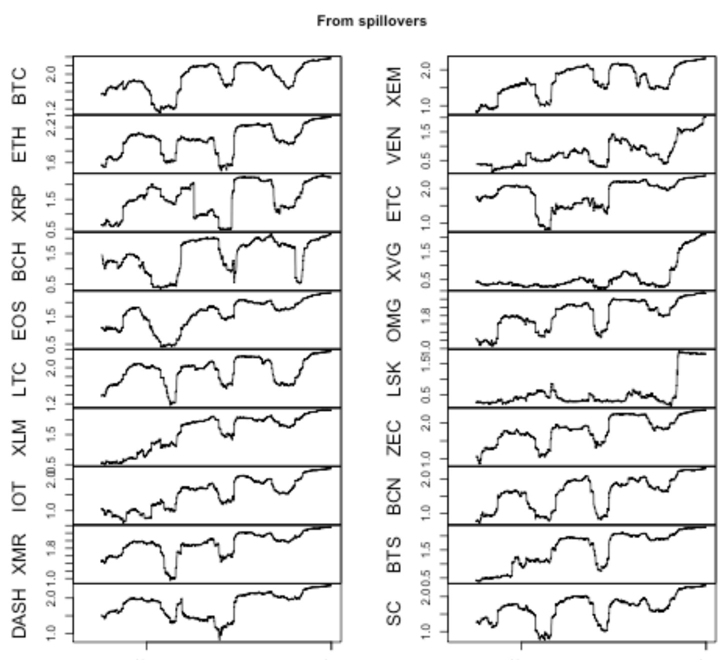
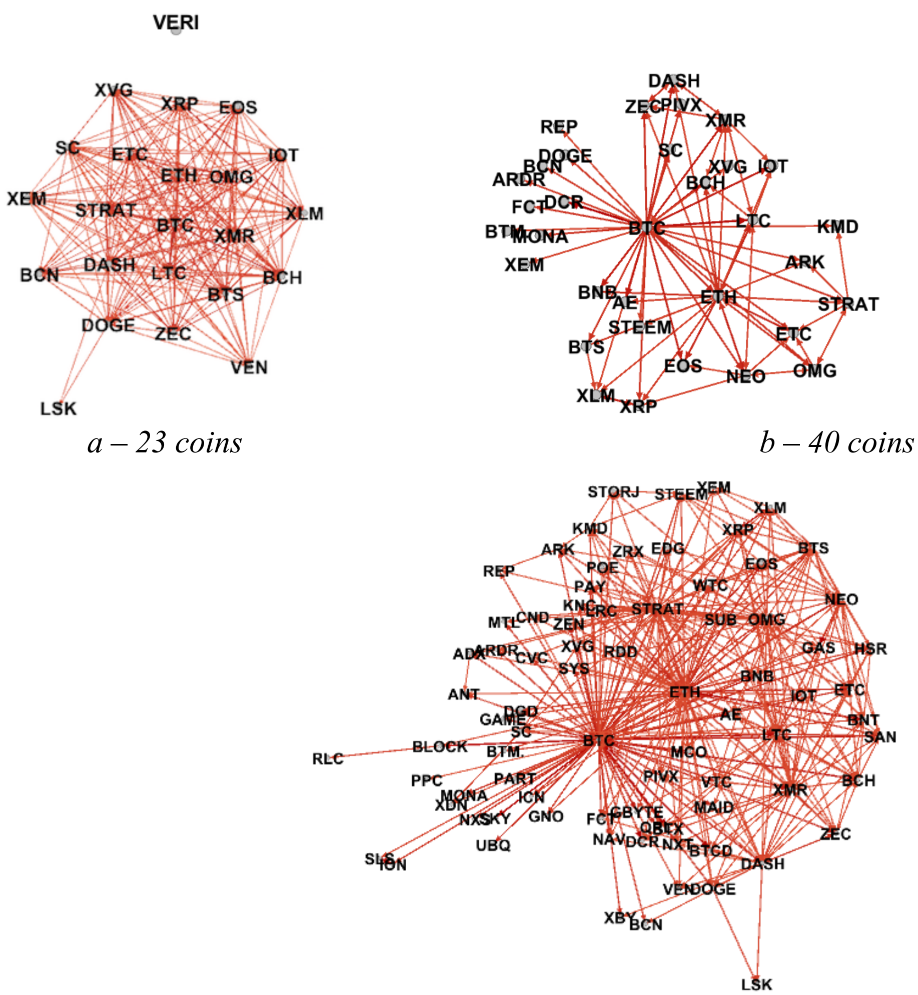


Figure 18 – From Connectedness for selected coins, network of 40 cryptocurrencies’ hourly return, October – December 2017, rolling window estimation

Hourly data allows to analyze more coins in a network. Return network of 90 coins has higher total connectedness - 72.12. The 5 most connected coins are the same, but their order slightly changed: the most connected is Bitcoin, followed by Ethereum (almost the same value of connectedness as for Bitcoin), Monero, Ethereum Classic and OmiseGo (Figure 15c).

2. January – March 2018

Starting with the small network, results show that total connectedness of return network is 85.15 and more connected coins are Bitcoin, Ethereum, Monero, Litecoin, the less connected coins are Veritaseum and Lisk (Figure 19a).



a – 23 coins

b – 40 coins

c – 90 coins

Figure 19 – Network of cryptocurrencies' hourly returns, January – March 2018[19]

[19] Network with filtered edges – pairwise connectedness greater 0.04 for 23 coins, 0.035 for 40 coins, 0.0175 for 90 coins.

Dynamic connectedness (Figure 20) shows a big jump in January. It is related to large fall in the cryptocurrencies market. It is similar to what occurred in September 2017: now South Korea, following the example of China, announced possible bans of cryptocurrencies trading on January, 16[20]. During this shock, Bitcoin and Ethereum as major cryptocurrencies lost about 20% and 30% of its value respectively, as well as other coins, thus increasing connectedness of network. During February, connectedness remains at level 85-90 and after slight decrease to 80 it comes back to 86 to the end of March.

Decrease at the end February – beginning of March can be explained by recovery of the market after fall in January. With growing market, connectedness of return network becomes lower.

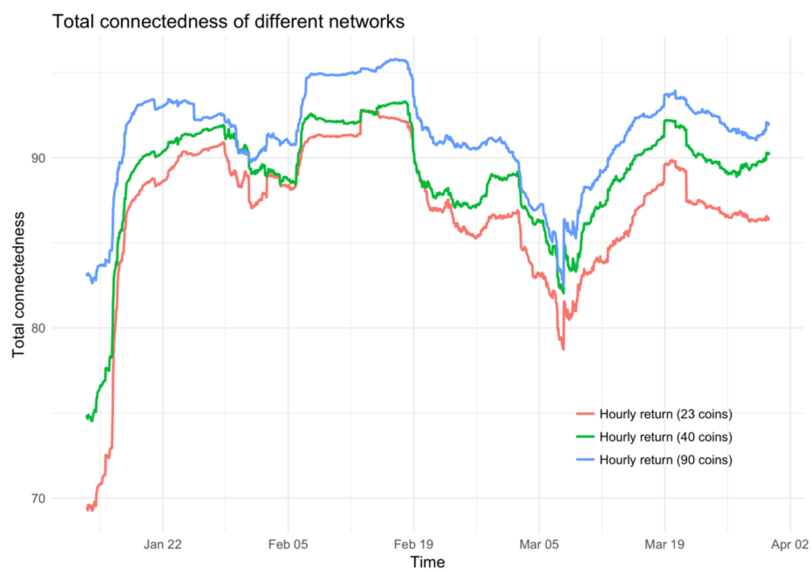


Figure 20 – Total connectedness of 23, 40 and 90 cryptocurrencies' hourly return networks, January – March 2018, rolling window estimation[21]

'From others' connectedness for individual coins follow the same trend: high spike in January. As for net connectedness (Figure 21), there are coins that exhibit evident decreasing tendency of connectedness measure, such as DigitalCash, Iota, Bitecoin.

With larger number of coins in the network (40), total connectedness of return network for the same period is slightly less – 87.2 (Figure 19b) and its dynamics follow the similar tendency as with network of 23 coins, the same is hold for dynamical connectedness of individual coins (Figure

[20] http://fortune.com/2018/01/24/south-korea-bitcoin-privacy-fines/
[21] For hourly data spillover window is set to 300.

22). In the network of 40 coin, there more cryptocurrencies with negative net connectedness at the end of period (DigitalCash, Verge, Waves, NEM, etc.). But some coins increase their ‘to others’ connectedness, such as Status, DigiByte, Ardor.

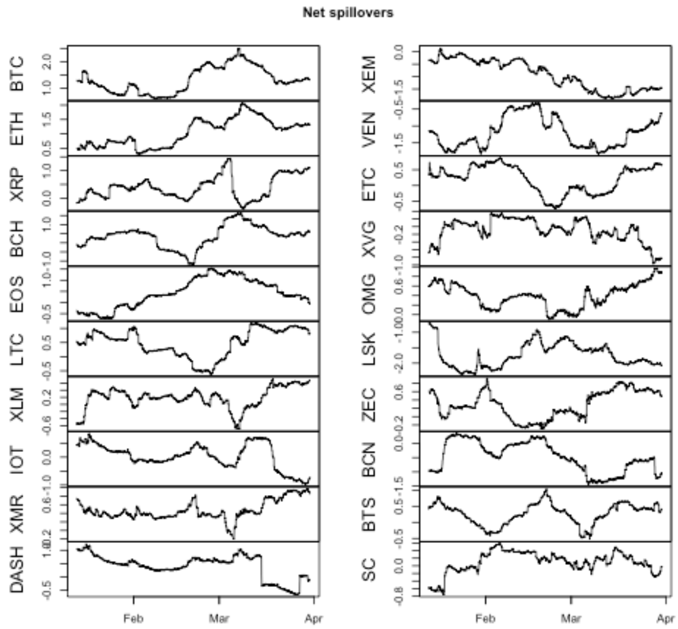


Figure 21 – Net Connectedness for selected coins, network of 23 cryptocurrencies’ hourly return, January – March 2018, rolling window estimation

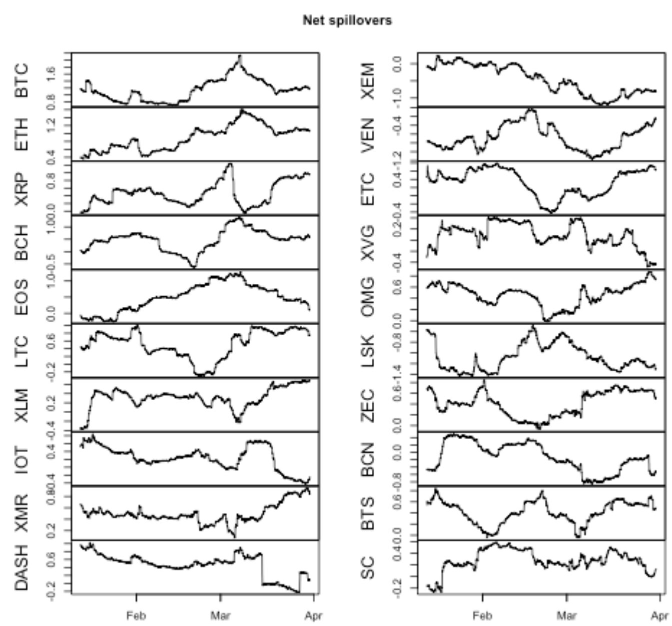


Figure 22 – Net Connectedness for selected coins, network of 40 cryptocurrencies’ hourly return, January – March 2018, rolling window estimation

Network of 90 coins' return have slightly higher connectedness – 89.8 (Figure 19c), but the same coins have the highest connectedness measure (Bitcoin, Ethereum, Stratis, Monero, OmiseGo, DigitalCahs, NEO). Dynamics show the same path as with network of 23 and 40 coins, but 2-3 points higher (Figure 20).

Compared to 23 coins' network, with larger number of coins, net connectedness of Bitcoin (Figure 23) is smaller in the end January and has one spike only in March.

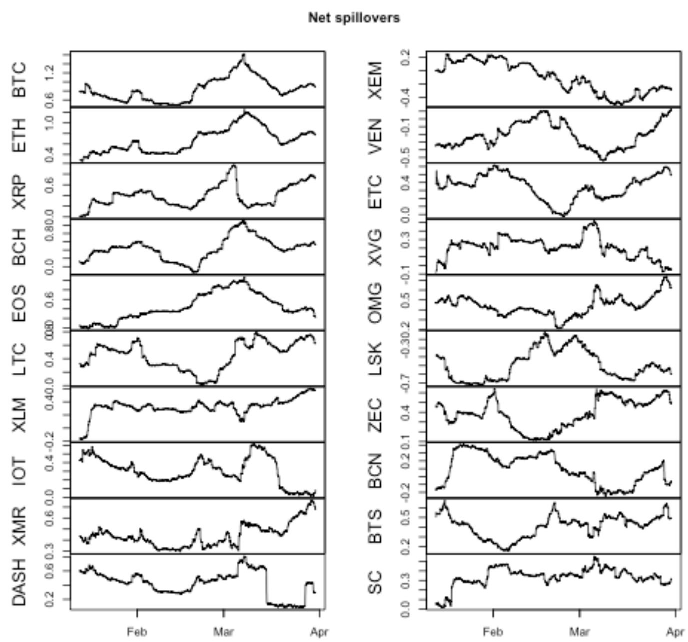


Figure 23 – Net Connectedness for selected coins, network of 90 cryptocurrencies' hourly return, January – March 2018, rolling window estimation

Summarizing analysis of networks of hourly return:

- The more coins are added to the network, the higher is connectedness, but the same coins remain the most connected regardless number of nodes;
- Ethereum, Monero and Bitcoin were most connected during October-December 2017 and January – March 2018;
- As in daily network, with hourly specification there are coins from TOP-10 that have small connectedness: during October-December – Ripple, EOS, Stellar, VeChain, BitcoinCash, but during shock period their connectedness significantly increase.

