University of Tartu

School of Economics and Business Administration

Macroeconometrics

Empirical project paper

“VAR model for cryptocurrencies data”

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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 1400 different coins[1]. 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 can be observed in present time is that they are mostly used not as a payment method, but as financial assets. People invest into 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[2]. Another interesting example is a sharp increase of Bitcoin price in November-December 2017 (from 4K to 19K USD), accompanied with price growth of other cryptocurrencies.

The field of cryptocurrencies connectedness is not well discovered since the topic itself is young. There exist a lot of papers aimed to improve the underlying technology of cryptocurrencies, discuss their technical fundamentals, mining opportunities, blockchain techniques. In addition, the number of economical research 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). 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. Kim at al. (2016) model the prediction of the cryptocurrencies price fluctuations based on sentiment analysis of comments posted in the online crypto communities.

Mostly, researchers investigate Bitcoin, and there exist less paper dedicated to altcoins. Among others, I would note the paper by Halaburda and Gandal (2014) which examines competition

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

between 4 coins. They distinguish two periods, where Bitcoin price was stable (in May–September 2013 it benefited from 'winner-take-all effect') and volatile (October 2013–February 2014 with reversed dynamics) and find out existing network effects between cryptocurrencies in 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 are seemed incomplete.

Within a project, I apply the similar approach implemented for larger dataset. I use VAR analysis to investigate how cryptocurrency returns interact with each other, conduct the impulse response analysis and the forecast error variance decomposition.

The remainder of the paper is organized as follows. Section 2 provides the framework and applied methodology. Sections 3 describes data and its transformation. Sections 4 presents empirical results and Section 5 contains discussion, alternative approaches and possible extensions.

2. Theoretical background and methodology

Linear dependencies among multiple time series are modelled by Vector Autoregression (VAR) which generalize univariate AR models and allow two and more evolving variables.

The VAR(p) model is defined as follows:

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

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).

In lag operator notation, the VAR(p) is written as:

$$\boldsymbol{\Pi}(L)\boldsymbol{Y_t} = \boldsymbol{c} + \varepsilon_t$$

where $\boldsymbol{\Pi}(L) = \boldsymbol{I_n} - \boldsymbol{\Pi}_1 L - \ldots - \boldsymbol{\Pi}_p L^p$. The VAR(p) is stable if the roots of

$$\det(\boldsymbol{I_n} - \boldsymbol{\Pi}_1 z - \cdots - \boldsymbol{\Pi}_1 z^p) = 0$$

lie outside the complex unit circle[3].

For a given sample of the endogenous variables $\boldsymbol{Y_1}, \ldots, \boldsymbol{Y_T}$ and sufficient presample values $\boldsymbol{Y_{p+1}}, \ldots, \boldsymbol{Y_0}$, the coefficients of a VAR(p)-process can be estimated efficiently by least-squares applied separately to each of the equations.

Starting from the concise matrix:

$$\boldsymbol{Y} = \boldsymbol{\Pi Z} + \boldsymbol{U}$$

The multivariate least squares (MLS) approach for estimating Π yields:

$$\widehat{\boldsymbol{\Pi}} = \boldsymbol{Y Z'}(\boldsymbol{Z Z'})^{-1}$$

It can be rewritten in the following way:

$$Vec(\widehat{\boldsymbol{\Pi}}) = (((\boldsymbol{Z Z'})^{-1}\boldsymbol{Z} \otimes I_k)\, Vec(\boldsymbol{Y}),$$

where ⊗ is Kronecker product and Vec stands for vectorization of the matrix.

This estimator is consistent and asymptotically efficient. It is furthermore equal to the conditional maximum likelihood estimator[4].

VAR can be modelled with different lag *p*. To choose 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)). For testing the lack of serial correlation in the residuals, Portmanteau test and Breusch-Godfrey LM are applied.

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:

[3] Eric Zivot, Jiahui Wang (2006) Vector Autoregressive Models for Multivariate Time Series. In: Modeling Financial Time Series with S-PLUS. Springer, New York, NY

[4] Hamilton, James D. (1994). Time Series Analysis. Princeton University Press

$$Y_t = \mu + \varepsilon_t + \Psi_1\varepsilon_{t-1} + \Psi_2\varepsilon_{t-2} \quad + \cdots, \text{ where}$$

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

The impulse response is the *(i,j)-th* element of the matrix Ψ_s: $\psi_{ij}^s = \frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial y_{i,t}}{\partial \varepsilon_{j,t-s}}, i, j = 1, \dots, n$

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

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). What is important is that the different ordering of variables can produce different result.

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, or, in other words, the contribution of variable j to the h-step forecast error variance of variable *i*[5].

3. Data

Data for analysis is 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. To estimate VAR model, I choose TOP-30 cryptocurrencies based on 24 hours Sales Volume and filter list based on the period which coins exist (more than 5 months to have enough data for daily analysis). The final list of 23 coins is presented in Table 1.

[5] Pfaff B (2008). "VAR, SVAR and SVEC Models: Implementation Within R Package vars." Journal of Statistical Software, 27(4). URL http://www.jstatsoft.org/v27/i04/.

Table 1 – List of coins used for analysis

N	Coin	Symbol	Market Capitalization, Mln $	Trading period, # of days[6]
1	Bitcoin	BTC	200 658	2739
2	Ethereum	ETH	105 827	892
3	Ripple	XRP	55 737	1090
4	BitcoinCash	BCH	31 052	167
5	Litecoin	LTC	10 653	1544
6	NEM	XEM	9 795	227
7	Stellar	XLM	8 630	363
8	EOS	EOS	8 201	200
9	IOTA	IOT	7 870	216
10	DASH	DASH	6 606	1437
11	Monero	XMR	5 571	1082
12	EthereumClassic	ETC	3 126	537
13	Lisk	LSK	2 692	327
14	VeChain	VEN	2 222	1546
15	OmiseGO	OMG	1 826	185
16	Verge	XVG	1 586	705
17	Zcash	ZEC	1 567	444
18	Siacoin	SC	1 468	874
19	Stratis	STRAT	1 386	229
20	Bytecoin	BCN	1 323	227
21	BitShares	BTS	961.6	1085
22	Doge	DOGE	856.8	1444
23	Veritaseum	VERI	791.6	221

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. I obtain different datasets for Analysis[7]:

- Daily prices from August, 1 to January, 18 (171 observations),
- Hourly prices from October, 27 to January, 18 (2000 observations),
- 5-min prices from January, 17 12:25 to January, 18 21:45 (400 observations),

[6] Data for 14.01.2018
[7] All data for 2018 year

- Minute prices from January, 17 11:46 to January, 18 21:06 (2000 observatoins).

Each dataset is crawled twice: in USD and BTC prices (since Hayes (2017) says that USD price can affect volatility of cryptocurrency market, it is interesting to look at both variants).

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 is not stationary. That is why all data is transformed to continuously compounded returns r_t:

$$r_t = p_t - p_{t-1} = logP_t - logP_{t-1}, \text{ where } P_t \text{ is close price.}$$

Figures 1, 2, 3 present daily, hourly and 5 minutes returns for selected coins respectively (in BTC prices).