- Connectedness during period with negative shocks on the market increases compared to time of market ‘up’. This tendency is related to financial literature, e.g. Diebold and Yimaz (2014) where connectedness measure for the stock market in the USA jumped during financial crisis 2008, Anufriev and Panchenko (2015), that demonstrate an increase in the network effect between Australian banks during post-2008 period, Eratalay and Vladimirov (2017) which presents the rise of interconnectedness between major Russian firms during financial distress in 2014.

6. Conclusions

This paper analyzes the network of cryptocurrencies using variance decomposition method combined with generalized VAR and LASSO to deal with high dimensionality of data. The results present the static connectedness measurements using full sample estimation during different periods, as well as dynamics of network using rolling window estimation. Varying object for connectedness measure (return, volatility), periodicity of data (hourly, daily), number of nodes in the network, results can differ across specifications. Connectedness of daily return exhibits higher level than connectedness of daily volatility, but within daily specification, networks of 23 and 40 major coins are similar to each other in terms of connectedness measure and strongest/weakest coins. Within hourly periodicity, adding more coins (23, 40, 90) increases connectedness of network, but the proportion of net-‘receiver’ nodes increases as well. During growing market period both with hourly and daily data, connectedness is less compared to ‘down’ period – market shocks make the network almost fully connected. The last fact is related to the literature on cryptocurrencies (Elendner et al. (2016), Ciaian et al. (2018)), as well as to financial literature (Baruník et al. (2017), Demirer et al. (2017)).

Answering the first research questions (How strong is connectedness of cryptocurrencies’ market? How does connectedness change over time?), results conclude that there exist spillovers between different coins and the network of cryptocurrencies has high connectedness which increases more during negative market periods.

The next research questions (What are the most influential coins? What coins are less affected by market shocks?) found the following answers. Albeit Bitcoin is the most popular cryptocurrency, it is not the most connected node in the network. The most connected coins in terms of daily return are Ethereum, ZeroCash, in terms of daily volatility – Ethereum, OmiseGo, Monero. With hourly return, during growing market period Ethereum and Monero connectedness exceed connectedness of Bitcoin, only during shock they switch places.

Analysis of different networks shows that there are coins with large market capitalization and large daily trading volume but small connectedness and vice versa. For example, such popular cryptocurrencies as Ripple, Eos, Iota are less connected coins in the network, while TenX, AdEx, Vertcoin, Monaco (their ranks are >80) have much higher connectedness measure. Another insight is that there are coins with positive average return (for period January – March when the whole market goes down) and small connectedness: DigixDao, Aeternity, Binance Coin. Less connectedness means that they receive less net influence from others coins in the network and changes in other coins should not affect such cryptocurrencies a lot. The importance of the findings is such that this information is of particular interest for hedge investments to reduce risk within the portfolio.

One limitation of this paper is the fact that cryptocurrencies' market is young and there is not much data for some coins. As time goes by, more historical information will be available for deeper study. In addition, future research can supplement the cryptocurrencies network analysis by including market capitalization of coins, the similarity of underlying technologies, or sentiment analysis of blogs, twits, etc.

Working on this paper, I prepare framework[22] that allows to analyze cryptocurrencies market data and identify stronger/weaker connected coins in the network. Within the paper, I concentrate more on general analysis of the network. But this tool also can be used by investors who would like to get more insights into particular cryptocurrency of their interest and support or disprove the investment decision.

[22] Available at https://github.com/LizaLebedeva/cryptocurrencies-research

References

Anufriev, M., Panchenko, V., Connecting the Dots: Econometric Methods for Uncovering Networks with an Application to the Australian Financial Institutions (January 29, 2015). Journal of Banking and Finance, 61, 2015. Available at: https://ssrn.com/abstract=2560594

Barigozzi, Matteo and Brownlees, Christian T., NETS: Network Estimation for Time Series (February 4, 2018). Available at: https://ssrn.com/abstract=2249909

Baruník, Jozef and Krehlik, Tomas, Measuring the frequency dynamics of financial connectedness and systemic risk (2017). Papers. Available at: https://EconPapers.repec.org/RePEc:arx:papers:1507.01729

Baek, C., Elbeck, M., Bitcoins as an investment or speculative vehicle? A first look (2015). Applied Economics Letters, 22:1, 30-34. Available at: http://dx.doi.org/10.1080/13504851.2014.916379

Beikverdi A, Song J. Trend of centralization in Bitcoin's distributed network. In: Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), (2015). 16th IEEE/ACIS International Conference on; 2015. p. 1–6.

Billio, Monica, Lo, Andrew W., Getmansky, Mila and Pelizzon, Loriana, Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors, Journal of Financial Economics, 104, 535-559, 2012. Available at: http://www.sciencedirect.com/science/article/pii/S0304405X11002868

Buterin, V. A Next-Generation Smart Contract and Decentralized Application Platform, 2015. Available at https://github.com/ethereum/wiki/wiki/White-Paper.

Caporale, Guglielmo Maria and Plastun, Alex, Price Overreactions in the Cryptocurrency Market, No 1718, Discussion Papers of DIW Berlin, DIW Berlin, German Institute for Economic Research, (2018). https://EconPapers.repec.org/RePEc:diw:diwwpp:dp1718.

Catalini, Christian, Gans, Joshua S., Some Simple Economics of the Blockchain. NBER Working Paper No. 22952 (2016). Available at: http://www.nber.org/papers/w22952

Ciaian, Pavel, Rajcaniova, Miroslava, Kancs, d'Artis, Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets, Journal of International Financial Markets, Institutions and Money, Volume 52, 2018, Pages 173-195. Available at: https://doi.org/10.1016/j.intfin.2017.11.001

Chiu, Jonathan and Koeppl, Thorsten, The Economics of Cryptocurrencies - Bitcoin and Beyond, No 1389, Working Papers, Queen's University, Department of Economics (2017).

Chohan, Usman W., Cryptocurrencies: A Brief Thematic Review (August 4, 2017). Available at: https://ssrn.com/abstract=3024330

Chu, Jeffrey, Chan, Stephen, Nadarajah, Saralees and Osterrieder, Joerg, GARCH Modelling of Cryptocurrencies, Journal of Risk and Financial Management, 2017, 10, issue 4, p. 1-15,. Available at: https://EconPapers.repec.org/RePEc:gam:jjrfmx:v:10:y:2017:i:4:p:17-:d:113895.

Demirer, M, Diebold, F X, Liu, L, Yilmaz, K. Estimating Global Bank Network Connectedness. J Appl Econ. 2017;1–15. Available at: https://doi.org/10.1002/jae.2585

Diebold, F.X. and Yilmaz, K., Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets, Economic Journal, Royal Economic Society, vol. 119(534), 2009, pages 158-171, 01.

Diebold, F.X. and Yilmaz, K., Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers, Koç University-TUSIAD Economic Research Forum Working Papers 1001, Koc University-TUSIAD Economic Research Forum (2010). Available at: https://ideas.repec.org/p/koc/wpaper/1001.html

Diebold, F.X. and Yilmaz, K., On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms, Journal of Econometrics, 2014, 182, 119-134.

Elendner, Hermann; Trimborn, Simon; Ong, Bobby; Lee, Teik Ming, The cross-section of crypto-currencies as financial assets: An overview, SFB 649 Discussion Paper, No. 2016-038, 2014. Available at: http://hdl.handle.net/10419/148874

Eratalay, H., Vladimirov, E., Mapping the Stocks in MICEX: Who Is Central in Moscow Stock Exchange?, EUSP Department of Economics Working Paper Series 2017/01, European University at St. Petersburg, Department of Economics, 2017. Available at: https://eu.spb.ru/images/ec_dep/wp/Ec-2017_01.pdf

Garcia, David, Claudio Juan Tessone, Pavlin Mavrodiev, Nicolas Perony. The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy. Journal of the

Royal Society Interface, pp. 20140623, vol. 11 (2014). Available at: https://arxiv.org/abs/1408.1494

Garman, M.B., Klass, M.J., On the estimation of security price volatilities from historical data, Journal of Business, vol. 53(1) (January), 1980, pp. 67–78.

Granger, C., Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica, 37(3), 1969, 424-438.

Haferkorn M., Quintana Diaz J.M., Seasonality and Interconnectivity Within Cryptocurrencies - An Analysis on the Basis of Bitcoin, Litecoin and Namecoin. In: Lugmayr A. (eds) Enterprise Applications and Services in the Finance Industry. Lecture Notes in Business Information Processing, vol 217. Springer, Cham, 2015.

Halaburda, Hanna and Gandal, Neil, Can We Predict the Winner in a Market with Network Effects? Competition in Cryptocurrency Market. Games 2016, 7(3), 16; Available at: http://www.mdpi.com/2073-4336/7/3/16

Hamilton, J. D., Time Series Analysis. Princeton University Press, 1994.

Hanley, Brian P. The false premises and promises of Bitcoin. arXiv preprint arXiv:1312.2048 (2013).

Hayes, A. S., Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. Telematics and Informatics, 2016.

Hileman, Garrick and Rauchs, Michel, Global Cryptocurrency Benchmarking Study (April 6, 2017). Available at: https://ssrn.com/abstract=2965436

Iwamura, Mitsuru and Kitamura, Yukinobu and Matsumoto, Tsutomu, Is Bitcoin the Only Cryptocurrency in the Town? Economics of Cryptocurrency and Friedrich A. Hayek (February 28, 2014). Available at: https://ssrn.com/abstract=2405790

Kaminski, Jermain, Nowcasting the Bitcoin Market with Twitter Signals, 2016. Available at: https://arxiv.org/abs/1406.7577

Kim,Y.B., Kim, J.G., Kim W.,Holm, J.,Kim, T.H.,Kang S.J., Kim C.H., Predicting Fluctuations in Cryptocurrency Transactions Based on User Comments and Replies. Plos One, 11, 8 (2016).

Kokes, Josef and Bejcek, Michal, Control Strategy to Trade Cryptocurrencies, No 4407038, Proceedings of Business and Management Conferences, International Institute of Social and Economic Sciences, 2016. Available at: https://EconPapers.repec.org/RePEc:sek:ibmpro:4407038

Luther, William J., Cryptocurrencies, Network Effects, and Switching Costs. Contemporary Economic Policy, Vol. 34, Issue 3, pp. 553-571, 2016. Available at: https://ssrn.com/abstract=2784996

Nakamoto, Satoshi, Bitcoin: A peer-to-peer electronic cash system. (2008). Available at: http://bitcoin.org/bitcoin.pdf

Nakatani, T., Teräsvirta, T., Testing for volatility interactions in the Constant Conditional Correlation GARCH model, Econometrics Journal, vol 12, 2009, no. 1, pp. 147-163. DOI: 10.1111/j.1368-423X.2008.00261.x

Paraskevi, P., Volatility estimation for Bitcoin: A comparison of GARCH models. Economics Letters, 158: 3-6, 2017.

Silvennoinen, Annastiina and Teräsvirta, Timo, Multivariate GARCH models, No 669, SSE/EFI Working Paper Series in Economics and Finance, Stockholm School of Economics, 2008, Available at: https://EconPapers.repec.org/RePEc:hhs:hastef:0669

Sims, Christopher A., Macroeconomics and Reality, Econometrica, vol. 48, no. 1, 1980, pp. 1–48. JSTOR, JSTOR, Available at: www.jstor.org/stable/1912017.

Vasek M, Thornton M, Moore T. Empirical Analysis of Denial-of-Service Attacks in the Bitcoin Ecosystem. In: Bhme R, Brenner M, Moore T, Smith M, editors. Financial Cryptography and Data Security. vol. 8438 of Lecture Notes in Computer Science. Springer Berlin Heidelberg; 2014. p. 57–71. Available at: http://dx.doi.org/10.1007/978-3-662-44774-1_5.

Yli-Huumo J., Ko D., Choi S., Park S., Smolander K., Where Is Current Research on Blockchain Technology? A Systematic Review. PLOS ONE, 2016, 11(10): e0163477. https://doi.org/10.1371/journal.pone.0163477

Xie, P., Predicting digital currency market with social data: implications of network structure and incentive hierarchy (2017). Dissertation for the Degree Doctor of Philosophy in the Scheller College of Business. Available at: http://hdl.handle.net/1853/58692

Appendix 1. List of cryptocurrencies[23]

N	Coin	Symbol	Market Cap, mln	# days existing
1	Bitcoin	BTC	151,426	3,387
2	Ethereum	ETH	61,115.71	990
3	Ripple	XRP	34,296.10	1,188
4	Bitcoin Cash	BCH	19,930.65	265
5	EOS	EOS	9,414.48	298
6	Litecoin	LTC	8,354.31	1,642
7	Stellar	XLM	6,984.71	461
8	IOTA	IOT	5,754.04	314
9	Monero	XMR	4,089.28	1,180
10	Dash	DASH	3,656.82	1,535
11	NEM	XEM	3,487.53	325
12	VeChain	VEN	2,018.87	1,644
13	Ethereum Classic	ETC	1,943.08	635
14	OmiseGO	OMG	1,579.32	283
15	Lisk	LSK	1,229.89	425
16	Zcash	ZEC	1,029.76	542
17	Verge	XVG	1,019.35	803
18	Bytecoin	BCN	887.40	325
19	BitShares	BTS	692.66	1,183
20	Siacoin	SC	646.28	972
21	Dogecoin	DOGE	623.48	1,542
22	Stratis	STRAT	566.93	620
23	Veritaseum	VERI	233.87	319
24	NEO	NEO	4,871.09	261
25	Binance Coin	BNB	1,477.33	252
26	Bytom	BTM	878.88	306
27	Steem	STEEM	778.26	736
28	DigixDAO	DGD	591.77	1,180
29	Status	SNT	526.21	298
30	Waves	WAVES	519.07	262
31	Aeternity	AE	486.69	328
32	Decred	DCR	470.05	961
33	Augur	REP	425.64	566
34	Komodo	KMD	411.97	444
35	Ardor	ARDR	372.33	557
36	DigiByte	DGB	342.85	736
37	Ark	ARK	320.34	397
38	PIVX	PIVX	307.96	356
39	Factom	FCT	263.98	931
40	MonaCoin	MONA	233.98	1,176
41	0x	ZRX	499.56	255
42	Loopring	LRC	427.52	228
43	Waltonchain	WTC	388.36	228
44	Hshare	HSR	333.55	228
45	Substratum	SUB	272.85	332
46	Syscoin	SYS	256.39	1,238
47	Gas	GAS	245.73	228
48	ReddCoin	RDD	228.08	1,238
49	Kyber Network	KNC	216.76	975
50	FunFair	FUN	214.71	715
51	Monaco	MCO	204.04	490
52	Nxt	NXT	201.44	1,376
53	ZCoin	XZC	194.93	437
54	Bancor	BNT	180.15	282
55	TenX	PAY	176.51	332
56	Byteball Bytes	GBYTE	174.12	443
57	MaidSafeCoin	MAID	168.14	325
58	Storj	STORJ	155.28	297
59	Skycoin	SKY	147.14	332
60	Iconomi	ICN	144.24	545
61	Emercoin	EMC	142.37	838
62	Particl	PART	141.49	276
63	Bitcore	BTX	140.34	1,095
64	Cindicator	CND	138.44	237
65	ZenCash	ZEN	130.95	321
66	Nexus	NXS	129.46	578
67	Civic	CVC	128.28	280
68	Decentraland	MANA	123.02	279
69	Santiment Network	SAN	120.29	285
70	Po.et	POE	119.45	234
71	Gnosis	GNO	118.73	357
72	GameCredits	GAME	116.94	886
73	iExec RLC	RLC	116.55	368
74	Vertcoin	VTC	113.08	1,532
75	Metal	MTL	112.20	288
76	Ubiq	UBQ	107.30	438
77	BOScoin	BOS	103.86	332
78	Aragon	ANT	103.45	341
79	DigitalNote	XDN	95.34	325
80	Blocknet	BLOCK	95.31	1,182
81	NavCoin	NAV	92.31	1,237
82	BitcoinDark	BTCD	88.40	1,238
83	AdEx	ADX	78.80	299
84	Pillar	PLR	73.05	291
85	Quant. Res. Ledger	QRL	65.40	317
86	SaluS	SLS	60.24	823
87	Peercoin	PPC	59.77	1,302
88	ION	ION	59.29	428
89	Edgeless	EDG	57.54	385
90	XTRABYTES	XBY	32.37	471

[23] Data retrieved 23.04.2018

Appendix 2. Descriptive Statistics of cryptocurrencies' daily prices

	BTC	ETH	XRP	BCH	EOS	LTC	XLM	IOT	XMR	DASH	XEM	VEN	ETC	XVG	OMG
nobs	273	273	273	273	273	273	273	273	273	273	273	273	273	273	273
Min	2,720.5	218.1	0.2	220.3	0.5	41.9	0.01	0.3	43.2	181.6	0.2	0.1	10.0	0.002	1.4
Max	19,345.5	1,385.0	2.8	3,715.9	21.4	357.5	0.9	5.3	467.5	1,433.4	1.8	8.2	42.5	0.2	25.5
1. Q.	4,777.5	306.7	0.2	546.7	1.2	56.9	0.02	0.6	96.3	310.2	0.2	0.1	14.0	0.01	8.1
3. Q.	10,735.5	751.8	0.9	1,407.5	8.5	180.6	0.3	2.0	284.2	667.5	0.5	4.0	28.2	0.1	15.6
Mean	8,424.6	554.7	0.6	1,091.1	5.4	129.5	0.2	1.6	198.6	521.3	0.4	2.2	20.7	0.04	11.7
Variance	14,636,567.0	79,394.5	0.3	472,841.0	20.9	5,892.8	0.04	1.4	10,999.0	74,429.5	0.1	5.3	69.6	0.003	21.6
Stdev	3,825.8	281.8	0.6	687.6	4.6	76.8	0.2	1.2	104.9	272.8	0.3	2.3	8.3	0.1	4.7
Skewness	0.7	0.8	1.6	1.0	0.7	0.7	0.8	1.1	0.3	1.1	1.9	0.7	0.6	1.4	0.6
Kurtosis	-0.2	-0.3	2.7	0.7	-0.2	-0.5	-0.3	0.3	-1.1	0.3	3.2	-0.9	-0.8	1.7	-0.2

	LSK	ZEC	BCN	BTS	SC	STRAT	DOGE	VERI	NEO	BTM.	STEEM	DGD	DCR	WAVES	AE
nobs	273	273	273	273	273	273	273	273	273	273	273	273	273	273	273
Minimum	2	161.9	0.001	0.04	0.003	2.8	0.001	6.1	0	0	0.8	58.1	23.4	0	0.2
Maximum	40.1	757.2	0.02	0.9	0.1	21.9	0.02	459.7	188.6	1.2	8.0	558.5	121.8	17.2	5.0
1. Quartile	6.0	228.9	0.001	0.1	0.01	4.1	0.001	89.3	30.1	0.1	1.1	76.1	31	4.3	0.4
3. Quartile	19.0	399.9	0.005	0.3	0.02	8.1	0.01	244.6	85.1	0.4	3.4	241.5	77.9	7.5	1.9
Mean	12.2	322.6	0.003	0.2	0.02	7.1	0.004	170.3	62.3	0.3	2.4	174.4	56.0	6.6	1.3
Variance	69.8	16,612.0	0.000	0.03	0.000	16.4	0.000	12,194.3	1,570.7	0.1	2.4	13,149.8	707.3	11.4	0.8
Stdev	8.4	128.9	0.003	0.2	0.02	4.1	0.003	110.4	39.6	0.3	1.6	114.7	26.6	3.4	0.9
Skewness	0.9	1.2	1.9	1.7	1.9	1.4	1.4	1.0	0.8	1.2	1.1	1.0	0.6	1.3	0.9
Kurtosis	-0.2	0.7	4.8	2.4	4.0	1.4	2.1	-0.4	-0.4	1.3	0.5	0.3	-0.9	0.8	0.8

	SNT	KMD	REP	ARDR	ARK	DGB	PIVX	FCT	MONA	BNB	ZRX	LRC	HSR	WTC	SUB
nobs	273	273	273	273	273	273	273	273	273	273	273	273	273	273	273
Minimum	0.03	0.9	15.7	0.1	0.6	0.001	1.7	11.7	0.4	0	0	0	0	0	0
Maximum	0.6	11.5	105.5	2.9	10.3	0.1	13.8	75.4	14.9	22.8	2.3	2.2	37.2	42.2	3.2
1. Quartile	0.04	2.0	19.9	0.2	2.5	0.001	3.2	19.1	0.8	1.3	0.2	0.1	6.4	4.9	0
3. Quartile	0.2	4.1	46.4	0.5	4.1	0.04	5.7	30.8	5.6	10.9	0.9	0.6	14.7	14.9	0.7
Mean	0.1	3.6	37.3	0.5	3.6	0.03	5.0	27.6	4.3	6.3	0.6	0.4	11.1	10.7	0.5
Variance	0.01	5.7	504.8	0.3	3.3	0.001	7.7	157.3	13.2	32.9	0.3	0.1	53.8	77.8	0.3
Stdev	0.1	2.4	22.5	0.5	1.8	0.03	2.8	12.5	3.6	5.7	0.5	0.4	7.3	8.8	0.5
Skewness	2.0	1.6	1.3	2.0	1.2	1.5	1.4	1.6	1.2	0.6	1.2	1.4	0.7	1.0	2.0
Kurtosis	4.1	1.8	0.7	3.7	1.0	2.5	1.1	2.4	1.1	-0.7	0.8	2.5	0.9	0.8	5.0

Appendix 2 (Cont.)

	GAS	FUN	SYS	KNC	GBYTE	SKY	RDD	NXT	XZC	MAID	BNT	STORJ	PAY	CND	EMC
nobs	273	273	273	273	273	273	273	273	273	273	273	273	273	273	273
Min	0	0.000	0.1	0.9	149.1	2.1	0.001	0.1	3	0.2	1.3	0.3	0.9	0	0.4
Max	87.2	0.2	1.0	20.5	1,177.5	50.5	0.03	1.7	135.1	1.2	10.7	2.6	5.1	0.3	9.4
1. Q.	16.7	0.02	0.2	1.2	216.6	3.7	0.001	0.1	3	0.4	2.3	0.5	1.6	0.02	0.8
3. Q.	31.5	0.1	0.6	3.9	460.9	17.7	0.01	0.2	53.6	0.6	4.8	1.1	2.7	0.1	3.5
Mean	24.5	0.04	0.4	3.8	376.3	13.0	0.01	0.2	37.0	0.5	3.6	0.9	2.3	0.1	2.3
Variance	253.3	0.001	0.05	16.4	44,479.7	125.5	0.000	0.1	1,071.5	0.04	3.3	0.2	1.0	0.004	3.4
Stdev	15.9	0.04	0.2	4.1	210.9	11.2	0.01	0.3	32.7	0.2	1.8	0.5	1.0	0.1	1.9
Skewness	0.7	2.1	0.6	1.7	1.1	1.3	1.7	3.0	0.9	1.5	1.3	1.3	0.9	1.2	1.1
Kurtosis	0.7	5.9	-0.8	1.8	0.3	1.2	3.2	11.0	0.2	1.9	1.3	1.6	-0.1	1.1	1.1

	ZEN	NXS	ICN	CVC	VTC	MANA	PART	BOS	GAME	UBQ	GNO	BLOCK	MTL	MCO	SAN
nobs	273	273	273	273	273	273	273	273	273	273	273	273	273	273	273
Min	4.0	0.9	0.7	0.2	0.4	0.01	5.3	0.1	0.9	1.1	55.1	10.9	3.1	0.9	0.2
Max	61.6	12.7	5.4	1.4	9.4	0.3	47.7	5.9	6.6	6.9	407.1	55.9	13.5	22.9	7.6
1. Q.	9.2	1.4	1.3	0.3	1.2	0.02	8.0	0.4	1.8	1.4	86.3	18.8	4.3	6.3	0.3
3. Q.	37.5	3.1	2.3	0.5	4.4	0.1	20.0	1.2	2.5	2.7	176.1	30.4	8.2	11.9	2.3
Mean	25.6	2.7	1.8	0.4	3.3	0.1	14.3	1.1	2.4	2.4	139.3	25.1	6.3	9.3	1.7
Variance	217.2	4.4	0.7	0.05	5.3	0.004	68.7	1.1	1.1	1.7	4,927.2	91.1	5.6	17.3	3.1
Stdev	14.7	2.1	0.8	0.2	2.3	0.1	8.3	1.0	1.1	1.3	70.2	9.5	2.4	4.2	1.8
Skewness	0.2	2.7	1.3	1.8	0.8	0.6	1.2	2.0	1.7	1.5	1.5	1.0	0.7	0.7	1.6
Kurtosis	-1.0	8.4	1.6	2.9	-0.3	0.3	1.1	4.1	2.8	1.6	2.6	0.5	-0.5	0.1	1.9

	POE	BTX	ANT	PLR	NAV	BTCD	ION	ADX	PPC	XBY	RLC	XDN	QRL	EDG	SLS
nobs	273	273	273	273	273	273	273	273	273	273	273	273	273	273	273
Min	0	0.8	1.1	0.05	0.2	39.4	0.9	0.1	1.2	0.01	0	0.001	0.3	0.4	9.8
Max	0.2	40.3	7.7	1.6	4.8	375.9	7.2	3.3	11.0	0.8	4	0.1	4.0	2.9	120.5
1. Q.	0.01	5.6	1.9	0.1	0.8	75.2	1.4	0.8	1.6	0.02	0	0.002	0.6	0.6	14.5
3. Q.	0.1	22.8	4.0	0.5	1.8	129.8	2.9	1.4	3.5	0.2	1.4	0.02	1.3	1.0	60.6
Mean	0.04	13.2	3.1	0.4	1.4	119.1	2.2	1.2	2.8	0.1	0.9	0.01	1.1	1.0	39.7
Variance	0.002	91.3	2.1	0.2	0.9	5,607.7	1.0	0.4	3.1	0.02	0.8	0.000	0.4	0.3	772.1
Stdev	0.04	9.6	1.5	0.4	1.0	74.9	1.0	0.6	1.8	0.2	0.9	0.01	0.7	0.6	27.8
Skewness	1.9	0.6	0.9	1.3	1.2	1.9	1.2	1.3	1.9	2.1	1.5	1.5	1.5	1.8	0.7
Kurtosis	3.9	-1.1	-0.04	0.3	0.9	3.0	2.4	1.6	4.3	4.8	2.9	2.1	2.4	2.2	-0.7