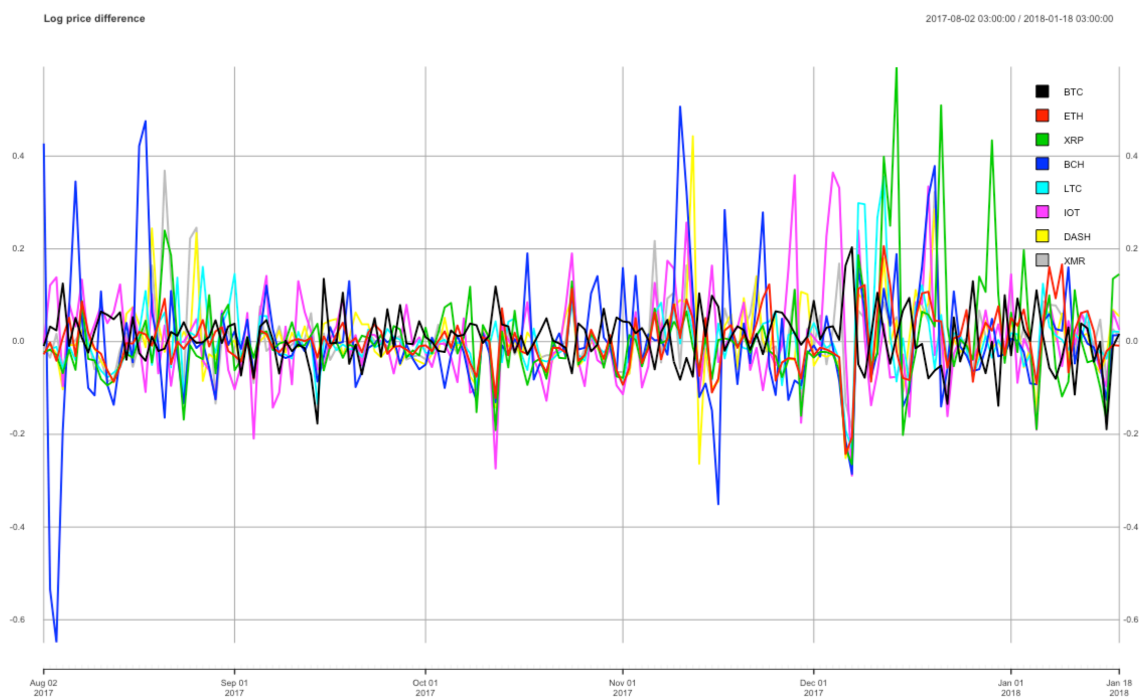

Figure 1 – Daily returns in BTC prices for major cryptocurrencies

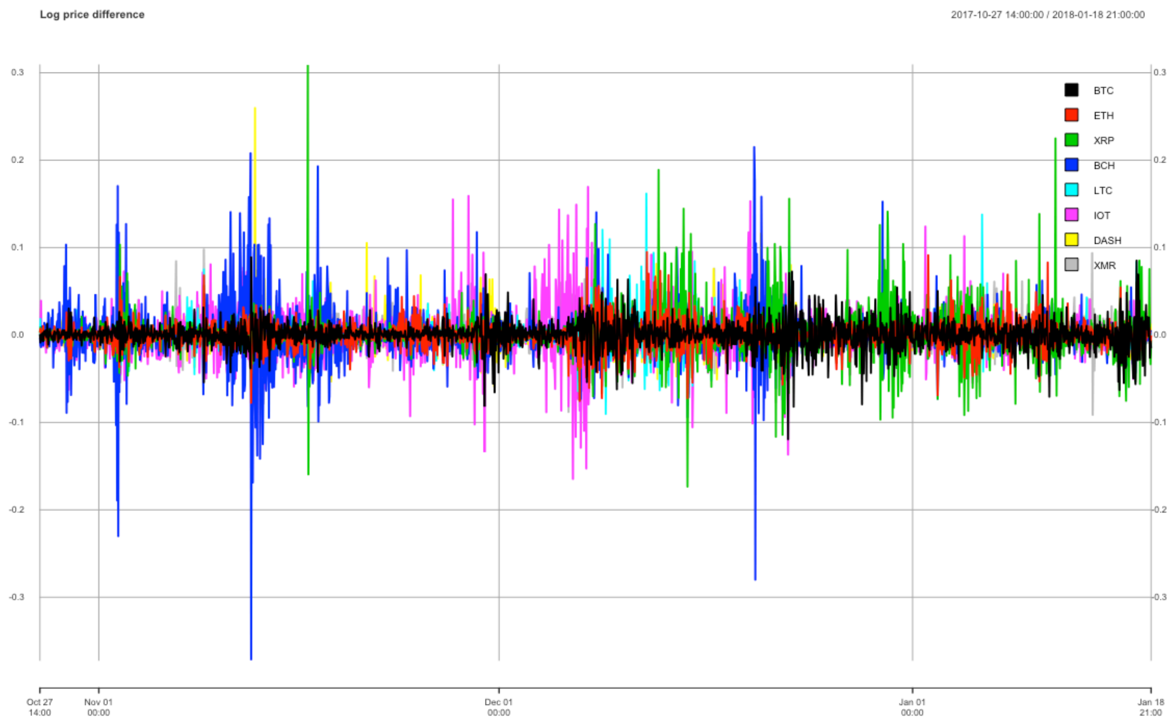

Figure 2 – Hourly returns in BTC prices for major cryptocurrencies

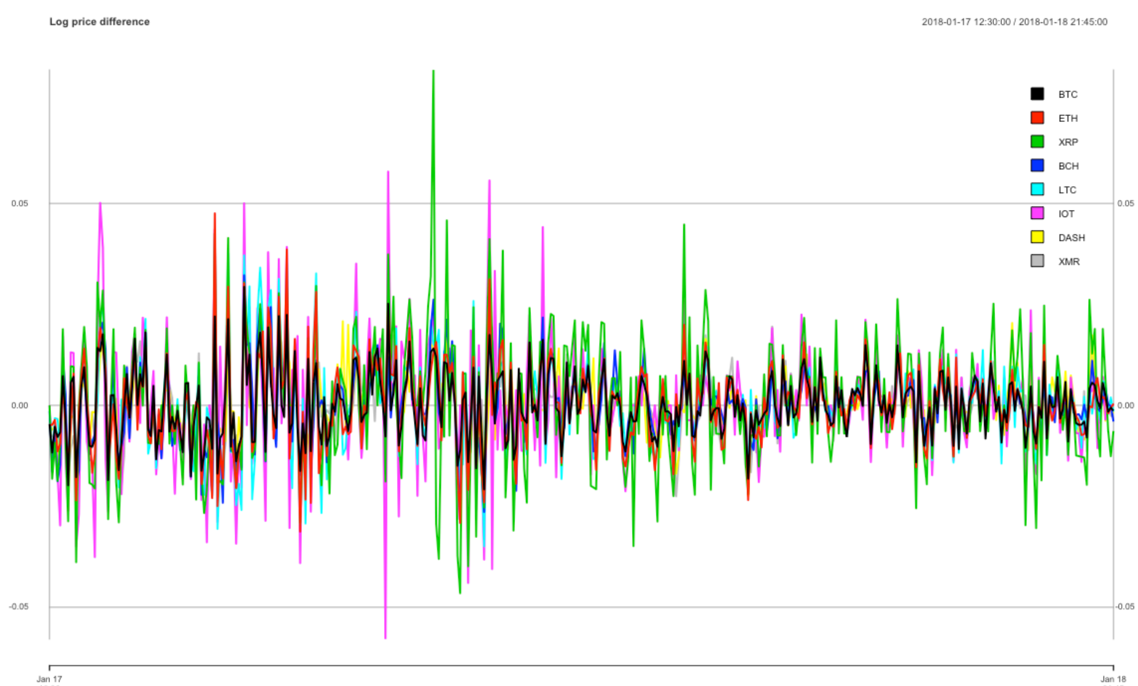

Figure 3 – 5-minutes returns in BTC prices for major cryptocurrencies

4. Empirical Results

Daily Data

I start VAR analysis with daily data[8]. Based on minimized AIC, the best lag for VAR is 5 (AIC $= -1.209$), but considering its low degrees of freedom (48 compared to 144 for lag 1), VAR(1) is chosen for analysis (AIC (lag 1) $= -1.139$ is slightly greater than AIC(lag 5)). Results of estimated model are provided in Appendix 1.

What it can be observed is that lag 1 of Bitcoin price return is positively affected other prices (looking at statistically significant coefficients[9]). BitcoinCash has a different direction of lagged influence (positive effect for Ethereum, Dash, EthereumClassic and negative for Bitcoin, Bytecoin, OmiseGO). Miota negatively affects returns of other coins on average.

Graphical analysis of residuals (diagram of fit and residuals, Normal Q-Q plot (as an example, Figures 4 and 5), autocorrelation of residuals (some of them are presented in Appendix 2)) suggests that most of them could be normally distributed.

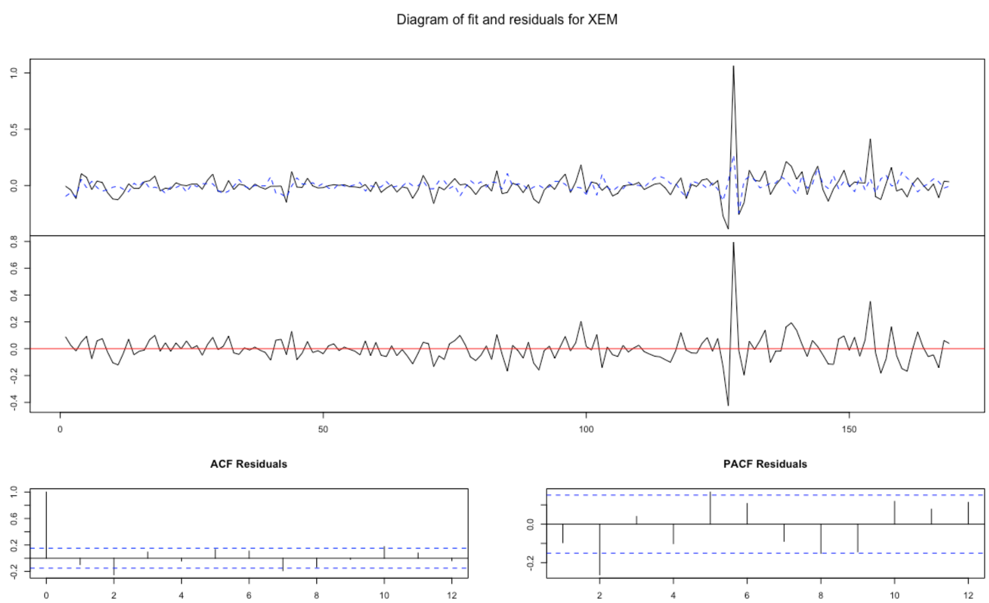

Figure 4 – Example of graphical analysis of NEM residuals for VAR(1) daily model

[8] Both variants of VAR are estimated – for USD and BTC prices. Model with BTC price transformation gives higher R^2 for equations, greater number of significant coefficients, more significant F-statistics. Also, taking into account the long period (169 days), BTC price transformation is applied for analysis.
[9] Hereinafter, explanations are given for statistically significant coefficients at least at confidence level 90%.

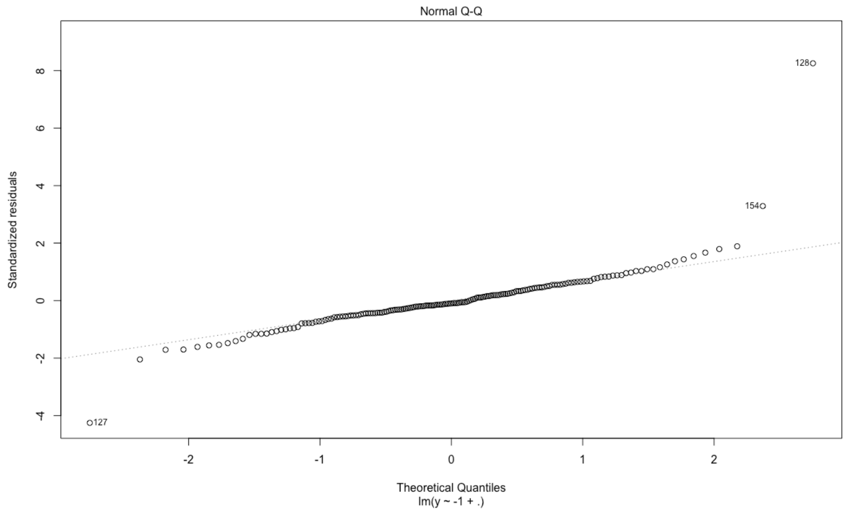

Figure 5 – Q-Q plot of standardized residuals for NEM series of VAR(1) daily model

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.

To investigate the dynamic effect of returns, I conduct impulse response analysis. What can be observed is:

- Orthogonal impulse response from Bitcoin (Figure 6) has negative effect for majority of coins, but after 3-5 days it wears off (without orthogonal part, magnitudes of effect are higher which is obvious by construction);
- In contrast, most of the coins have positive initial response for a shock in Ethereum, which decreases after day 1, and wears off after 2 days (Figure 7);
- For shock in Ripple (Figure 8), such coins as NEM, Miota, Monero respond positively initially, but then direction changes to opposite (it is worth to notice, that for altcoins, magnitudes of response are much smaller than those from Bitcoins);
- Some coins also represent negative response at first period from the shock in Miota (Figure 9).