Appendix 3. Results of VAR(1) daily model

	Dependent variable:																						
	BTC (1)	ETH (2)	XRP (3)	BCH (4)	LTC (5)	XEM (6)	XLM (7)	IOT (8)	DASH (9)	XMR (10)	ETC (11)	LSK (12)	XVG (13)	ZEC (14)	BCN (15)	SC (16)	VEN (17)	STRAT (18)	BTS (19)	VERI (20)	EOS (21)	OMG (22)	DOGE (23)
BTC.l1	0.084	-0.0004	-0.207	-0.302	0.222	0.620^{***}	0.162	0.434^{**}	-0.141	0.030	0.140	-0.280	-0.646	-0.081	0.011	0.107	0.301	0.137	-0.045	1.098^{*}	0.160	-0.114	-0.079
ETH.l1	0.003	0.095	0.362	0.731^{**}	-0.088	0.407	-0.088	-0.020	0.069	0.286	0.141	-0.238	0.644	0.259	0.288	0.133	0.218	0.340	0.094	-1.586^{**}	0.226	-0.125	0.103
XRP.l1	-0.046	-0.086	0.088	-0.115	-0.082	-0.060	0.006	-0.191^{*}	-0.138^{*}	-0.128	-0.142^{*}	-0.077	-0.038	-0.154^{**}	-0.111	-0.194^{*}	-0.026	-0.244^{**}	0.044	0.132	-0.101	-0.183^{*}	-0.157
BCH.l1	-0.103^{**}	-0.018	-0.044	0.247^{**}	-0.035	-0.015	-0.102	0.042	0.059	0.017	0.031	0.014	0.182	0.056	-0.241^{***}	-0.033	-0.015	-0.122	-0.010	0.443^{*}	0.020	-0.167^{*}	-0.104
LTC.l1	-0.027	0.126	0.130	-0.007	0.134	-0.250	0.049	-0.198	0.072	0.007	0.062	0.012	0.880^{***}	0.087	-0.182	0.133	-0.545^{***}	-0.197	0.159	0.142	0.283^{*}	0.185	0.141
XEM.l1	-0.073	0.057	-0.081	-0.053	0.134^{*}	-0.289^{***}	-0.076	0.041	0.007	-0.045	0.013	-0.084	-0.409^{**}	-0.051	-0.027	0.012	0.047	0.014	0.006	-0.048	-0.163^{*}	0.103	-0.080
XLM.l1	0.006	0.001	-0.021	0.067	-0.022	0.021	0.199^{*}	0.067	0.005	0.004	0.094	-0.028	0.244	0.017	-0.082	0.010	0.087	0.111	0.069	-0.014	-0.002	0.038	-0.019
IOT.l1	0.036	-0.134^{**}	-0.164	-0.016	-0.172^{**}	-0.110	-0.082	0.098	0.010	0.019	-0.194^{**}	0.009	0.058	-0.096	-0.048	-0.133	-0.124	-0.132	-0.001	-0.188	-0.052	-0.181^{*}	-0.025
DASH.l1	0.059	0.081	0.227	0.157	0.235^{*}	0.199	0.356	0.035	-0.107	-0.036	0.199	0.263	-0.122	-0.077	0.220	0.161	0.430^{*}	0.039	0.070	1.128^{**}	0.006	0.173	0.136
XMR.l1	-0.041	-0.027	0.158	-0.039	-0.051	-0.088	-0.139	-0.071	0.083	-0.018	-0.183	0.144	-0.060	0.029	-0.050	-0.026	-0.271	-0.077	-0.118	-1.478^{***}	-0.071	-0.266	-0.024
ETC.l1	-0.025	-0.110	-0.263	-0.252	-0.012	-0.126	0.008	-0.001	0.106	-0.067	-0.101	0.069	-0.705^{**}	-0.090	-0.062	-0.190	0.178	-0.058	-0.165	-0.163	-0.095	-0.013	-0.186
LSK.l1	-0.052	-0.120^{**}	-0.048	-0.025	-0.047	-0.064	0.026	-0.038	-0.059	0.150^{*}	-0.142^{*}	-0.100	0.079	-0.035	-0.086	-0.068	-0.041	0.084	0.010	0.428	-0.031	-0.194^{*}	-0.105
XVG.l1	0.023	0.010	0.030	0.016	0.030	0.070^{*}	0.070	-0.006	0.041	0.021	0.076^{**}	0.089^{**}	-0.177^{**}	0.059^{*}	0.070^{*}	0.077^{*}	0.042	0.082^{*}	0.084^{*}	0.009	0.047	0.080^{*}	0.050
ZEC.l1	-0.062	0.062	-0.170	-0.365	0.012	-0.035	-0.336	-0.257	-0.164	-0.252	0.003	0.007	-0.782^{*}	-0.093	-0.273	-0.215	-0.198	-0.160	-0.044	-0.146	-0.015	0.178	-0.090
BCN.l1	0.145^{**}	0.123^{*}	0.086	0.051	0.197^{**}	0.161	0.119	0.084	0.044	0.058	0.131	0.178	0.140	0.155^{*}	0.060	0.112	-0.022	-0.091	0.109	0.011	0.090	0.144	0.135
SC.l1	-0.108^{*}	-0.033	0.057	-0.133	-0.045	0.008	-0.109	0.187	-0.050	0.029	-0.051	0.106	-0.189	0.022	0.228^{*}	0.042	0.253	0.128	-0.049	0.416	-0.046	-0.001	0.146
VEN.l1	0.022	-0.019	-0.025	-0.056	0.047	0.056	-0.084	0.014	-0.044	-0.059	-0.017	0.059	0.011	-0.022	-0.013	0.033	-0.138	-0.115^{*}	-0.012	-0.021	0.086	0.017	0.014
STRAT.l1	0.024	0.030	-0.068	-0.012	0.096	0.135	-0.055	-0.097	-0.018	-0.053	0.058	-0.091	-0.047	-0.044	0.005	-0.010	0.135	-0.223^{**}	-0.069	0.339	-0.145^{*}	0.033	0.008
BTS.l1	0.134^{**}	0.030	-0.002	0.051	0.025	0.080	-0.043	0.065	0.063	0.131	0.028	0.025	0.510^{**}	0.024	0.207^{*}	0.113	-0.061	0.202	-0.009	0.340	0.259^{**}	0.089	0.203^{*}
VERI.l1	-0.007	-0.005	-0.014	0.039^{*}	-0.021	-0.013	0.001	-0.003	0.004	-0.004	-0.016	0.012	-0.046	-0.005	-0.020	-0.018	0.008	-0.042^{*}	-0.018	-0.251^{***}	-0.023	-0.048^{**}	-0.012
EOS.l1	0.061	-0.043	0.093	0.009	-0.140^{*}	-0.116	0.025	0.021	0.018	0.004	0.033	0.032	0.178	0.049	0.009	0.077	-0.027	-0.080	0.047	-0.115	-0.025	-0.030	0.061
OMG.l1	-0.031	0.113^{*}	0.027	-0.033	0.036	-0.030	0.144	0.201^{*}	0.009	0.018	0.109	0.074	-0.114	0.098	-0.037	0.059	0.111	0.106	0.149	0.410	0.047	0.118	0.011
DOGE.l1	-0.116	-0.130	-0.038	0.090	-0.280^{**}	-0.236	-0.073	-0.377^{**}	-0.084	-0.212^{*}	-0.216^{*}	-0.077	0.244	-0.148	-0.071	-0.261	-0.128	0.089	-0.262^{*}	-0.678	-0.235	-0.231	-0.235
const	0.015	-0.002	-0.004	0.005	-0.006	-0.014	-0.018	0.004	0.014	0.011	-0.008	0.015	0.016	0.002	0.007	-0.028	-0.010	-0.016	-0.021	-0.071	-0.030^{*}	0.035^{*}	-0.009
trend	-0.0001	0.0001	0.0002	0.00002	0.0002	0.0002	0.0004^{*}	0.0001	-0.00003	0.00001	0.0001	-0.00004	0.00002	0.00004	0.0001	0.0004^{**}	0.0004	0.0003	0.0003	0.001	0.0004^{**}	-0.0002	0.0002
Observations	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169
R^2	0.197	0.189	0.152	0.152	0.187	0.249	0.109	0.173	0.120	0.121	0.209	0.172	0.218	0.138	0.198	0.155	0.153	0.218	0.104	0.267	0.191	0.209	0.156
Adjusted R^2	0.063	0.054	0.011	0.011	0.051	0.124	-0.040	0.035	-0.027	-0.026	0.077	0.033	0.088	-0.005	0.064	0.014	0.012	0.088	-0.045	0.145	0.056	0.077	0.016
Residual Std. Error (df = 144)	0.055	0.059	0.103	0.121	0.082	0.103	0.130	0.109	0.075	0.083	0.084	0.106	0.211	0.078	0.104	0.114	0.142	0.115	0.107	0.323	0.099	0.108	0.098
F Statistic (df = 24; 144)	1.472^{*}	1.400	1.079	1.077	1.378	1.992^{***}	0.732	1.251	0.815	0.823	1.586^{*}	1.243	1.675^{**}	0.962	1.481^{*}	1.102	1.084	1.676^{**}	0.699	2.183^{***}	1.416	1.588^{*}	1.111

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix 4. Results of VAR(2) hourly model

	Dependent variable:																						
	BTC	ETH	XRP	BCH	LTC	XEM	XLM	IOT	DASH	XMR	ETC	LSK	XVG	ZEC	BCN	SC	VEN	STRAT	BTS	VERI	EOS	OMG	DOGE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
BTC.l1	-0.086**	-0.083**	-0.094	0.066	-0.135***	-0.136**	-0.167**	-0.106	-0.125**	-0.080	-0.107*	-0.082	-0.054	-0.135***	-0.094	-0.196**	0.095	-0.057	-0.280***	-0.165	-0.081	-0.195***	-0.023
ETH.l1	-0.037	-0.086**	0.104	-0.040	0.097**	0.043	0.094	-0.004	0.083*	0.061	0.068	0.077	0.161	0.135***	0.056	0.118	-0.031	0.145	0.079	1.768**	0.067	0.160***	0.117*
XRP.l1	-0.018	-0.022	-0.104***	0.005	-0.043**	0.014	0.101***	-0.010	-0.019	-0.028	0.004	-0.040	-0.059	-0.020	-0.043	-0.053	-0.009	-0.046	0.068**	-0.564*	0.021	-0.024	-0.023
BCH.l1	0.009	0.012	-0.012	-0.024	0.013	0.002	-0.030	0.013	0.073***	0.029	0.051**	-0.018	-0.040	0.042**	0.020	0.019	0.013	-0.064*	0.033	-0.031	-0.012	0.020	0.020
LTC.l1	-0.023	0.109***	0.021	0.014	0.007	0.122**	0.034	-0.063	0.042	0.036	0.056	0.099*	-0.111	0.007	0.087*	-0.030	-0.069	0.056	0.028	-0.277	0.050	0.025	-0.053
XEM.l1	0.054***	0.0002	0.027	0.011	0.023	-0.105***	0.032	0.095***	0.017	0.039*	0.019	-0.023	0.171**	0.042**	0.077***	0.041	0.068	0.038	0.008	0.534*	0.047	0.048*	0.032
XLM.l1	-0.006	0.006	-0.027	-0.018	-0.011	0.008	-0.189***	0.027	0.004	0.0004	-0.016	-0.007	0.037	-0.013	-0.005	-0.030	-0.023	0.037	0.018	0.081	-0.004	0.001	0.009
IOT.l1	0.032**	-0.008	-0.002	-0.027	0.019	0.045*	0.065**	-0.094***	0.005	0.016	0.016	-0.023	0.052	0.008	0.006	0.034	0.0002	0.022	0.030	0.066	-0.012	-0.010	0.028
DASH.l1	0.029	0.012	0.040	-0.049	0.073**	0.061	0.067	0.081	-0.080**	0.122***	-0.045	-0.044	0.034	0.077**	0.012	0.007	-0.008	0.055	0.049	-0.180	0.018	0.006	0.047
XMR.l1	0.044	-0.005	0.008	-0.102**	-0.020	0.005	0.006	0.019	-0.020	-0.221***	-0.056	0.161***	0.372***	0.003	-0.018	0.035	0.276***	-0.022	0.001	-0.180	-0.030	0.006	0.034
ETC.l1	-0.031	-0.011	-0.043	0.046	0.009	-0.059	0.001	0.027	-0.011	0.006	-0.107***	-0.018	-0.215*	-0.011	-0.030	-0.068	-0.107	-0.046	-0.058	0.338	-0.023	-0.019	-0.033
LSK.l1	-0.019*	-0.012	-0.007	-0.013	-0.027*	-0.036*	-0.021	-0.062***	-0.036**	-0.041***	-0.013	-0.196***	0.030	-0.031**	-0.029	-0.029	0.043	-0.025	-0.021	0.020	-0.045**	-0.002	-0.077***
XVG.l1	0.001	-0.001	0.002	0.001	-0.004	-0.001	0.002	0.008	0.007	-0.003	0.0001	0.006	-0.277***	0.001	0.007	0.008	0.006	0.005	0.007	-0.017	0.004	0.005	0.008
ZEC.l1	-0.004	0.021	0.114***	0.068	-0.002	-0.051	-0.031	0.043	-0.023	0.012	0.037	0.090*	-0.347***	-0.139***	-0.023	0.099*	-0.135	0.002	0.029	-0.699	0.066	0.064	0.057
BCN.l1	0.006	0.014	0.009	-0.036	-0.001	0.012	0.008	0.009	-0.010	-0.001	-0.006	0.036	0.103	-0.007	-0.175***	0.046	0.059	0.005	-0.024	0.371	-0.051*	0.025	0.031
SC.l1	-0.028**	0.005	-0.023	0.016	0.011	-0.016	0.008	0.009	0.016	0.002	0.010	0.011	0.003	0.008	0.018	-0.174***	0.117**	0.032	-0.021	-0.211	0.004	0.027	0.070***
VEN.l1	-0.008	0.003	0.008	0.007	0.002	-0.020	-0.008	0.002	0.005	0.002	0.027***	-0.001	-0.002	0.011	0.005	0.004	-0.414***	-0.021	-0.017	-0.108	0.011	0.002	-0.016
STRAT.l1	-0.002	-0.008	-0.012	-0.002	-0.007	0.005	-0.016	-0.017	-0.012	-0.003	0.010	-0.004	-0.080	0.007	0.008	0.019	-0.023	-0.262***	-0.009	-0.171	-0.012	-0.002	0.012
BTS.l1	-0.049***	-0.054***	-0.078***	0.002	-0.043*	-0.044	-0.011	-0.065*	-0.064***	-0.031	-0.044*	-0.058	0.028	-0.023	-0.037	-0.050	0.027	-0.043	-0.111***	0.559*	-0.032	-0.074***	-0.086***
VERI.l1	0.001	-0.001	0.002	-0.001	-0.001	-0.001	-0.002	-0.002	-0.0003	-0.00001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	0.0002	-0.002	-0.003	-0.663***	-0.001	-0.002	0.0002
EOS.l1	0.019	0.028*	0.032	0.011	0.005	0.038	-0.0005	0.038	0.023	0.014	0.004	-0.004	0.147*	0.027	0.029	0.009	0.056	0.027	0.052*	-0.160	-0.039	0.025	0.003
OMG.l1	0.034*	0.034	0.019	0.060	0.042	0.075**	0.043	0.020	0.098***	0.069**	0.058*	0.018	-0.016	0.047*	0.069*	0.109**	0.197***	0.149***	0.086**	-0.488	0.062	-0.134***	0.006
DOGE.l1	0.006	0.005	0.008	-0.026	-0.018	-0.024	0.008	-0.032	-0.014	-0.030	-0.002	0.096**	0.142	-0.035	0.152***	0.055	0.039	0.006	0.016	0.290	-0.061*	-0.011	-0.121***
BTC.l2	0.024	0.032	0.015	-0.069	0.085*	-0.120*	0.066	-0.048	0.006	0.034	0.013	0.197**	0.035	-0.027	0.027	0.043	-0.024	-0.088	0.025	-1.317*	0.062	0.0002	-0.014
ETH.l2	-0.106***	-0.187***	-0.084	-0.055	-0.115**	-0.203***	-0.237***	-0.177**	0.009	-0.099**	-0.063	-0.162**	-0.006	-0.096*	-0.169**	-0.093	-0.052	-0.097	-0.148**	0.350	-0.090	-0.045	-0.031
XRP.l2	-0.029*	-0.028	-0.005	-0.005	-0.020	-0.020	0.070**	-0.063*	-0.023	-0.028	-0.004	0.079**	-0.054	-0.023	-0.028	-0.008	0.049	-0.063	0.004	-0.193	-0.009	-0.028	-0.047*
BCH.l2	0.020	0.007	0.023	-0.085***	-0.017	0.022	0.020	0.022	0.020	0.027	-0.006	-0.014	0.006	0.018	0.013	-0.012	0.051	-0.007	0.021	-0.106	0.048*	-0.006	0.029
LTC.l2	-0.021	-0.001	-0.065	-0.035	-0.078**	0.012	-0.037	-0.043	-0.018	-0.041	0.004	-0.055	-0.195	-0.043	-0.035	0.002	0.001	-0.085	-0.026	0.026	-0.033	-0.115***	0.017
XEM.l2	0.033**	0.015	0.043	0.059**	0.027	0.104***	0.070**	0.052	0.008	0.041*	0.033	-0.059*	0.077	0.035*	0.023	0.067**	0.061	0.087**	0.036	0.297	0.005	0.051**	0.067***
XLM.l2	0.009	0.035**	0.011	0.043	0.035*	0.029	-0.014	0.057*	0.032	0.020	0.014	-0.009	0.079	0.054**	-0.018	0.039	0.109**	0.070*	0.038	-0.348	0.034	0.035	0.037
IOT.l2	0.004	-0.004	-0.001	0.004	-0.002	-0.010	0.013	-0.060**	-0.011	0.0003	-0.027	0.024	0.052	0.004	-0.009	-0.023	-0.072	0.045	0.023	-0.104	0.027	-0.019	-0.004
DASH.l2	-0.005	0.056**	-0.022	0.188***	0.006	-0.030	-0.002	0.044	-0.056*	0.015	0.042	0.013	0.020	0.092***	0.050	0.021	0.022	0.111*	0.019	-0.552	0.016	0.006	0.004
XMR.l2	0.020	-0.037	-0.043	0.010	-0.023	0.006	0.053	-0.005	-0.016	-0.091**	-0.039	-0.001	0.220	-0.029	-0.001	-0.057	0.036	0.016	-0.016	0.125	0.014	-0.039	0.017
ETC.l2	-0.013	0.001	-0.044	0.029	-0.0002	-0.018	0.005	0.013	-0.015	0.007	-0.096***	-0.092*	0.029	0.003	-0.035	-0.111**	-0.088	-0.033	-0.040	0.092	0.005	0.037	-0.051
LSK.l2	-0.006	-0.011	0.012	-0.038*	-0.016	-0.006	-0.023	-0.015	-0.007	-0.014	-0.014	-0.041*	0.032	-0.022	0.022	0.024	-0.005	0.027	-0.013	-0.050	-0.026	-0.021	-0.001
XVG.l2	-0.003	-0.003	0.004	0.002	-0.008	-0.0003	-0.010	-0.016*	0.003	-0.001	-0.007	-0.007	-0.139***	0.004	0.004	-0.017*	-0.019	-0.008	0.009	0.029	0.005	-0.001	0.001
ZEC.l2	0.012	0.025	0.001	0.015	0.025	-0.022	-0.033	-0.007	-0.009	0.033	0.032	0.223***	0.039	-0.100***	-0.002	0.041	-0.057	-0.062	-0.019	-0.074	-0.061	0.066	-0.002

Appendix 4 (Cont.)

BCN.l2	-0.013	-0.038**	-0.032	0.012	-0.016	-0.001	-0.093***	-0.005	-0.034	-0.034	-0.014	-0.040	-0.111	-0.016	-0.157***	-0.054	-0.007	-0.050	-0.050*	0.396	-0.038	-0.045*	-0.028
SC.l2	-0.024*	-0.015	-0.016	-0.017	-0.014	-0.018	0.016	0.019	0.0002	-0.004	-0.005	-0.007	-0.024	-0.008	0.027	-0.064**	0.017	-0.048	0.002	-0.032	-0.028	-0.013	0.017
VEN.l2	-0.006	-0.012*	-0.006	-0.027**	-0.019**	-0.025**	-0.033**	-0.014	-0.008	-0.009	-0.011	-0.015	0.058*	-0.004	-0.008	-0.035**	-0.175***	-0.038**	-0.026**	0.017	-0.007	-0.012	-0.018
STRAT.l2	0.005	0.002	0.036*	-0.008	0.024*	0.032	0.007	0.020	0.017	0.017	0.015	0.017	-0.065	0.009	0.021	0.016	0.053	-0.077***	0.019	0.185	-0.011	0.015	0.017
BTS.l2	0.028*	0.006	-0.002	-0.006	0.027	0.041	0.035	0.028	0.010	0.047**	0.003	0.026	0.038	0.032	0.059*	0.094***	-0.076	-0.005	-0.059*	0.473	0.013	0.003	0.027
VERI.l2	-0.001	-0.001	-0.001	-0.003*	-0.001	-0.001	0.0004	-0.002	-0.001	-0.0005	-0.001	0.0001	0.001	-0.001	-0.002	-0.003	-0.001	-0.001	-0.001	-0.325***	-0.001	-0.002	-0.0001
EOS.l2	-0.014	-0.007	-0.012	-0.007	-0.011	-0.003	0.005	0.018	-0.001	0.007	-0.009	0.008	-0.027	0.028	-0.004	0.004	0.016	0.029	-0.005	0.005	-0.055*	0.014	-0.032
OMG.l2	-0.009	0.013	0.010	-0.048	-0.030	0.009	-0.045	-0.003	0.009	-0.028	0.026	0.018	-0.142	-0.039	0.018	-0.062	-0.009	0.105**	-0.032	0.575	0.004	-0.036	-0.027
DOGE.l2	-0.002	0.011	0.048	-0.007	0.006	-0.00005	0.00003	0.008	-0.004	-0.006	0.0002	-0.020	-0.050	0.002	0.109***	0.096**	-0.016	-0.013	0.071**	-0.145	0.042	0.018	-0.023
const	0.001*	0.001	0.001	0.003**	0.001	0.001	0.001	0.003*	0.002*	0.001	0.002*	0.001	0.001	0.0003	0.0002	0.001	0.0002	0.0003	0.002*	0.003	0.003**	0.0005	0.002
trend	-0.00000	0.00000	0.00000	-0.00000*	-0.00000	0.00000	0.00000	-0.00000	-0.00000	-0.00000	-0.00000	0.00000	0.00000	-0.00000	0.00000	0.00000	0.00000	0.00000	-0.00000	-0.00000	-0.00000	-0.000	-0.00000
Observations	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997
R^2	0.053	0.053	0.040	0.038	0.048	0.050	0.057	0.041	0.050	0.056	0.040	0.078	0.099	0.053	0.066	0.063	0.172	0.082	0.051	0.337	0.029	0.044	0.050
Adjusted R^2	0.030	0.030	0.017	0.015	0.025	0.027	0.034	0.018	0.027	0.033	0.017	0.056	0.077	0.030	0.043	0.040	0.152	0.060	0.028	0.321	0.005	0.021	0.027
Residual Std. Error (df = 1949)	0.016	0.017	0.027	0.028	0.021	0.029	0.031	0.032	0.021	0.022	0.024	0.034	0.080	0.021	0.029	0.034	0.055	0.038	0.029	0.310	0.030	0.026	0.026
F Statistic (df = 47; 1949)	2.307***	2.331***	1.728***	1.646***	2.094***	2.180***	2.492***	1.765***	2.168***	2.451***	1.724***	3.527***	4.556***	2.299***	2.917***	2.781***	8.586***	3.722***	2.235***	21.085***	1.235	1.913***	2.184***

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix 5. Results of VAR(2) 5-minutes model