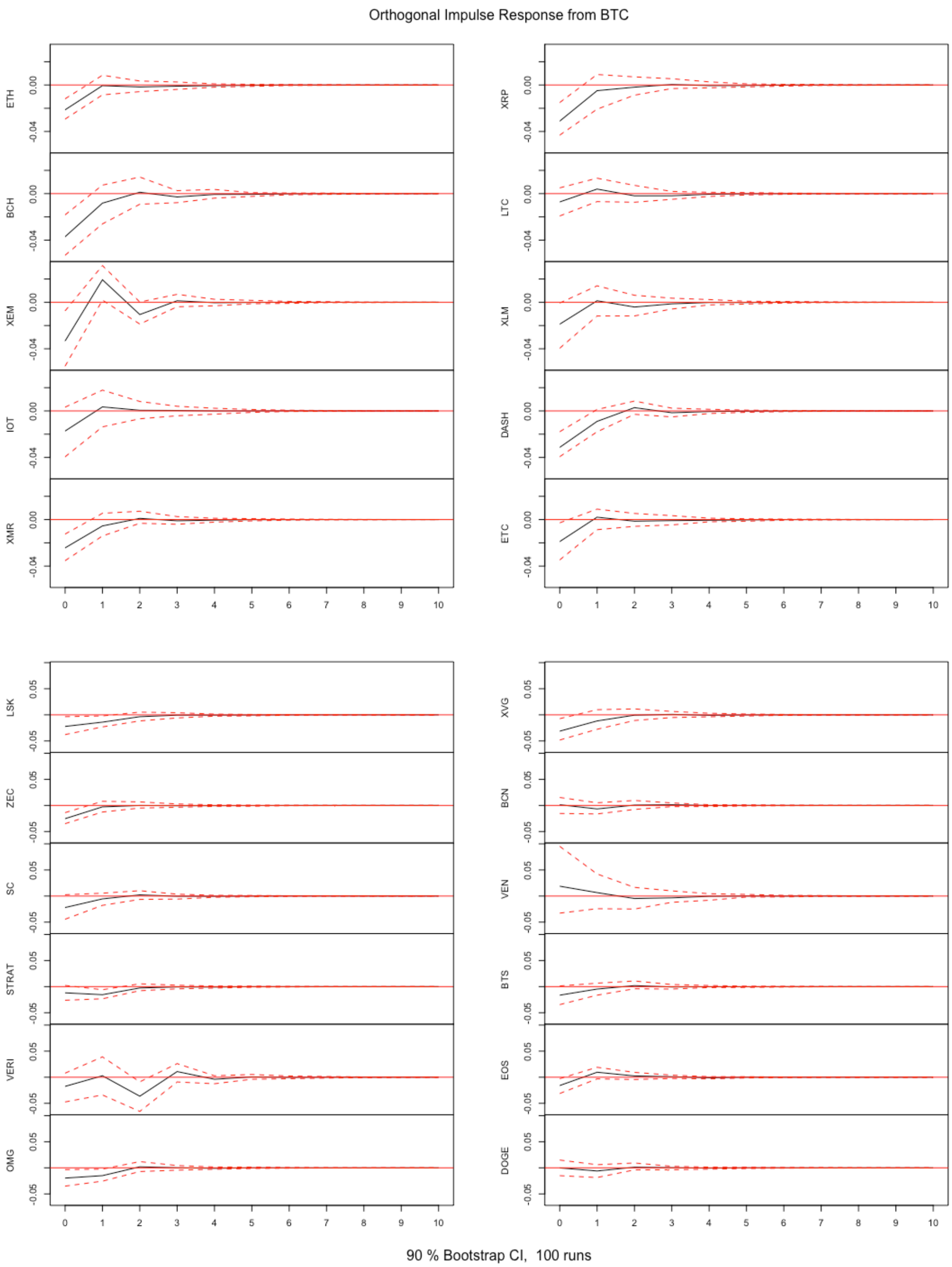

Figure 6 – Orthogonal Impulse Response from Bitcoin (VAR(1) daily model)

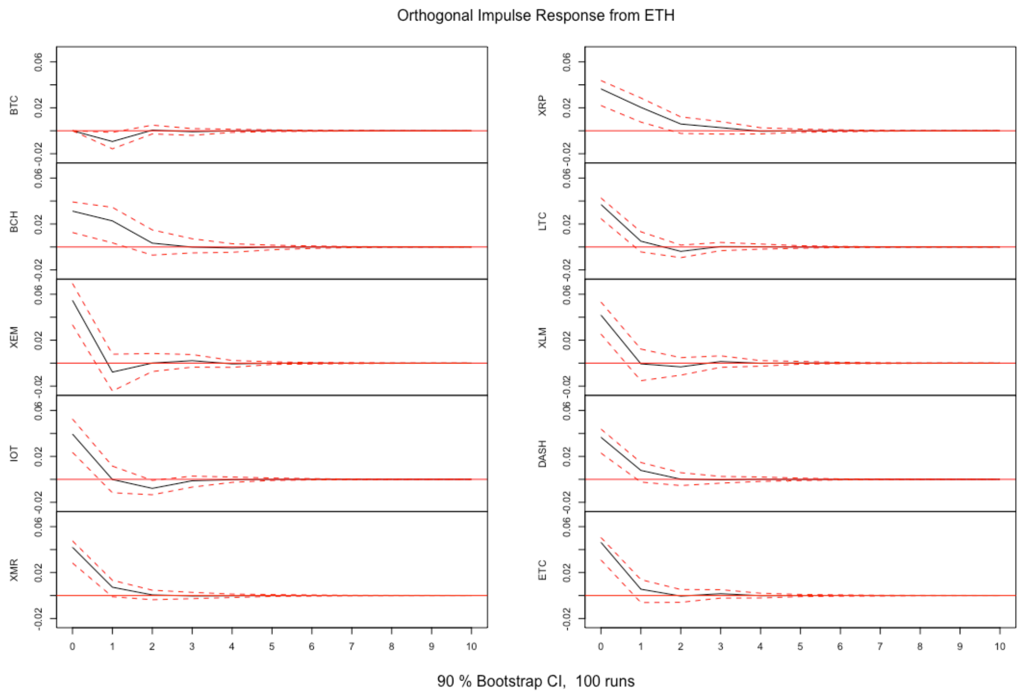

Figure 7 – Orthogonal Impulse Response from Ethereum (VAR(1) daily model)

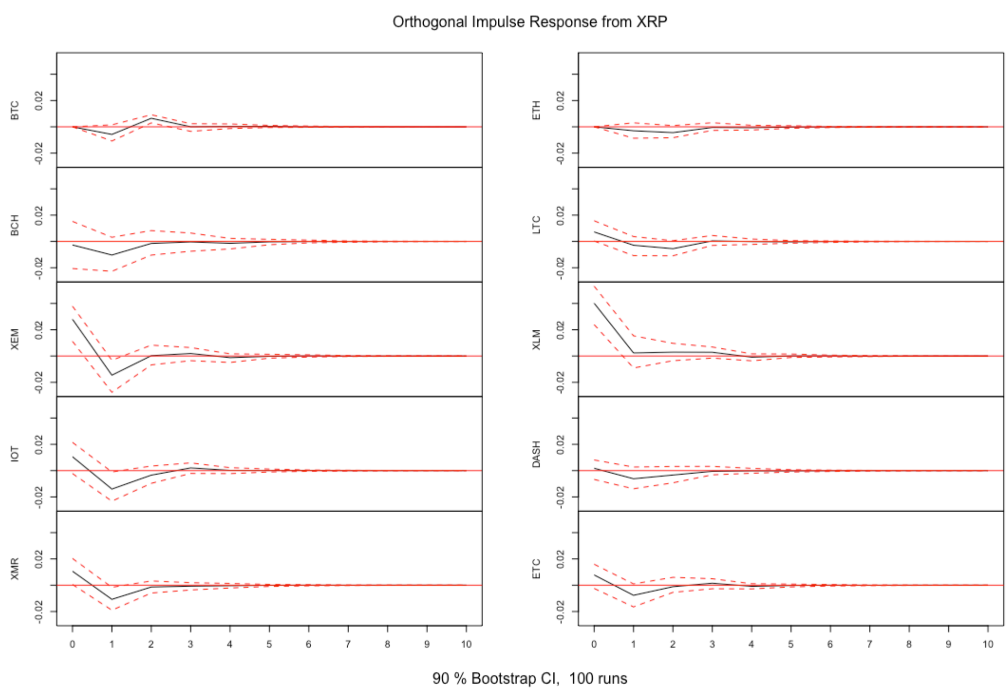

Figure 8 – Orthogonal Impulse Response from Ripple (VAR(1) daily model)

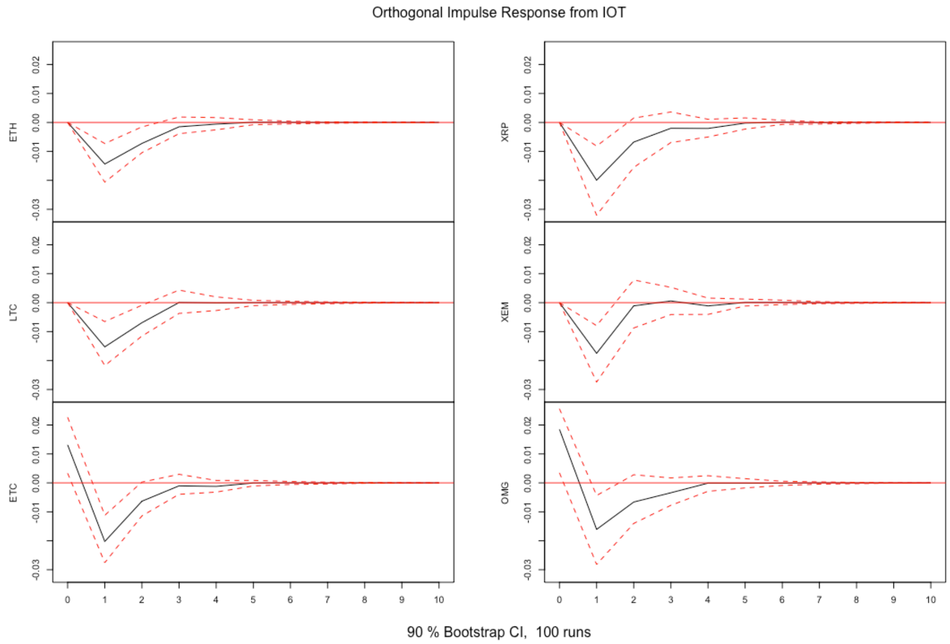

Figure 9 – Orthogonal Impulse Response from Miota (VAR(1) daily model)

Results of forecast error variance decomposition are presented in Table 2. Most of the variance of the forecast errors for coins using daily data comes from its own innovations. In addition, Bitcoin explains about 10-15% of forecast error variance for such cryptocurrencies as Ethereum, NEM, Dash, Monero, Zcash (but interestingly, Bitcoin explain less for BitcoinCash – 6.8%). Result shows that Ethereum contribute more in the forecast error variance of Ripple (13.4%), Litecoin (23.6%), Monero (25.8%), Ethereum Classic (28.8%), Zcash (31.6%) – that is higher than Bitcoin does. Then, Bytecoin contribute to Siacoin (14.7%) and Doge (12.1%).

Table 2 – Forecast error variance decomposition for VAR(1) daily model[10]

	BTC	ETH	XRP	BCH	LTC	XEM	XLM	IOT	DASH	XMR	ETC	LSK	XVG	ZEC	BCN	SC	VEN	STRAT	BTS	VERI	EOS	OMG	DOGE
BTC	76.9	2.3	2	3.2	0.7	0.6	0.5	0.8	0.3	0.2	0.8	0	0.3	0.3	0.1	1.6	4.6	0.4	1.8	0.2	0.7	0.1	1.5
ETH	11.2	63	0.7	2	1.6	0.5	1.5	6.3	1.1	0.1	0.6	1.1	0.2	0.6	0.1	1.4	0.1	2.5	1	0	2	1.6	0.7
XRP	7.4	13.4	62.1	0.3	1.3	0.1	2.3	3.4	1.4	0.5	1.8	0.2	2.8	0	0.1	0.5	0.2	0.6	0.8	0.1	0.3	0.1	0.4
BCH	6.8	7	0.6	75	0.1	0.1	0.2	0.9	0.1	0.5	1.2	1.9	0.3	0.2	0	0	0.1	1	0.3	2.3	0.8	0.1	0.6
LTC	1.2	23.6	1.5	1.9	48	2.9	2.6	4.7	2.3	0.5	0	0.3	0.8	0	0.1	0.4	0.8	1.4	1.5	0.5	3.8	0.4	0.6
XEM	9.9	19	6.2	1.2	2.8	48.9	1.7	1.9	1	0.1	0.2	0.3	1.5	0.1	0	0.2	0.1	2.3	0.2	0	1.4	0.1	0.8
XLM	2.1	10.1	9.3	0.3	0.2	5.7	65.3	0.8	1	0.2	0	0.1	0.9	0.9	0.8	0.5	0.3	0	0.7	0	0.1	0.4	0.1
IOT	2.6	13.4	2.7	1	0.4	7.5	5	58.7	0.1	0.8	0	0.2	0.1	0.6	0.2	3.8	0.5	0	0	0	0	1.5	0.9
DASH	15.1	19.7	0.7	7.1	1.7	1.1	0.4	0.4	48.6	1.1	1	0.5	0.1	0.1	0.1	0.1	0.1	0.7	0.3	0.3	0.6	0	0.5
XMR	8.9	25.8	3.3	1.7	0.3	0.3	4.5	1.3	5.9	44.5	0.2	0.3	0.9	0.3	0.3	0.3	0.2	0.5	0.1	0.1	0.3	0.1	0
ETC	4.8	28.8	1.6	4.9	2.2	1.7	2.3	8.2	1.8	1.9	36.5	0.5	0.8	0.1	0.4	0.6	0.5	0.5	0.5	0.1	0.4	0.6	0.2
LSK	6	15.7	1.6	4.1	1.2	5.8	1.6	3.4	7	0.8	1	42.9	2.8	0.1	0.4	0.2	2.8	0.7	0.3	0.3	0.5	0.6	0.1
XVG	4.3	3.3	0.9	0.8	1.5	4.4	1.3	0.6	1.9	0.8	2.4	1.3	70.7	0.5	0.2	0.5	0.8	0.3	1.9	0.2	0.6	0.6	0.2
ZEC	9.6	31.6	3.8	4.7	0.7	1	2.7	3.6	8	0.9	0.8	2.5	2	25.4	0.2	0.4	0.2	0.3	0.8	0	0.4	0.4	0.1
BCN	0.5	3.8	1.3	2.8	0.4	1.2	1.1	1.1	2.3	0.1	0.2	3.1	16.2	0.8	58.7	4.2	0.5	0.8	0.5	0.2	0.2	0.1	0
SC	3.8	11.8	2.1	2.2	1	3.2	1.3	1.5	1.8	0.1	0.8	4.3	13.4	0.3	14.7	35.7	0.6	0.9	0.3	0.1	0.2	0.1	0
VEN	0.5	1.3	0.3	0.3	0.4	1.3	0.4	1.1	0.4	0.1	0.2	1.3	1.8	0.1	0.4	0.8	82.9	0.4	2	0	3.2	0.3	0.5
STRAT	4.4	13.8	1.3	0.1	0.2	5.5	4.1	5.3	1.6	1.1	1.8	0.7	4.2	0.5	0.6	2.8	0.7	46.9	1.4	0.2	1.4	0.8	0.8
BTS	2.6	19.4	5.2	2.9	0.9	5.1	7.4	1.3	1.6	0.6	2.3	0.2	4.7	0.3	2.2	0.6	0.2	0.7	40.3	0.2	0.2	0.9	0.4
VERI	1.3	2.3	1.1	1.4	0.7	0.4	0.9	0.1	1.5	5.7	0.1	4.1	0.2	1.8	1	2.1	0.6	2.6	0.4	70.4	0	0.6	0.6
EOS	3.7	18.7	1.2	2.8	2.6	1.1	0.9	3	0.6	1.1	0.1	0.9	0.1	1.2	0.9	0.7	0.8	2	0.8	0.5	55.7	0.1	0.4
OMG	4.7	17.8	0.2	1.6	1	6.3	0.8	5	3.1	1.4	0.7	0.7	1.9	1.3	0.2	1.4	1	2.1	1.4	1.5	1.1	44.7	0.1
DOGE	0.4	7.5	4	0.4	1.5	1.9	3.5	1	3.5	0.6	4.1	0.7	9.5	0.2	12.1	4.4	3.5	0.6	0.7	0.3	0.3	0.4	39.1

Hourly Data

Now let's look at VAR model for hourly data[11]. I choose lag 2 for VAR model as it gives smallest AIC (-168.63). Results are shown in Appendix 3 and 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, Miota, 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.

[10] Variance decomposition are presented by rows: each cell means the contribution of jth column to ith row forecast error variance. The same logic is applied in Table 2-3.
[11] For hourly and minute estimation, I choose data for return in USD prices (both variants are estimated). Time period is not big, so fluctuation in USD price should not affect results.

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 from. Figure 10 contains the example of Ethereum).

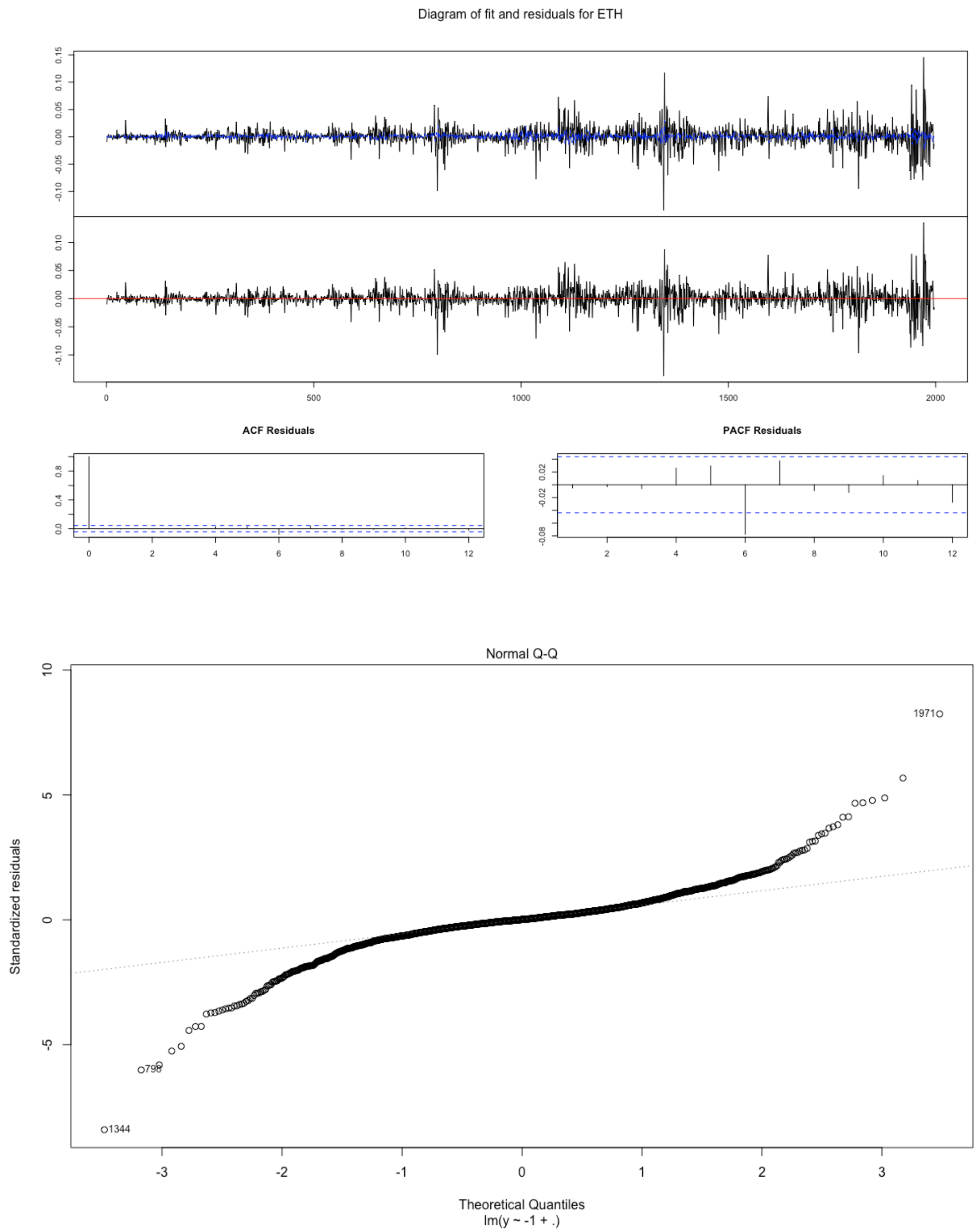

Figure 10 – Residual analysis of Ethereum series VAR(2) hourly model

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.