	Dependent variable:																						
	BTC (1)	ETH (2)	XRP (3)	BCH (4)	LTC (5)	XEM (6)	XLM (7)	IOT (8)	DASH (9)	XMR (10)	ETC (11)	LSK (12)	XVG (13)	ZEC (14)	BCN (15)	SC (16)	VEN (17)	STRAT (18)	BTS (19)	VERI (20)	EOS (21)	OMG (22)	DOGE (23)
BTC.l1	0.102	0.342	0.089	0.183	0.202	0.573	0.834**	0.503	0.228	0.289*	0.368*	0.273	0.530	0.231	0.017	0.335	1.085**	0.279	0.191	0.352	0.500*	0.255	0.331
ETH.l1	0.098	-0.183	0.129	0.122	0.201	0.250	0.126	-0.021	0.251**	0.274***	0.215*	-0.309	-0.074	0.197*	0.186	0.213	0.335	0.110	0.462***	-0.157	0.234	0.318**	0.259
XRP.l1	0.076	0.121**	-0.035	0.107**	0.073	0.126	0.132	0.136	0.040	0.108**	0.098*	0.003	0.582***	0.130***	-0.046	0.093	0.053	0.165***	0.211***	0.063	0.161**	0.115*	0.111
BCH.l1	-0.011	-0.081	-0.019	0.032	0.007	-0.256	0.070	0.205	-0.068	-0.083	0.064	-0.071	-0.393	0.037	-0.068	0.220	-0.274	-0.135	-0.066	-0.442	-0.121	0.025	-0.182
LTC.l1	-0.195**	-0.143	-0.200	-0.176*	-0.310**	-0.028	-0.053	-0.368**	-0.164*	-0.217**	-0.209**	0.112	-0.415	-0.182**	-0.108	-0.358**	0.025	-0.090	-0.280**	0.015	-0.212	-0.310**	-0.165
XEM.l1	-0.065**	-0.092**	-0.141**	-0.062*	-0.086*	-0.186***	-0.091	-0.081	-0.040	-0.074**	-0.059	-0.108	-0.087	-0.039	-0.077	-0.077	0.045	-0.059	-0.007	-0.024	-0.040	-0.052	-0.090*
XLM.l1	-0.018	-0.012	-0.091	-0.071**	-0.046	-0.098	-0.474***	-0.034	-0.005	-0.084***	-0.048	-0.0002	-0.149	-0.052*	-0.052	-0.067	0.013	-0.088**	-0.007	0.064	-0.081	-0.025	-0.064
IOT.l1	0.002	-0.002	0.033	0.037	0.033	-0.029	-0.173*	-0.371***	0.020	0.013	0.011	-0.0005	0.009	-0.051	0.116	0.096	-0.021	0.036	-0.156**	0.250*	-0.036	-0.012	0.069
DASH.l1	-0.115	-0.131	-0.016	-0.106	-0.247*	-0.137	-0.190	-0.161	-0.103	0.003	-0.162	-0.358	0.032	-0.060	0.215	0.137	0.047	-0.086	-0.056	-0.059	-0.249*	0.007	0.152
XMR.l1	0.022	-0.009	-0.110	-0.020	0.050	0.064	0.100	-0.055	0.046	-0.031	0.092	-0.077	0.159	0.025	-0.205	-0.021	-0.223	0.052	-0.025	-0.568*	0.045	0.075	0.135
ETC.l1	0.203**	0.241*	0.338*	0.136	0.415***	0.123	0.117	0.258	0.032	0.112	0.086	0.269	-0.210	0.160*	0.175	0.042	-0.070	0.247**	0.312**	-0.037	0.452***	0.114	0.175
LSK.l1	-0.014	-0.001	-0.010	-0.012	-0.012	0.018	-0.023	-0.001	-0.005	-0.017	-0.005	0.001	-0.024	-0.034*	-0.019	-0.026	0.012	-0.023	-0.044	-0.025	-0.020	-0.026	-0.019
XVG.l1	0.003	-0.003	-0.020	-0.004	0.009	-0.041	-0.055*	-0.027	-0.003	-0.003	-0.017	0.021	-0.242***	0.003	-0.010	-0.007	-0.011	-0.017	-0.012	-0.007	0.0003	-0.001	0.00004
ZEC.l1	0.055	0.074	0.090	-0.012	0.057	0.289	0.071	0.041	0.019	-0.004	-0.032	0.088	0.230	-0.130	0.039	-0.132	-0.431*	0.148	0.083	0.294	-0.049	0.127	0.096
BCN.l1	-0.045	-0.038	-0.047	-0.014	-0.087	-0.022	0.197**	-0.142*	-0.026	-0.035	-0.009	-0.009	-0.176	0.029	-0.208***	-0.023	0.032	0.046	-0.036	0.083	-0.066	-0.035	-0.057
SC.l1	-0.116**	-0.081	-0.101	-0.109**	-0.092	-0.177*	0.112	-0.101	-0.125***	-0.057	-0.114**	0.073	-0.130	-0.089**	-0.166**	-0.360***	-0.083	-0.133**	-0.145**	-0.105	-0.131*	-0.117*	-0.111
VEN.l1	-0.006	-0.002	0.006	-0.007	-0.011	-0.036	-0.056	-0.013	0.011	-0.012	-0.009	0.012	0.060	-0.003	0.052	-0.0003	-0.345***	-0.015	-0.014	-0.057	-0.013	-0.015	-0.019
STRAT.l1	-0.077	-0.111	-0.136	-0.068	-0.149*	-0.090	0.058	-0.022	-0.073	-0.026	-0.044	0.022	0.141	0.004	-0.174*	-0.189*	0.099	-0.404***	-0.111	-0.009	-0.146	-0.086	-0.157*
BTS.l1	0.015	0.083	0.214*	0.066	0.019	0.126	0.118	0.134	0.088*	0.015	0.011	0.080	0.222	0.057	-0.020	0.125	0.002	0.173**	-0.078	0.121	-0.017	0.058	0.096
VERI.l1	0.025	0.047*	0.067*	0.029	0.035	0.002	0.051	0.038	0.016	0.003	0.024	0.048	0.045	0.020	0.072**	0.036	-0.009	0.077***	0.023	-0.073	0.049	-0.015	0.063**
EOS.l1	0.036	0.022	0.132	0.049	-0.004	0.003	-0.060	0.021	0.052	-0.002	0.031	0.281	0.220	-0.013	0.191	0.014	-0.259	-0.016	0.035	0.084	-0.255**	0.049	0.018
OMG.l1	0.012	0.003	0.023	0.082	-0.006	-0.116	0.113	-0.035	0.042	0.132**	0.023	-0.385**	0.189	0.028	0.094	0.199*	-0.060	0.130	-0.037	-0.015	-0.007	-0.254***	0.008
DOGE.l1	0.087*	0.097	0.065	0.033	0.100	0.143	0.075	0.220**	0.037	0.041	0.045	0.032	0.160	-0.008	0.215***	0.113	0.172	0.039	0.082	0.161	0.090	0.084	-0.261***
BTC.l2	-0.444***	-0.487**	-0.460	-0.344*	-0.422*	-0.266	0.099	-0.437	-0.444***	-0.285*	-0.396**	-0.167	0.339	-0.394**	-0.547**	-0.221	0.099	-0.325	-0.544**	-0.148	-0.277	-0.456**	-0.359
ETH.l2	0.053	0.006	0.070	0.066	0.105	-0.008	0.091	0.061	0.236**	0.155	0.186	0.272	-0.353	0.137	0.130	-0.077	0.203	0.039	0.246	-0.262	0.115	0.176	0.146
XRP.l2	0.027	0.061	-0.040	0.017	0.034	0.189*	0.149	-0.013	0.006	0.094**	0.055	-0.033	0.076	0.063	0.074	0.021	-0.128	0.076	0.104	0.075	0.085	-0.003	0.008
BCH.l2	-0.207*	-0.291**	-0.460**	-0.242*	-0.380**	-0.115	-0.522**	-0.087	-0.068	-0.211**	-0.092	0.135	-0.070	-0.034	-0.238	-0.211	-0.244	-0.322**	-0.297*	-0.690**	-0.241	-0.263*	0.033
LTC.l2	0.079	0.105	0.017	0.090	-0.032	0.061	-0.069	0.040	-0.023	0.023	0.077	-0.065	-0.137	-0.012	0.023	0.253	0.066	0.121	-0.024	0.097	0.007	0.204	0.047
XEM.l2	-0.030	-0.028	-0.144**	-0.043	-0.010	-0.155**	-0.014	-0.066	-0.032	-0.041	-0.046	-0.181**	-0.031	-0.074**	-0.109**	-0.091	0.015	-0.024	-0.021	-0.135	-0.038	0.016	-0.050
XLM.l2	0.042	0.037	0.047	0.040	0.034	0.019	-0.106*	0.064	0.027	0.011	0.054	-0.048	0.022	0.020	0.074	0.039	0.057	0.040	0.058	0.009	0.007	0.054	-0.015
IOT.l2	0.002	0.024	0.063	0.027	0.067	0.133	-0.093	-0.079	0.043	-0.008	-0.032	-0.129	0.011	-0.065	0.079	-0.025	-0.065	0.018	-0.045	0.290*	-0.026	0.024	-0.037
DASH.l2	0.017	0.027	-0.007	-0.002	0.080	-0.099	-0.196	-0.033	0.186**	-0.028	-0.024	0.044	-0.236	-0.062	0.019	0.118	-0.054	-0.040	0.068	0.215	0.002	0.024	-0.029
XMR.l2	0.050	0.120	0.107	0.124	0.192	0.060	-0.028	0.153	0.038	0.122	0.109	0.297	0.092	0.041	0.233	-0.074	0.541**	0.141	0.153	0.051	0.065	0.076	0.227
ETC.l2	0.173*	0.115	0.112	0.061	0.208	-0.031	0.112	0.191	-0.016	0.091	0.032	-0.214	0.272	0.186**	0.110	0.148	-0.033	0.217*	0.195	0.316	0.264*	0.118	0.077
LSK.l2	0.009	0.012	-0.008	0.018	0.017	0.037	0.030	0.009	0.008	0.002	-0.001	-0.002	0.047	-0.002	-0.017	0.002	0.056	0.031	-0.006	0.153***	-0.011	-0.006	0.022
XVG.l2	-0.020	-0.019	-0.055*	-0.024	-0.013	-0.027	-0.032	-0.059**	-0.002	-0.005	-0.028	0.030	-0.248***	-0.023	-0.037	-0.040	-0.024	-0.029	-0.034	-0.038	-0.016	-0.016	-0.038
ZEC.l2	0.052	0.126	0.149	0.078	0.053	0.160	0.129	-0.102	0.123	0.096	0.220**	0.510**	0.279	0.055	-0.175	0.083	-0.009	-0.060	-0.023	0.169	0.068	0.110	-0.089
BCN.l2						0.106		0.093	0.036		0.037	0.085	-0.040	0.062	0.008		0.138	0.018	0.094			0.088	

Appendix 5 (Cont.)

	0.100**	0.129**	0.193**	0.084*	0.150***		0.199**			0.064*						0.132*				0.311**	0.115*		0.117*
SC.l2	-0.009	-0.011	0.053	-0.011	-0.011	-0.071	0.127	-0.009	-0.044	0.026	0.019	0.034	-0.084	-0.005	-0.015	-0.016	-0.045	0.047	0.001	-0.151	-0.022	-0.012	-0.001
VEN.l2	0.008	0.016	0.021	0.002	0.002	-0.042	0.021	0.034	0.005	-0.003	-0.002	-0.003	0.043	0.022	-0.001	0.013	-0.287***	-0.005	0.014	-0.017	0.041	-0.009	-0.026
STRAT.l2	-0.128**	-0.152**	-0.139	-0.056	-0.168**	-0.080	0.164	-0.112	-0.124**	-0.071	-0.117*	-0.175	0.215	-0.088	-0.045	-0.179*	-0.021	-0.175**	-0.145	-0.038	-0.149*	-0.099	-0.111
BTS.l2	0.044	0.108	0.116	0.107*	0.116	0.221**	0.020	0.204**	0.034	0.044	0.063	0.075	-0.095	0.113**	0.198**	-0.012	0.247*	0.124*	0.067	-0.008	0.090	0.041	0.094
VERI.l2	-0.010	-0.010	-0.014	0.001	-0.003	-0.013	-0.041	-0.025	-0.021	-0.018	-0.013	-0.013	0.061	-0.014	0.001	0.012	-0.143***	0.011	0.011	0.010	-0.013	0.017	0.010
EOS.l2	0.061	0.013	0.095	0.055	-0.023	0.031	0.122	-0.056	0.054	-0.041	-0.014	0.041	0.091	0.070	0.078	0.029	0.141	0.016	0.034	0.047	-0.111	-0.001	0.036
OMG.l2	0.036	0.060	0.119	0.007	-0.011	-0.001	-0.097	0.024	0.068	0.083	0.008	-0.214	-0.219	0.031	-0.013	0.106	-0.003	0.055	-0.004	-0.064	0.072	-0.171*	0.142
DOGE.l2	-0.013	-0.014	-0.015	-0.031	-0.015	0.006	0.079	0.054	0.002	-0.035	-0.067	0.007	0.279*	-0.019	0.091	-0.032	0.119	0.032	0.074	0.119	0.005	0.014	-0.131*
const	-0.0003	-0.001	-0.00000	-0.001	-0.0004	-0.001	0.0002	0.0001	-0.0004	-0.001	-0.0001	-0.002	-0.0004	0.0002	-0.001	-0.001	-0.001	-0.0003	-0.0001	-0.002	-0.00004	-0.00004	0.0001
trend	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00001	-0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000
Observations	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398	398
R^2	0.169	0.162	0.145	0.220	0.185	0.209	0.443	0.170	0.244	0.332	0.249	0.071	0.236	0.304	0.212	0.200	0.271	0.387	0.224	0.128	0.169	0.163	0.229
Adjusted R^2	0.057	0.049	0.030	0.115	0.076	0.103	0.368	0.058	0.142	0.242	0.148	-0.054	0.133	0.210	0.106	0.093	0.174	0.305	0.120	0.011	0.058	0.051	0.125
Residual Std. Error (df = 350)	0.008	0.010	0.016	0.009	0.011	0.015	0.015	0.014	0.007	0.007	0.009	0.022	0.026	0.007	0.013	0.014	0.020	0.010	0.012	0.023	0.012	0.011	0.012
F Statistic (df = 47; 350)	1.515**	1.437**	1.262	2.096***	1.692***	1.972***	5.925***	1.521**	2.398***	3.694***	2.463***	0.569	2.295***	3.247***	2.001***	1.863***	2.775***	4.711***	2.153***	1.096	1.520**	1.455**	2.208***

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 6. *B* matrix of ECCC GARCH[24]

A – daily data

	BTC	ETH	XRP	LTC	XMR	DASH	SC	XVG	BTS	DOGE
BTC	0.7834 ***	0	0	0	0	0	0	0	0	0
ETH	0	0.7023 ***	0	0	0	0	0	0	0	0.0037
XRP	0	0	0.8055 ***	0	0	0	0	0	0	0
LTC	0	0	0.1848 ***	0.3760 ***	0	0	0	0	0	0
XMR	0	0	0	0	0.7195 ***	0.0465	0	0	0	0
DASH	0.0021 *	0	0	0	0	0.6648 ***	0	0	0	0
SC	0	0.2391 ***	0.0899 ***	0	0.0866	0	0.1993 ***	0	0	0.0247
XVG	0	0	0	0	0.4264 ***	0	0	0.5205 ***	0	0
BTS	0.0224	0.0595	0	0	0	0	0	0.0141 ***	0.6388 ***	0
DOGE	0	0	0	0	0	0	0.6104 ***	0	0	0