As before, the impulse response analysis is performed. Orthogonal impulse responses from Bitcoin are positive for all coins at the period of shock, but then it declines and becomes almost zero (Figure 11). Similar tendency is observed for Orthogonal impulse response from Ethereum (Figure 12). For other coins, impulse responses have small magnitudes and in most cases, are not statistically significant (as an example, Figure 13 presents orthogonal impulse response from VeChain).

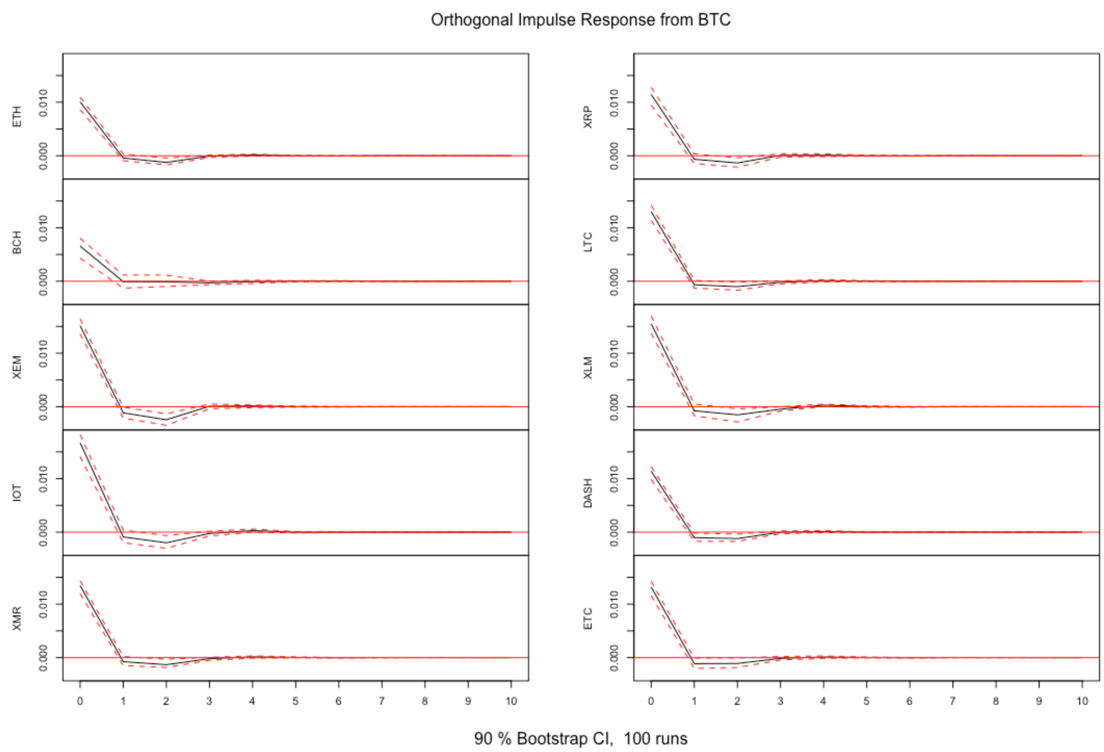

Figure 11 – Orthogonal Impulse Response from Bitcoin (VAR(2) hourly model)[12]

[12] Due to lack of space, Impulse Response plots are presented for selected coins

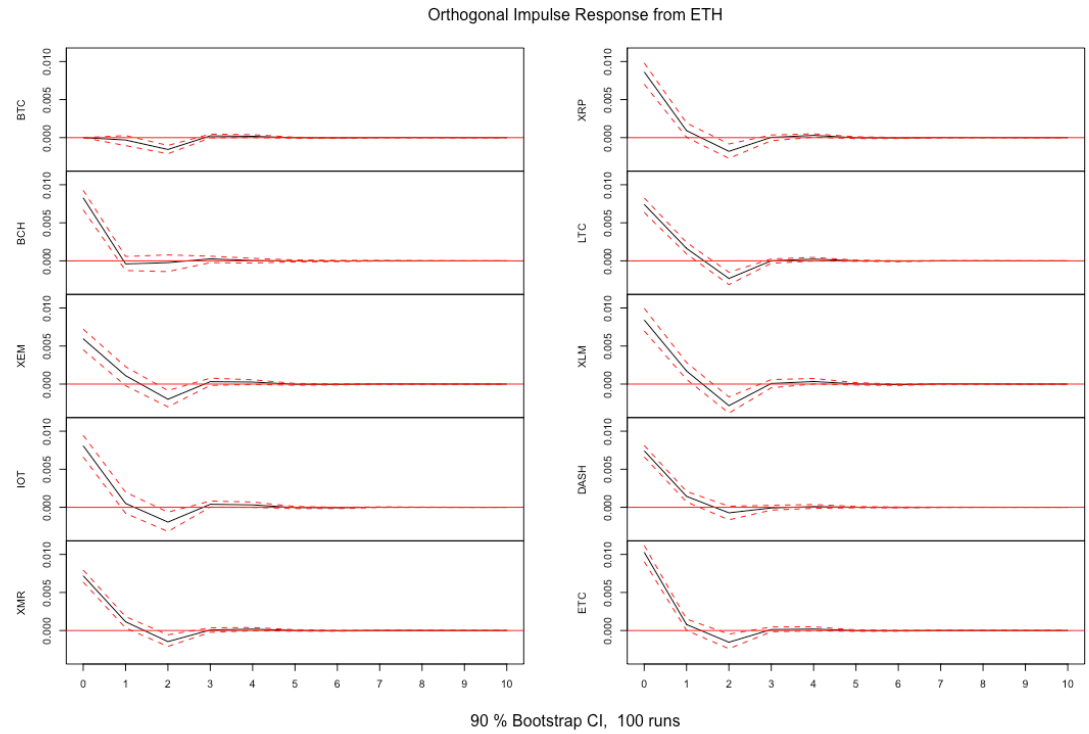

Figure 12 – Orthogonal Impulse Response from Ethereum (VAR(2) hourly model)

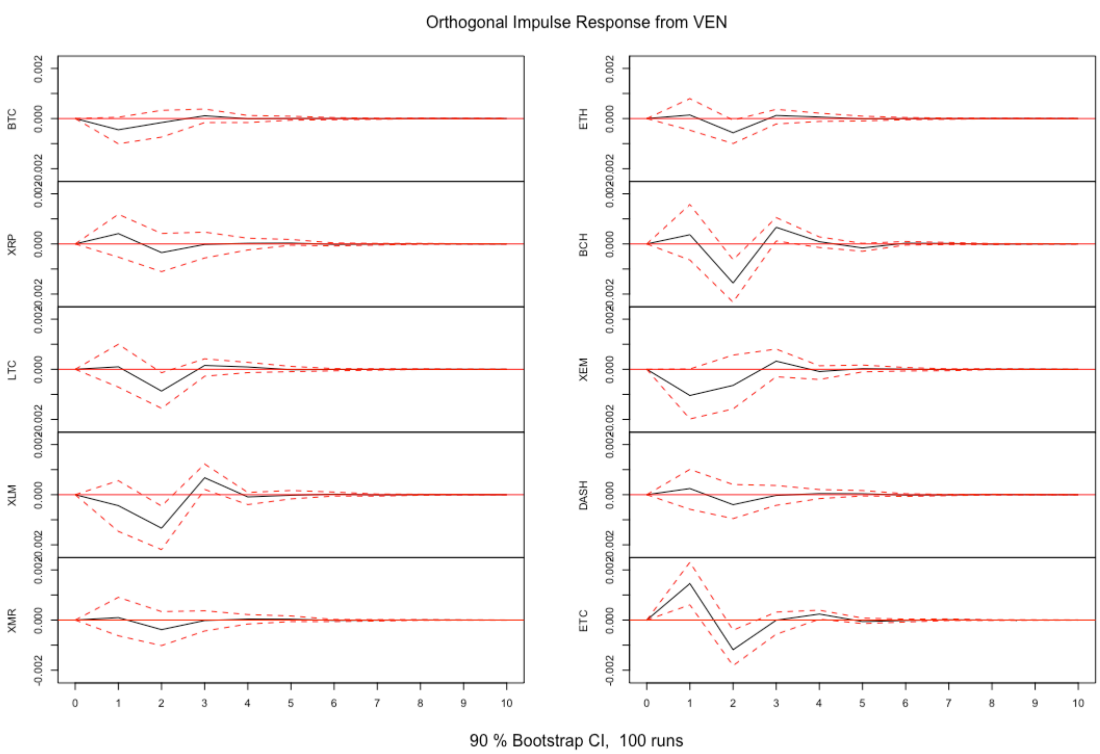

Figure 13 – Orthogonal Impulse Response from VeChain (VAR(2) hourly model)

The forecast error variance decomposition is represented in Table 3. As for daily data, most of the variance of the forecast errors for coins come from its own innovations. But the difference is that now Bitcoin shocks are leading in contributing to forecast error variance for other cryptocurrencies (20-30%), compared to Ethereum (10-15%). Shares of other altcoins are less than 1% on average. Thus, Bitcoin and Ethereum play the central role in explaining the forecast error variance of cryptocurrencies based on VAR(2) hourly data.

Table 3 – Forecast error variance decomposition for VAR(2) hourly model

	BTC	ETH	XRP	BCH	LTC	XEM	XLM	IOT	DASH	XMR	ETC	LSK	XVG	ZEC	BCN	SC	VEN	STRAT	BTS	VERI	EOS	OMG	DOGE
BTC	95.5	1	0.2	0.1	0	0.8	0	0.3	0.1	0.1	0.1	0.2	0.1	0	0.1	0.3	0.1	0	0.5	0.1	0.2	0.2	0
ETH	34.9	61.8	0.1	0.1	0.9	0.1	0.2	0	0.2	0.1	0	0.1	0	0.1	0.4	0	0.1	0	0.4	0	0.2	0.1	0
XRP	17	10	70.6	0.1	0.1	0.2	0.1	0	0.1	0.1	0.1	0	0	0.3	0	0.1	0	0.3	0.3	0.2	0.1	0	0.1
BCH	5.1	8.2	0.1	83.5	0	0.3	0.1	0	1	0.1	0.1	0.2	0	0.1	0.1	0.1	0.4	0	0	0.1	0	0.3	0
LTC	38.3	14.1	0.6	0.2	44.8	0.1	0.2	0.1	0.2	0.1	0	0.2	0.1	0	0	0	0.2	0.2	0.2	0.1	0	0.2	0
XEM	26.6	4.6	2.3	0	0.6	64.4	0.1	0.2	0.1	0	0.1	0.2	0	0.1	0	0	0.2	0.1	0.1	0	0.1	0.2	0
XLM	23.7	8	6.6	0.1	0.3	1.5	57.9	0.3	0.1	0	0	0.1	0.1	0	0.5	0	0.2	0	0	0.1	0	0.1	0
IOT	26.5	6.5	0.3	0.2	0.8	0.9	0.6	62.5	0.2	0	0	0.4	0.3	0	0	0.1	0	0.1	0.2	0	0.1	0	0
DASH	29.5	12.9	0.7	1.4	1.6	0.7	0.2	0.3	50.7	0	0	0.3	0.1	0	0.1	0.1	0	0.2	0.3	0.1	0.1	0.7	0
XMR	37.3	11.3	1.1	0.7	1.2	0.7	1.4	0.8	4.5	39.6	0	0.4	0	0.1	0.1	0	0	0.1	0.2	0	0	0.4	0.1
ETC	29.8	18.4	0.9	1	0.4	0.2	0.9	0.5	1.1	0.7	44.9	0.1	0.1	0.1	0	0	0.6	0.1	0.1	0	0	0.2	0
LSK	2.6	1.6	0.7	0.7	0.3	0.2	0.1	0.5	0.4	0.6	0.2	90.3	0.1	0.8	0.2	0	0	0	0.2	0	0	0	0.4
XVG	4.1	0.8	0.5	0.1	0.1	0.3	0.1	0.1	0.1	0.3	0.2	0	91.8	0.4	0.3	0	0.1	0.1	0	0	0.2	0.1	0.2
ZEC	30.1	15.6	0.7	0.6	0.8	0.8	0.8	0.8	4.2	1.7	0.4	0.3	0.2	42	0	0	0.1	0	0.1	0.1	0.2	0.2	0.1
BCN	31.7	3	0.8	0.1	0.3	0.7	0.3	0.3	0.4	0.1	0.2	0.6	0.3	0.1	59	0.4	0.1	0.1	0.2	0	0.1	0.2	1.3
SC	22.6	5.8	0.8	0.2	0.1	0.7	1	0.7	0.8	0.3	0.4	0.7	0.8	0.2	0.9	62.3	0.3	0.1	0.4	0.1	0	0.5	0.3
VEN	4.9	1.2	0.3	0.1	0.1	0.3	0.2	0.6	0.1	0.5	0.1	0.2	0.1	0.1	0.2	0.4	89.5	0.1	0.3	0	0.1	0.4	0
STRAT	13.5	3.6	0.9	0.2	0.2	1.1	2	0.4	0.2	0.5	0.1	0.1	0.1	0.1	0.5	0.4	0.4	74.9	0	0	0.1	0.5	0
BTS	23.1	12.2	3.1	0.2	0.5	1.1	2.3	0.3	1	0.1	0.3	0.2	0.1	0.2	0.2	0.9	0.2	0.3	52.9	0.1	0.2	0.4	0.1
VERI	0.2	0.1	0.2	0	0.1	0.1	0.6	0.1	0.1	0.1	0.1	0	0.1	0.1	0.1	0.1	0.1	0.2	0.1	97.3	0	0.3	0.1
EOS	22	9.7	0.5	0.2	0.2	0.4	0.4	1.7	0.2	0.1	0.5	0.3	0	0.2	0.2	0.5	0.1	0	0.3	0	62	0.1	0.2
OMG	28.5	14.6	2	0.1	0.6	0.9	1.5	1	1	0.4	0.9	0.1	0.3	0.5	0.3	0.6	0	0.3	1.2	0.1	0.2	44.8	0
DOGE	34.8	2.6	0.7	0.1	0.1	0.8	0.7	0.3	0.3	0.2	0.3	1.2	0.2	0.3	1.3	1	0.2	0.1	0.6	0	0.1	0.1	54.3

5 minutes data

Results of VAR model for 5 min data are presented in Appendix 4. I choose lag 2 because AIC is almost the same – for lag 1 (-219.853) and lag 2 (-219.16), but R^2 is higher for equations in VAR(2). Main things to notice are:

- While lag 1 of Bitcoin return has positive effect on 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 Dash equation (positive effect);
- Both lags of NEM provide negative influence on coins;

• Litecoin and Stellar lag 1 coefficients show negative effect on Bitcoin, BitcoinCash, Miota, 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 (Figure 14). 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.

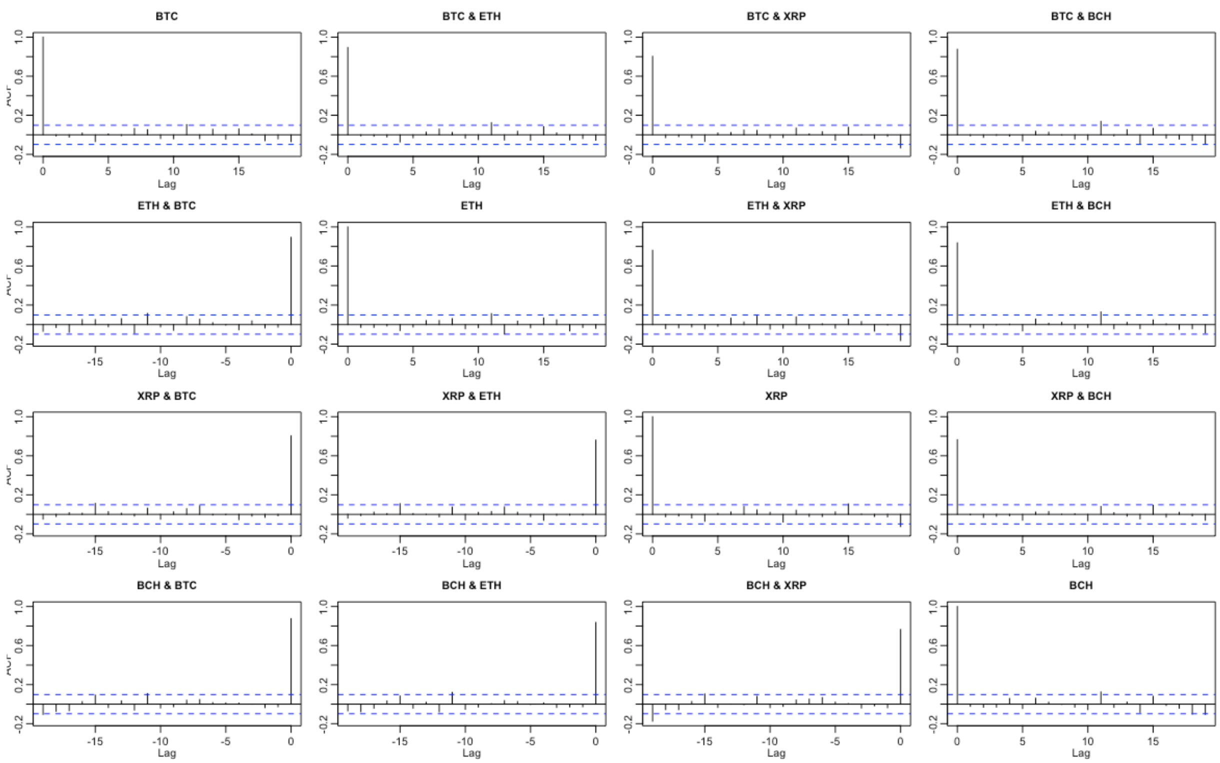

Figure 14 – Cross-correlation plot of residuals of VAR(2) 5-minutes model for some variables

Impulse response analysis provides the following results. In response to orthogonal shock in Bitcoin, the coins' returns initially increase, but after two periods responses vanish (Figure 15). The same is held for responses from Ethereum shock, but magnitudes are smaller. As for shock in BitcoinCash, it has a significant negative cumulative orthogonal response of Bitcoin, Ethereum, Ripple (Figure 16).

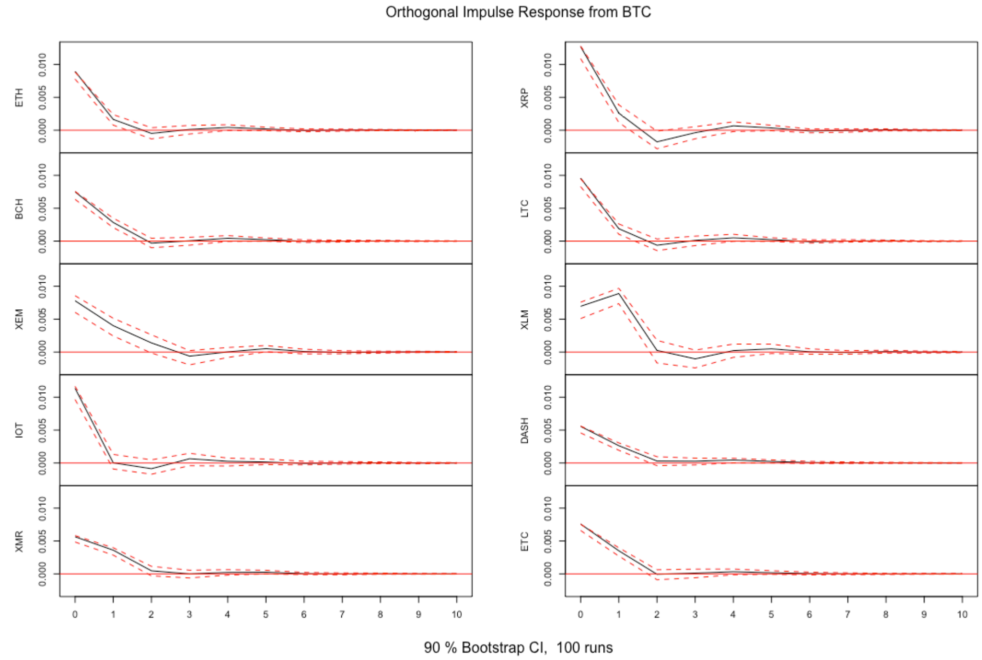

Figure 15 – Orthogonal Impulse Response from Bitcoin (VAR(2) 5-minutes model)