[24] *p<0.1; **p<0.05; ***p<0.01

B – hourly data

	BTC	ETH	XRP	BCH	LTC	XEM	XLM	IOT	DASH	XMR	ETC	LSK	XVG	ZEC	BCN	SC	VEN	STRAT	BTS	VERI	EOS	OMG	DOGE
BTC	0.8534 ***	0	0	0	0	0	0.0034	0.0026	0	0	0	0	0.0003	0	0	0.0020	0	0	0.0001	0	0.0001	0	0
ETH	0	0.6131 ***	0.0001	0	0	0	0.0099	0	0	0	0	0	0	0.0007	0.0154	0	0	0	0	0	0	0	0
XRP	0	0.0002	0.7391 ***	0	0.0131	0	0	0	0	0	0	0	0	0	0.0001	0.0002	0	0	0	0	0	0	0
BCH	0	0	0	0.7545 ***	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0004	0	0	0	0	0
LTC	0	0.0001	0.0043	0	0.7624 ***	0	0.0019 ***	0.0016	0	0	0.0162	0	0.0004	0	0.0001	0	0	0	0	0	0.0031	0	0
XEM	0.0011	0.0001	0.0001	0	0.0276	0.7857 ***	0.0001	0	0	0	0.0110	0	0.0001	0.0001	0	0	0	0	0.0001	0	0	0.0001	0
XLM	0.0004	0.0001	0	0	0.0001	0.0013	0.7793 ***	0	0	0.0001	0	0	0	0	0	0	0	0	0	0	0.0002	0	0
IOT	0.0001	0.0003	0	0	0.0001	0	0	0.8059 ***	0	0.0001	0	0.0001	0.0012	0	0.0001	0	0	0	0	0	0.0042	0	0
DASH	0	0.0001	0	0.0434 ***	0.0014	0	0	0	0.6825 ***	0.0001	0	0	0.0009	0	0	0	0	0	0.0277	0	0	0	0
XMR	0.0013	0.0212 ***	0	0.0073 **	0.0072	0	0.0001	0.0546 ***	0.0014	0.4340 ***	0.0002	0.0001	0	0.0028	0.0077	0.0218	0	0	0.0002	0	0.0001	0	0
ETC	0.0001	0.0002	0	0	0	0	0	0.0025	0	0	0.7511 ***	0	0.0010	0.0002	0.0027	0	0	0	0	0	0.0200	0	0
LSK	0.0022	0.0006	0.0040	0.0001	0	0	0.0001	0	0.0002	0.0005	0.0001	0.6963 ***	0	0.0969 ***	0.0022	0.0007	0	0	0.0001	0	0.0001	0.0001	0.0009
XVG	0.0005 ***	0.0002	0	0.0003	0.0001	0	0	0.0002	0.0003 ***	0.0002	0	0	0.9365 ***	0.0001	0	0	0	0.0104	0.0001	0	0	0.0001	0
ZEC	0	0.0017	0.0001 ***	0	0.0001	0	0.0057	0.0007	0.0001	0	0	0	0	0.8335 ***	0.0106 ***	0	0	0.0021	0	0	0	0	0
BCN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.8771 ***	0.0001	0	0.0001	0	0	0	0	0
SC	0.0005	0.0001	0	0	0.0017	0	0 *	0	0	0.0001	0	0	0	0	0.0002 **	0.8546 ***	0	0	0.0003	0	0.0009	0	0.0002
VEN	0.0013	0.0004	0	0	0	0	0.0001	0.0962	0.0002 **	0.0010	0.0004	0.0001	0.0120	0.0002	0.0002	0.0001	0.2497 ***	0.0560 ***	0.0002	0.0040 **	0.0250 ***	0.0001	0.0001
STRAT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.923 ***	0	0.0004	0	0	0
BTS	0.0031	0.0008	0.0052	0.0052	0.0306 ***	0.0001	0.0024	0.0235 ***	0.0069	0.0005	0.0001	0.0001	0	0.0032	0	0.0060	0	0	0.7384 ***	0	0.0001	0.0003	0.0003
VERI	0.0094	0.0038	0.0002	0.0044	0.0009	0.0004	0.0002	0.0005	0.0045	0.0025	0.0009	0.0016	0.0001	0.0011	0.0002 *	0.0004	0	0.0014	0.0022	0.5103 ***	0.0028	0.0012 ***	0.0013 ***
EOS	0	0	0	0.0023	0	0	0.0002	0.0001	0	0	0	0	0.0010	0	0	0	0	0	0	0	0.7911 ***	0	0
OMG	0.1480 *	0.0041	0	0	0.0740 ***	0.0295	0.0005	0	0.0004	0.0002	0.0076	0.0001	0	0.0025	0	0	0	0	0.1753 ***	0	0.0231	0.3053 ***	0.0003
DOGE	0.0040	0.0013	0.0001	0	0.0011	0.0371 ***	0.0002	0	0.0003	0.0002	0.0002	0.0005	0.0005	0.0005	0.1118 **	0.0324	0	0	0.0005	0	0.0002 ***	0.0024	0.3442 ***

Appendix 7. Connectedness table for networks

A - 23 coins daily returns August 2017 – April 2018

	BTC	ETH	XRP	BCH	EOS	LTC	XLM	IOT	XMR	DASH	XEM	VEN	ETC	XVG	OMG	LSK	ZEC	BCN	BTS	SC	STRAT	DOGE	VERI	FROM others
BTC	15.56	6.43	2.32	1.54	4.07	5.94	3.01	4.44	5.23	4.42	3.08	1.38	4.78	1.15	4.15	2.69	4.49	5.93	3.99	3.59	5.39	6.10	0.33	3.67
ETH	4.81	11.62	3.75	2.40	4.16	6.67	3.18	3.90	5.22	5.14	3.98	1.20	6.56	0.71	5.06	3.14	6.38	3.52	4.72	3.92	5.07	4.47	0.43	3.84
XRP	2.74	5.94	18.40	1.65	3.91	4.25	5.39	2.47	4.38	3.20	4.99	1.74	4.96	1.69	3.35	3.43	6.02	3.13	5.43	4.00	3.77	5.14	0.01	3.55
BCH	2.66	5.57	2.42	26.94	3.79	3.63	1.62	2.46	4.98	6.78	3.16	0.58	6.16	1.33	1.33	1.73	6.24	2.72	4.92	4.45	3.34	3.12	0.06	3.18
EOS	4.75	6.50	3.86	2.56	18.17	4.37	3.50	4.21	3.82	3.70	3.91	1.13	5.69	1.05	4.20	2.91	5.60	2.82	4.89	3.31	4.60	3.87	0.57	3.56
LTC	5.62	8.44	3.40	1.98	3.54	14.72	2.64	3.98	4.57	4.53	3.98	1.33	6.49	0.41	4.21	2.92	4.97	3.73	3.98	3.96	4.64	5.23	0.73	3.71
XLM	3.35	4.74	5.08	1.04	3.34	3.11	17.33	4.77	5.05	2.79	5.19	2.32	5.18	0.52	3.90	2.66	5.11	3.35	6.84	4.10	5.62	4.56	0.05	3.59
IOT	4.59	5.40	2.16	1.47	3.73	4.35	4.42	16.09	5.58	4.20	4.41	1.87	5.80	0.38	5.21	3.52	5.38	3.36	4.75	3.58	5.88	3.48	0.40	3.65
XMR	4.59	6.13	3.25	2.52	2.87	4.23	3.98	4.73	13.63	6.75	3.17	1.64	5.31	1.14	3.78	3.27	7.38	3.56	4.63	3.95	5.11	4.37	0.02	3.76
DASH	4.16	6.48	2.55	3.69	2.98	4.51	2.36	3.82	7.26	14.65	3.35	1.23	4.15	1.64	4.49	3.43	8.17	3.50	4.59	4.45	3.87	4.52	0.15	3.71
XEM	3.24	5.59	4.43	1.91	3.51	4.41	4.89	4.48	3.80	3.74	16.34	1.59	4.95	1.67	4.10	3.32	5.15	3.64	4.94	4.37	5.05	4.51	0.35	3.64
VEN	2.99	3.49	3.19	0.73	2.10	3.05	4.51	3.92	4.05	2.82	3.27	33.71	3.16	0.40	3.26	3.84	3.53	3.78	3.11	3.70	3.69	3.25	0.47	2.88
ETC	3.96	7.29	3.48	2.95	4.04	5.69	3.86	4.65	5.03	3.65	3.91	1.21	12.91	0.56	4.51	3.32	5.89	2.93	5.13	4.05	5.68	4.95	0.34	3.79
XVG	2.94	2.44	3.67	1.98	2.30	1.12	1.20	0.95	3.33	4.47	4.09	0.48	1.74	39.95	1.84	2.38	4.81	3.76	4.21	6.20	2.02	4.08	0.05	2.61
OMG	4.13	6.74	2.83	0.76	3.59	4.44	3.48	5.02	4.29	4.75	3.89	1.50	5.41	0.71	15.50	3.34	5.36	3.57	5.11	4.20	6.26	4.87	0.25	3.67
LSK	3.34	5.23	3.61	1.24	3.10	3.84	2.96	4.24	4.64	4.53	3.93	2.20	4.98	1.15	4.18	19.35	6.56	3.73	3.32	4.20	4.90	4.45	0.33	3.51
ZEC	3.50	6.65	3.97	2.81	3.74	4.10	3.57	4.05	6.56	6.76	3.82	1.27	5.53	1.46	4.19	4.11	12.12	3.45	4.72	4.38	4.35	4.53	0.34	3.82
BCN	6.02	4.78	2.69	1.60	2.45	4.00	3.06	3.30	4.13	3.77	3.52	1.77	3.59	1.49	3.63	3.04	4.50	15.80	4.51	8.02	5.09	8.81	0.44	3.66
BTS	3.54	5.60	4.07	2.52	3.71	3.73	5.45	4.07	4.68	4.32	4.17	1.27	5.48	1.45	4.55	2.36	5.37	3.93	13.79	4.81	5.25	5.68	0.19	3.75
SC	3.34	4.88	3.15	2.39	2.63	3.90	3.43	3.22	4.19	4.39	3.87	1.59	4.54	2.24	3.92	3.14	5.23	7.35	5.05	14.47	5.28	7.53	0.28	3.72
STRAT	4.69	5.90	2.77	1.68	3.43	4.26	4.39	4.94	5.07	3.58	4.18	1.48	5.96	0.68	5.47	3.42	4.85	4.36	5.15	4.93	13.53	5.01	0.27	3.76
DOGE	5.22	5.12	3.72	1.54	2.83	4.74	3.50	2.88	4.27	4.10	3.68	1.28	5.11	1.36	4.18	3.06	4.97	7.43	5.48	6.92	4.93	13.31	0.36	3.77
VERI	1.51	2.61	0.03	0.17	2.20	3.53	0.18	1.77	0.13	0.75	1.53	0.98	1.84	0.08	1.06	1.19	1.97	1.96	0.97	1.35	1.41	1.89	70.86	1.27
TO others	3.73	5.30	3.06	1.79	3.13	3.99	3.24	3.58	4.36	4.05	3.61	1.35	4.67	1.01	3.68	2.88	5.13	3.72	4.37	4.19	4.40	4.54	0.28	80.05

B - 23 coins daily volatility August 2017 – April 2018

	BTC	ETH	XRP	BCH	EOS	LTC	XLM	IOT	XMR	DASH	XEM	VEN	ETC	XVG	OMG	LSK	ZEC	BCN	BTS	SC	STRAT	DOGE	VERI	FROM others
BTC	13.95	7.15	4.66	4.83	3.51	6.73	4.80	4.56	5.12	5.78	4.59	1.22	5.98	0.53	6.38	2.02	5.86	3.41	1.58	1.34	2.29	3.61	0.12	3.74
ETH	6.42	13.55	5.88	4.47	4.43	7.03	4.49	4.30	6.24	6.36	3.70	1.14	5.77	0.44	6.37	1.94	5.58	3.65	1.03	1.71	1.37	4.06	0.08	3.76
XRP	4.40	6.98	17.00	3.50	3.36	6.12	6.74	2.94	6.25	4.27	5.85	1.56	5.04	1.38	5.49	2.15	4.42	3.18	2.11	2.72	1.23	3.17	0.16	3.61
BCH	6.46	6.31	4.64	17.60	4.33	5.23	3.47	4.92	5.79	6.27	2.58	2.39	4.29	0.36	5.06	1.85	6.88	3.29	1.99	1.49	1.85	2.68	0.26	3.58
EOS	4.64	7.36	4.91	4.67	22.83	4.72	3.67	5.96	3.64	3.49	1.97	1.13	5.34	0.25	5.80	1.24	4.66	3.48	2.07	2.81	1.57	3.10	0.68	3.36
LTC	6.20	7.44	5.61	4.12	3.23	14.81	4.22	4.83	5.54	5.67	3.97	1.59	6.33	0.97	6.29	1.97	4.84	3.27	1.27	1.51	1.83	4.18	0.29	3.70
XLM	5.23	5.68	7.43	2.57	3.11	4.66	19.37	4.15	5.11	4.27	6.28	1.11	4.24	1.17	4.50	1.46	4.29	2.93	4.24	2.98	1.79	3.18	0.26	3.51
IOT	5.52	6.03	4.01	4.74	5.69	6.11	4.41	18.10	5.49	4.97	3.07	1.56	4.78	0.64	5.42	0.98	5.69	3.01	1.79	2.18	2.04	3.03	0.74	3.56
XMR	5.10	6.80	5.91	4.27	2.77	5.45	4.21	4.47	14.48	6.96	6.00	1.39	5.09	0.45	4.78	2.99	5.48	4.28	1.37	1.74	1.79	3.83	0.39	3.72
DASH	6.13	7.21	4.60	5.26	3.10	5.78	3.96	4.39	7.86	14.17	4.46	0.83	5.30	0.26	5.54	2.26	6.82	3.20	1.20	1.53	1.82	4.12	0.18	3.73
XEM	5.46	5.05	6.36	2.52	2.74	4.44	6.45	3.50	6.96	4.23	18.19	1.74	4.34	0.66	4.60	1.83	4.81	3.94	2.38	2.36	2.35	4.51	0.58	3.56
VEN	2.44	2.76	4.13	4.70	1.78	2.94	1.79	2.41	2.64	1.15	2.94	53.83	1.36	0.41	1.84	1.39	3.04	2.19	1.68	0.78	2.57	1.16	0.06	2.01
ETC	5.87	6.86	5.38	3.72	4.15	6.88	4.22	4.43	5.46	5.06	4.41	0.79	17.05	0.69	5.79	1.93	6.35	2.84	1.08	1.04	2.03	3.84	0.13	3.61
XVG	1.74	2.46	2.27	0.92	1.23	2.88	3.33	1.84	2.00	1.15	2.72	3.93	1.61	52.86	2.70	0.70	1.12	2.60	2.44	4.90	2.32	2.04	0.23	2.05
OMG	6.59	7.31	5.28	4.20	4.32	6.47	3.76	4.47	4.80	5.34	3.75	1.24	5.50	0.52	15.50	1.75	6.34	3.77	1.28	1.94	1.51	3.96	0.42	3.67
LSK	4.70	4.26	5.49	3.61	2.26	3.71	3.08	2.24	7.44	5.37	3.87	2.39	3.76	0.40	3.76	28.42	3.86	4.13	0.78	0.93	1.76	3.32	0.49	3.11
ZEC	6.05	6.50	5.05	5.47	3.36	5.15	4.32	4.69	6.21	6.55	4.97	1.82	6.02	0.46	6.18	1.77	13.46	2.74	1.37	1.62	2.12	3.84	0.27	3.76
BCN	5.00	5.81	4.61	3.79	3.73	4.48	3.63	3.45	6.30	4.35	4.59	1.61	3.50	0.77	5.32	2.52	3.16	19.72	2.22	3.44	1.35	6.46	0.19	3.49
BTS	3.61	2.67	4.67	1.56	5.05	2.82	8.26	2.90	2.96	1.92	3.26	1.78	2.24	1.44	2.78	0.56	2.43	2.95	32.85	5.82	2.87	3.29	1.31	2.92
SC	2.88	4.15	5.17	1.94	3.37	3.04	5.00	2.58	3.40	3.06	4.00	0.51	1.49	1.35	4.40	0.80	2.25	5.55	7.29	32.49	1.24	3.52	0.51	2.94
STRAT	4.96	3.73	3.04	3.01	3.34	3.99	3.97	3.99	4.31	3.55	4.65	3.60	3.43	0.98	3.58	2.00	4.44	2.98	2.71	1.83	28.37	3.31	0.27	3.11
DOGE	4.93	5.65	4.22	2.86	3.10	5.19	3.98	3.40	5.31	5.35	5.16	1.15	4.53	1.22	5.26	2.20	3.89	5.98	2.38	2.71	2.24	19.28	0.02	3.51
VERI	0.70	0.55	1.11	0.64	2.13	1.54	1.13	2.89	2.23	0.64	1.71	1.52	0.50	1.84	2.07	0.62	1.58	0.90	3.77	1.35	1.61	0.08	68.90	1.35
TO others	4.57	5.16	4.54	3.36	3.22	4.58	4.04	3.62	4.83	4.16	3.85	1.57	3.93	0.75	4.52	1.61	4.25	3.23	2.09	2.12	1.81	3.23	0.33	75.36