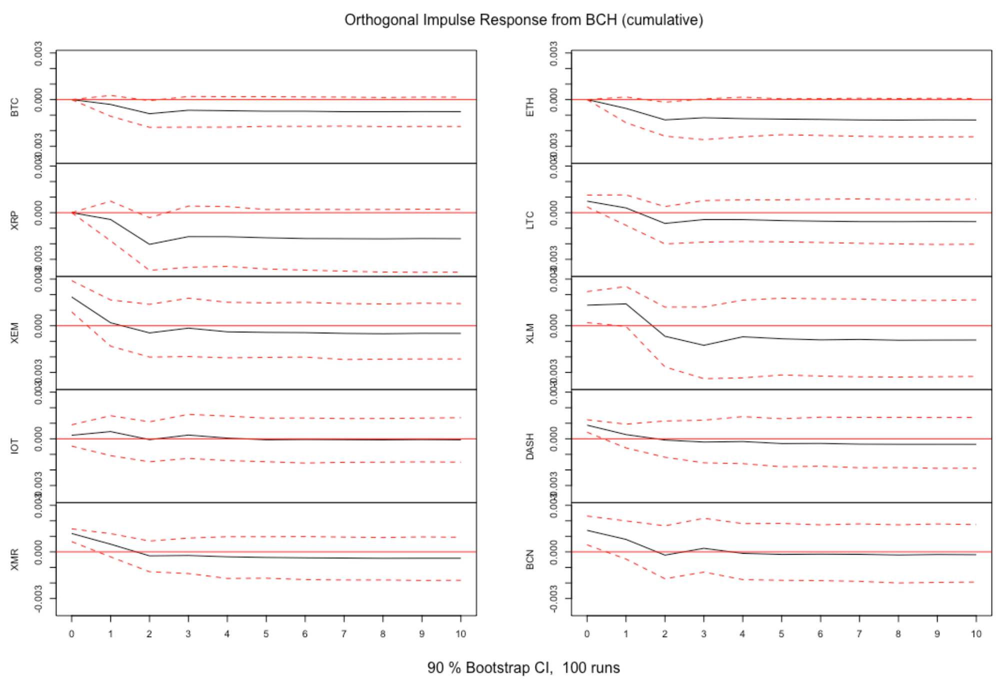

Figure 16 – Cumulative Orthogonal Impulse Response from BitcoinCash (VAR(2) 5-minutes model)

Forecast error variance decomposition (Table 4) shows that Bitcoin contributes to more than 30% to forecast error variance for the majority of coins, reaching 70% for Ethereum, 69% for

BitcoinCash, 69% for EthereumClassic, 61% for EOS. The coins that are not affected by such high influence are Lisk, VeChain, Veritaseum and Verge. Forecast error variance of currencies explained by Ethereum are about 1-3% on average, which is much less than was observed in daily and hourly data.

Table 4 – Forecast error variance decomposition for VAR(2) 5-minutes model

	BTC	ETH	XRP	BCH	LTC	XEM	XLM	IOT	DASH	XMR	ETC	LSK	XVG	ZEC	BCN	SC	VEN	STRAT	BTS	VERI	EOS	OMG	DOGE
BTC	85.2	0.3	1.1	0.7	1.5	1.5	0.8	0.1	0.3	0.2	1.4	0.3	0.5	0.1	1.6	1.5	0.1	0.8	0.2	0.3	0.3	0	1.1
ETH	69.7	17.7	1.3	0.7	0.6	1.4	0.5	0.3	0.4	0.3	1	0.1	0.3	0.3	1.5	0.5	0.1	0.8	0.7	0.7	0.1	0	0.8
XRP	58.9	0.9	29.7	1	0.2	1.8	1.2	0.3	0.2	0.2	0.6	0.1	0.5	0.2	1.2	0.3	0.1	0.4	1.1	0.7	0.3	0.1	0.1
BCH	68.9	1.6	1.6	17.3	0.9	1.4	1.9	0.3	0.2	0.3	0.6	0.2	0.4	0.2	0.6	1	0.1	0.3	0.9	0.4	0.3	0.3	0.2
LTC	67	3.7	0.7	1.3	15.2	1.2	0.7	0.5	0.8	0.7	2.2	0.3	0.3	0.1	2.1	0.6	0.1	0.9	0.4	0.3	0.1	0.1	0.7
XEM	26.5	0.7	1.4	2.3	0.1	61.4	0.7	0.8	0.2	0.1	0.6	0.2	0.3	0.9	0.4	0.9	0.5	0.3	0.9	0.1	0.1	0.2	0.6
XLM	33.4	0.9	2.1	1.7	1.3	1	49.9	0.6	0.3	0.3	0.8	0.1	0.6	0.5	1.3	0.9	0.7	0.9	0.3	0.9	0.6	0.2	0.6
IOT	52.7	1.7	0.9	0.2	1.9	0.7	0.4	33.1	0.3	0.3	0.5	0.1	0.8	0.1	1.6	0.3	0.2	0.4	1.4	0.2	0.1	0.1	1.9
DASH	54.5	1.9	1.4	1.8	0.6	1.2	1.2	0.5	30.5	0.2	0.2	0.1	0.1	0.6	0.4	1.8	0.2	0.9	0.9	0.3	0.3	0.1	0.2
XMR	56.9	1.2	3	3.1	1.4	2.2	2.4	0.2	1.2	23.5	0.7	0.3	0.2	0.4	0.5	0.4	0.2	0.7	0.4	0.1	0	0.9	0.3
ETC	67.6	1.1	1.4	1.2	1.1	1.5	1.9	0.2	1.2	0.6	16.7	0.1	0.6	0.9	0.6	1.1	0.1	0.9	0.2	0.2	0	0.1	0.5
LSK	0.3	0.3	0.1	0.1	0.1	1.6	0.1	0.3	0.6	0.3	0.4	92.3	0.3	0.6	0.1	0.1	0.1	0.3	0.1	0.2	0.4	1.2	0
XVG	13.2	0.6	3.5	1.6	0.5	0.4	0.8	0	0.4	0.3	1.2	0.1	72.3	0.6	0.6	0.3	0.2	0.6	0.4	0.4	0.2	0.8	0.9
ZEC	49.8	1.3	2.5	0.9	1.2	2.2	1.7	0.8	0.8	0.3	1.7	0.8	0.9	29.6	0.7	0.9	0.5	0.8	1.5	0.3	0.6	0.1	0.1
BCN	28.6	0.8	1.6	1.7	0.5	1.3	1.7	0.8	1.3	1.8	0.7	0.5	1	1.8	48.6	1.1	0.7	0.4	1	1	0.7	0.6	1.8
SC	47.3	1	0.8	1.1	1.5	2.5	1	1.4	0.4	0.5	0.3	0.1	0.6	0.6	0.4	37.6	0	0.8	0.5	0.2	0.1	0.6	0.5
VEN	6.4	0.3	1	0.7	0.7	0.2	0.9	0.2	0.7	2.3	0.3	0.5	0.1	1	0.7	0.1	78.6	0.4	1.5	1.2	1.2	0.1	0.7
STRAT	42	1.1	2.5	3.6	0.1	0.6	2.6	0.2	0.1	1.1	1.7	0.3	1	1.9	1.1	1.4	0.1	34.5	1.4	1.7	0.2	0.5	0.4
BTS	51.4	1.7	3	0.9	1.6	0.5	0.5	1.1	0.3	0.5	1.2	0.6	0.4	0.2	1.2	1.7	0.2	0.6	31.3	0.3	0.1	0.1	0.5
VERI	16.8	4.2	0.4	1.6	0.2	0.7	0.2	1.1	0.6	0.9	1	1.8	0.1	1	1.4	0.5	0.5	0	0.3	66	0.1	0.2	0.5
EOS	61.1	2.2	1.6	1.6	1.2	0.5	1.1	0.3	0.8	0.9	2.8	0.3	0.2	0.4	1.4	1.1	0.6	0.8	0.5	0.6	19.5	0	0.6
OMG	57.6	1.8	1	0.9	2.7	0.6	0.9	0.2	0.8	0.4	0.6	0.6	0.2	0.5	0.8	0.9	0.1	0.3	0.4	0.7	0.3	27.3	0.4
DOGE	36	1	2	1.6	0.2	1	1.3	0.5	0.7	1	0.4	0.3	1.6	1	1.3	1.1	0.4	2.5	0.6	1.5	0.2	0.3	43.5

Most probably, such results are due to the situation on the market itself that was happening on January, 17. 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[13]. During this shock, Bitcoin and Ethereum as major cryptocurrencies lost about 20% and 30% of its value respectively, as well as other coins. During next days, prices came back. Thus, this example and analysis of the shock time period show that Bitcoin remains the most central player on cryptocurrencies market, and even Ethereum still cannot reach it.

VAR model for minute data is also estimated and reflect 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.

[13] http://fortune.com/2018/01/24/south-korea-bitcoin-privacy-fines/

5. Discussion

Models estimated in the empirical part suggest that within daily periodicity, there are more interactions between cryptocurrencies returns, meaning that altcoins can affect and influence each other. In contrast, for hourly specification, the impact of Bitcoin increases and, looking, for example, at the forecast error variance, it contributes 3-4 or even 5 times more explaining other coins variances compared to the daily model. The example of VAR modelling during shock period (market down) shows strong central role of Bitcoin at cryptocurrencies market.

But I would like to mention possible concerns about the presented approach:

1. Models demonstrate the presence of heteroscedasticity, suggesting time variation in the variance of returns.
2. The ordering of variables in VAR model matters, that is rearranging variables will give different results.

One of the alternative approaches would be to use Autoregressive Conditional Heteroscedasticity (ARCH) model which describe changing volatile variance, or Generalized ARCH which model variance by past variances and squared observations.