C – 23 coins hourly returns, October – September 2017

	BTC	ETH	XRP	BCH	EOS	LTC	XLM	IOT	XMR	DASH	XEM	VEN	ETC	XVG	OMG	LSK	ZEC	BCN	BTS	SC	STRAT	DOGE	VERI	FROM others
BTC	17.63	7.08	2.64	1.04	3.55	7.27	3.34	4.37	6.65	4.94	3.29	0.13	5.73	0.10	5.14	0.32	4.54	4.52	4.07	4.41	4.41	4.76	0.06	3.58
ETH	6.05	15.06	3.71	2.31	4.25	7.63	3.52	4.36	6.83	6.03	2.39	0.04	7.24	0.07	6.35	0.47	5.60	2.39	4.70	3.96	4.42	2.51	0.10	3.69
XRP	4.20	6.91	28.04	1.09	3.02	5.12	4.36	3.16	5.36	4.27	2.54	0.08	5.77	0.10	5.00	0.52	3.93	2.44	4.76	3.26	3.68	2.33	0.05	3.13
BCH	2.65	6.85	1.73	44.67	2.06	4.30	1.47	2.59	4.66	4.47	0.69	0.0003	6.06	0.01	3.60	0.95	3.62	1.02	2.99	2.42	2.39	0.79	0.01	2.41
EOS	5.29	7.43	2.83	1.21	26.31	4.99	2.76	4.81	5.51	4.54	2.14	0.06	5.86	0.08	5.44	0.33	4.27	2.18	3.87	3.70	3.92	2.44	0.02	3.20
LTC	7.34	9.02	3.25	1.71	3.38	17.80	3.32	4.08	6.60	5.64	2.46	0.06	6.32	0.06	5.59	0.52	4.99	2.55	4.55	3.47	4.49	2.75	0.04	3.57
XLM	4.89	6.02	4.01	0.85	2.70	4.81	25.80	3.31	5.84	4.04	2.67	0.08	5.27	0.01	4.94	0.26	3.95	2.62	5.94	3.94	4.75	3.26	0.03	3.23
IOT	6.03	7.04	2.74	1.41	4.45	5.58	3.12	24.34	6.11	4.44	1.96	0.11	5.17	0.13	5.90	0.56	4.35	2.56	3.76	3.57	4.16	2.49	0.01	3.29
XMR	6.42	7.72	3.25	1.78	3.56	6.30	3.85	4.27	17.01	7.01	2.69	0.07	6.16	0.05	5.36	0.43	5.91	2.89	4.22	3.82	4.32	2.86	0.06	3.61
DASH	5.45	7.79	2.96	1.95	3.35	6.16	3.05	3.54	8.02	19.45	2.84	0.04	6.18	0.03	5.34	0.55	6.11	2.51	4.57	3.85	3.75	2.51	0.01	3.50
XEM	6.10	5.18	2.96	0.51	2.66	4.52	3.38	2.63	5.16	4.78	32.69	0.21	4.21	0.05	3.30	0.25	3.68	3.34	3.17	3.31	3.79	4.02	0.10	2.93
VEN	0.68	0.26	0.27	0.001	0.22	0.29	0.30	0.42	0.37	0.21	0.61	93.94	0.15	0.001	0.30	0.02	0.31	0.40	0.09	0.22	0.35	0.55	0.04	0.26
ETC	5.84	8.63	3.69	2.43	4.00	6.38	3.67	3.82	6.50	5.71	2.31	0.03	17.96	0.04	5.74	0.51	5.30	2.62	4.54	3.70	4.08	2.49	0.01	3.57
XVG	0.53	0.42	0.35	0.02	0.28	0.33	0.05	0.51	0.26	0.13	0.14	0.001	0.23	93.92	0.48	0.11	0.40	0.22	0.20	0.63	0.41	0.29	0.09	0.26
OMG	5.61	8.11	3.43	1.55	3.98	6.03	3.68	4.66	6.06	5.28	1.94	0.06	6.14	0.10	19.22	0.43	5.12	2.23	4.89	4.00	5.11	2.38	0.02	3.51
LSK	1.31	2.23	1.32	1.51	0.89	2.10	0.70	1.64	1.80	2.03	0.53	0.02	2.00	0.08	1.59	71.15	1.20	0.96	1.94	2.25	1.59	1.16	0.01	1.25
ZEC	5.40	7.80	2.94	1.70	3.41	5.88	3.22	3.75	7.30	6.60	2.36	0.07	6.20	0.09	5.59	0.35	20.99	2.46	3.99	3.51	3.58	2.76	0.04	3.44
BCN	7.85	4.87	2.67	0.70	2.53	4.39	3.11	3.23	5.19	3.95	3.13	0.13	4.47	0.07	3.56	0.41	3.59	30.62	2.76	3.70	3.35	5.67	0.04	3.02
BTS	5.15	6.95	3.78	1.49	3.28	5.69	5.14	3.44	5.52	5.24	2.16	0.02	5.64	0.05	5.67	0.61	4.24	2.01	22.29	4.25	4.86	2.49	0.01	3.38
SC	6.10	6.42	2.84	1.32	3.43	4.76	3.72	3.57	5.48	4.83	2.47	0.06	5.02	0.16	5.07	0.77	4.07	2.95	4.65	24.39	4.49	3.41	0.002	3.29
STRAT	5.72	6.72	3.01	1.23	3.41	5.78	4.22	3.91	5.81	4.42	2.65	0.09	5.20	0.10	6.09	0.51	3.90	2.51	4.99	4.21	22.90	2.62	0.01	3.35
DOGE	7.92	4.90	2.44	0.52	2.72	4.54	3.70	3.00	4.94	3.78	3.61	0.17	4.07	0.09	3.63	0.48	3.86	5.44	3.28	4.11	3.36	29.34	0.10	3.07
VERI	0.35	0.61	0.18	0.02	0.07	0.21	0.11	0.05	0.36	0.03	0.30	0.04	0.07	0.09	0.09	0.01	0.19	0.14	0.05	0.01	0.05	0.32	96.64	0.15
TO others	4.65	5.61	2.48	1.15	2.66	4.48	2.77	3.00	4.80	4.02	2.00	0.07	4.49	0.07	4.08	0.41	3.61	2.22	3.39	3.06	3.27	2.39	0.04	64.69

D – 23 coins hourly returns, January – March 2018

	BTC	ETH	XRP	BCH	EOS	LTC	XLM	IOT	XMR	DASH	XEM	VEN	ETC	XVG	OMG	LSK	ZEC	BCN	BTS	SC	STRAT	DOGE	VERI	FROM others
BTC	7.96	5.55	4.55	5.28	4.78	5.70	4.09	4.97	5.40	5.20	3.19	2.52	4.73	3.71	4.89	0.96	4.86	3.46	4.74	4.27	5.03	4.18	0.02	4.00
ETH	5.89	8.46	4.67	4.91	4.97	5.49	4.32	4.50	5.08	4.92	3.10	2.56	5.27	3.70	5.23	0.99	4.71	3.19	4.97	4.03	5.11	3.87	0.02	3.98
XRP	5.57	5.39	9.76	4.14	4.55	4.96	5.82	4.41	4.75	4.60	3.79	2.24	4.44	4.05	4.92	0.98	4.35	3.14	5.00	4.12	4.92	4.08	0.02	3.92
BCH	6.33	5.55	4.05	9.55	4.38	5.33	3.86	4.68	5.19	5.12	3.00	2.50	4.88	3.55	5.03	1.05	4.99	3.27	4.68	3.94	4.92	4.13	0.01	3.93
EOS	6.02	5.90	4.68	4.60	10.04	5.01	4.40	4.58	4.73	4.60	3.22	2.40	4.83	3.68	5.09	0.85	4.58	3.01	5.08	4.10	4.82	3.77	0.01	3.91
LTC	6.44	5.85	4.58	5.02	4.50	9.01	4.07	4.70	5.37	5.03	2.85	2.55	4.79	3.72	4.80	0.98	4.65	3.21	4.71	4.13	4.87	4.14	0.03	3.96
XLM	5.25	5.23	6.10	4.13	4.48	4.62	10.22	4.38	5.04	4.47	3.70	2.40	4.57	4.00	4.83	0.94	4.42	3.18	5.15	3.99	4.90	3.89	0.11	3.90
IOT	6.18	5.27	4.48	4.85	4.52	5.17	4.25	9.90	5.17	4.78	3.01	2.70	4.65	3.88	4.85	0.89	4.66	3.05	4.63	4.15	5.05	3.91	0.01	3.92
XMR	6.09	5.40	4.37	4.88	4.23	5.36	4.43	4.69	8.98	5.43	3.09	2.69	4.68	3.58	4.95	1.03	5.12	3.30	4.56	3.97	5.01	4.14	0.03	3.96
DASH	5.95	5.31	4.31	4.89	4.18	5.10	3.99	4.41	5.52	9.12	3.11	2.71	4.80	3.64	4.89	1.29	5.32	3.62	4.48	3.97	4.97	4.40	0.02	3.95
XEM	5.24	4.79	5.08	4.11	4.19	4.15	4.74	3.98	4.50	4.46	13.09	2.38	4.01	4.03	4.51	1.05	4.51	3.64	4.84	3.98	4.68	4.01	0.02	3.78
VEN	5.02	4.81	3.64	4.15	3.80	4.50	3.72	4.32	4.75	4.71	2.89	15.87	3.88	3.61	4.44	1.24	4.27	3.29	4.13	4.01	4.50	4.41	0.02	3.66
ETC	5.68	5.97	4.36	4.89	4.61	5.09	4.29	4.49	4.99	5.04	2.93	2.34	9.58	3.56	5.38	1.05	4.73	3.14	4.72	4.05	5.24	3.86	0.01	3.93
XVG	5.31	5.00	4.74	4.25	4.19	4.72	4.47	4.47	4.56	4.56	3.51	2.60	4.24	11.42	4.53	0.99	4.43	3.47	4.67	4.97	4.94	3.94	0.003	3.85
OMG	5.64	5.68	4.64	4.84	4.66	4.90	4.34	4.50	5.06	4.93	3.17	2.57	5.16	3.65	9.18	0.93	4.67	3.19	4.80	4.18	5.38	3.94	0.02	3.95
LSK	3.72	3.63	3.11	3.40	2.62	3.35	2.84	2.77	3.57	4.37	2.47	2.43	3.40	2.68	3.12	30.95	3.61	3.02	3.35	3.35	3.75	4.48	0.02	3.00
ZEC	5.83	5.33	4.26	5.00	4.36	4.93	4.13	4.50	5.44	5.58	3.29	2.57	4.72	3.70	4.86	1.11	9.56	3.44	4.76	3.64	4.85	4.15	0.01	3.93
BCN	5.54	4.82	4.11	4.36	3.82	4.54	3.97	3.93	4.68	5.06	3.55	2.65	4.18	3.88	4.43	1.24	4.59	12.76	4.28	4.44	4.39	4.76	0.04	3.79
BTS	5.60	5.55	4.83	4.62	4.77	4.93	4.75	4.41	4.78	4.63	3.48	2.46	4.64	3.85	4.93	1.02	4.70	3.17	9.43	4.27	5.03	4.10	0.04	3.94
SC	5.68	5.05	4.47	4.37	4.33	4.85	4.14	4.44	4.69	4.61	3.23	2.68	4.48	4.62	4.83	1.15	4.04	3.69	4.80	10.60	5.00	4.27	0.01	3.89
STRAT	5.74	5.49	4.58	4.68	4.37	4.91	4.36	4.64	5.07	4.95	3.25	2.58	4.98	3.93	5.33	1.10	4.61	3.13	4.85	4.29	9.09	4.07	0.001	3.95
DOGE	5.59	4.88	4.46	4.61	4.01	4.89	4.06	4.20	4.91	5.14	3.26	2.96	4.30	3.68	4.57	1.54	4.63	3.98	4.63	4.29	4.77	10.66	0.01	3.88
VERI	0.17	0.17	0.16	0.05	0.10	0.27	0.89	0.09	0.24	0.16	0.10	0.10	0.07	0.03	0.14	0.04	0.11	0.22	0.26	0.08	0.04	0.05	96.44	0.15
TO others	5.15	4.81	4.10	4.18	3.93	4.47	3.91	4.00	4.50	4.45	2.92	2.33	4.16	3.42	4.37	0.97	4.20	3.03	4.27	3.75	4.44	3.76	0.02	85.15

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