Regarding VAR, possible extension would be to try another ordering of variables and compare results. But if one is looking for connectedness measure, another approach can be more preferable because as Demirer et al. (2017) mentioned, VAR gives incomplete connectedness measures because of its construction (it ignores the covariance matrix of disturbances).

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 to biggest American financial firms' data. It is feasible to try to use a similar approach to build the network map of cryptocurrencies. It is reasonable to think that applying variance decomposition and building network map can help to more precisely answer a question: how the cryptocurrencies are connected to each other and how they can affect each other during shocks.

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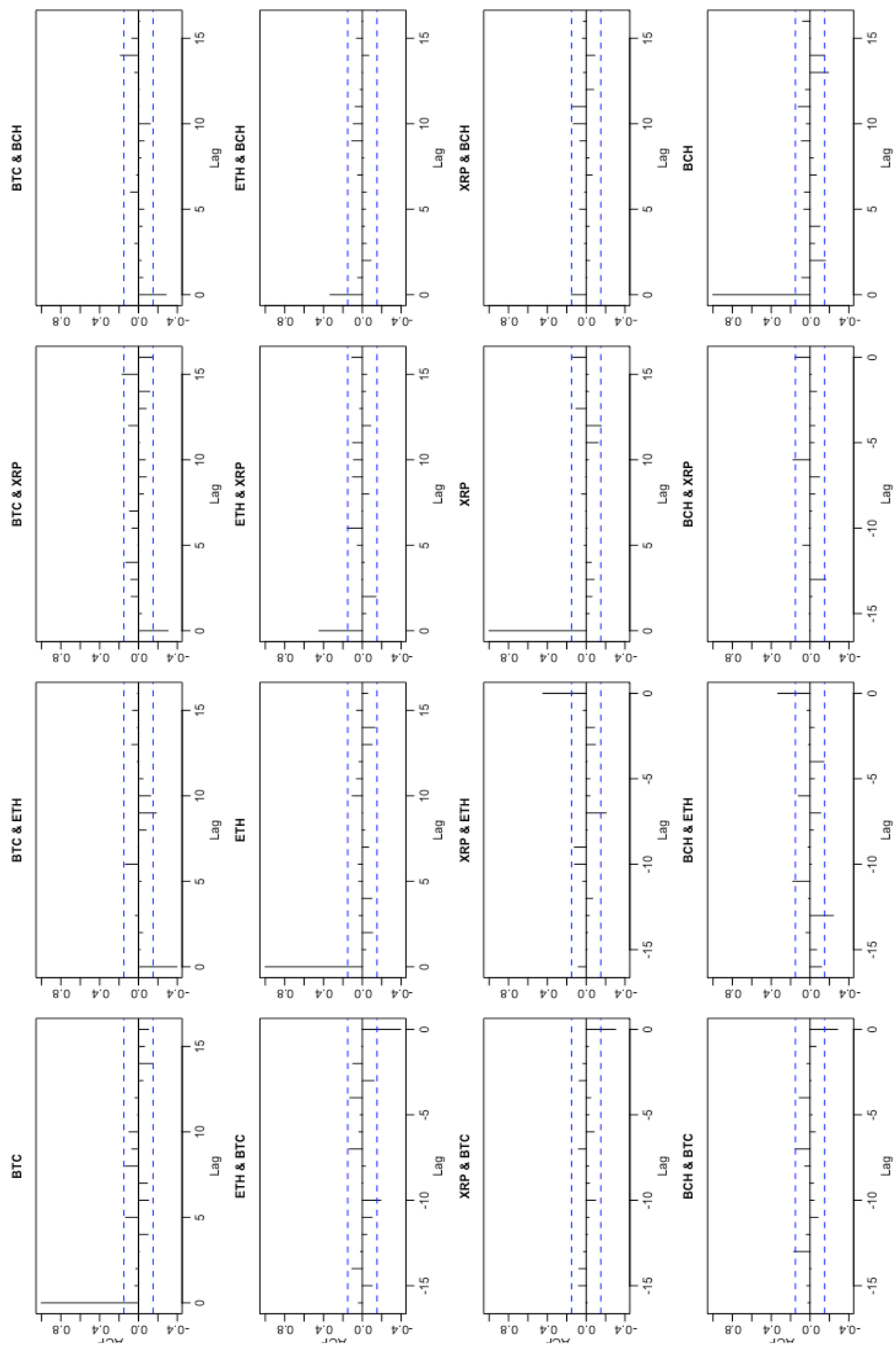
Appendix 1. Results of VAR(1) daily model

	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	-0.114	0.116	0.222	0.160	0.214*	0.427**	0.135	0.152	-0.099	-0.028	0.184	-0.126	-0.236	0.074	-0.054	-0.028	0.529	-0.179	0.179	0.112	0.278*	-0.274	-0.060
ETH.l1	0.006	0.098	0.366	0.759**	-0.096	0.283	-0.049	-0.031	0.034	0.270	0.105	-0.072	0.282	0.248	0.261	0.062	0.349	0.108	0.063	-1.569**	0.163	-0.179	0.037
XRP.l1	-0.062	-0.030	0.115	-0.054	-0.016	0.018	0.059	-0.135	-0.079	-0.092	-0.071	-0.122	0.067	-0.093	-0.101	-0.142	0.195	-0.132	0.106	0.140	-0.054	-0.092	-0.120
BCH.l1	-0.086**	0.084**	0.050	0.335***	0.056	0.074	-0.002	0.113	0.146***	0.073	0.119**	0.162**	0.012	0.130**	-0.141**	0.053	0.169	0.048	0.066	0.418*	0.081	-0.124*	-0.009
LTC.l1	-0.002	0.146*	0.225	0.084	0.140	-0.125	0.078	-0.126	0.113	0.058	0.079	0.086	0.471**	0.138	-0.076	0.178	-0.125	-0.014	0.246	0.107	0.332**	0.227	0.228*
XEM.l1	-0.085*	0.107**	0.027	0.033	0.188***	-0.164*	0.027	0.076	0.077	0.044	0.106	0.074	0.015	0.037	0.039	0.110	0.044	0.072	0.079	-0.172	-0.041	0.164*	0.062
XLM.l1	0.029	-0.035	-0.048	0.065	-0.059	-0.087	0.137	-0.012	-0.035	-0.039	0.035	-0.058	-0.077	-0.022	-0.064	0.009	0.165	0.066	0.020	-0.002	-0.019	-0.025	-0.056
IOT.l1	0.028	-0.158***	-0.147	0.016	-0.189***	-0.194*	-0.106	0.084	0.010	0.014	-0.224***	-0.092	0.013	-0.107	-0.048	-0.101	-0.088	-0.085	0.008	-0.390	-0.073	-0.175*	-0.029
DASH.l1	0.020	0.072	0.099	0.105	0.144	0.213	0.276	-0.032	-0.155	-0.088	0.140	0.061	0.078	-0.115	0.140	0.068	0.035	0.017	-0.001	0.806	-0.031	0.184	0.103
XMR.l1	-0.008	-0.013	0.175	0.055	0.021	-0.088	-0.068	-0.074	0.129	0.002	-0.103	0.197	-0.102	0.063	0.053	0.045	-0.157	0.002	-0.073	-1.343***	-0.014	-0.268*	0.008
ETC.l1	-0.031	-0.131	-0.259	-0.262	-0.028	-0.123	-0.038	0.010	0.152	-0.018	-0.135	-0.163	-0.546**	-0.067	-0.037	-0.173	0.263	-0.186	-0.165	-0.168	-0.045	-0.028	-0.245*
LSK.l1	-0.007	-0.121*	-0.045	-0.225	-0.006	-0.133	0.110	0.012	-0.058	0.072	-0.050	0.056	0.029	-0.017	-0.064	0.034	-0.254	-0.011	-0.058	1.025***	0.038	-0.194	-0.035
XVG.l1	0.027	-0.021	0.155**	0.056	0.031	0.092	0.160*	-0.006	0.029	0.065	0.071	0.117*	0.135	0.081*	0.174***	0.193***	0.335*	0.111**	0.170***	-0.038	0.021	0.087	0.142**
ZEC.l1	-0.088	0.136	-0.008	-0.191	0.089	0.143	-0.274	-0.181	-0.068	-0.110	0.069	-0.018	-0.275	0.011	-0.220	-0.146	0.204	0.184	0.145	-0.256	0.058	0.346*	-0.003
BCN.l1	0.122*	-0.068	-0.102	-0.080	0.008	-0.010	-0.109	-0.167	-0.084	-0.087	-0.070	0.046	-0.018	0.004	-0.128	-0.110	-0.109	-0.221**	-0.118	-0.402	-0.070	-0.077	0.004
SC.l1	-0.092	0.071	0.074	-0.043	0.040	0.060	-0.101	0.336***	0.019	0.059	0.016	0.065	-0.228	0.078	0.286***	0.049	0.307	0.157	0.038	0.451	0.073	0.126	0.123
VEN.l1	0.046***	0.003	-0.012	0.021	0.024	0.022	0.017	0.021	0.009	0.011	0.020	0.065**	0.053	0.003	0.025	0.027	0.043	0.022	0.002	-0.062	0.020	0.040	0.062**
STRAT.l1	-0.063	0.127*	-0.125	-0.130	0.141*	0.314**	-0.001	-0.018	-0.059	-0.058	0.071	-0.154	-0.187	-0.048	-0.134	-0.169	-0.154	-0.075	-0.102	0.610	-0.217**	0.094	-0.109
BTS.l1	0.133**	-0.102	-0.150	-0.113	-0.124	-0.068	-0.176	-0.037	-0.069	-0.036	-0.098	-0.095	0.288*	-0.114	0.105	-0.060	-0.590*	-0.184*	-0.156	0.218	0.119	0.003	0.106
VERI.l1	-0.007	0.004	-0.009	0.075***	-0.013	0.009	0.004	0.004	0.013	-0.002	-0.005	0.022	-0.022	0.001	-0.011	-0.010	0.011	-0.008	-0.013	-0.241***	-0.014	-0.044**	-0.006
EOS.l1	0.064	-0.104*	-0.019	-0.121	-0.195***	-0.201*	-0.038	-0.028	-0.066	-0.040	-0.032	-0.063	0.081	-0.007	-0.043	0.024	-0.732**	-0.157*	-0.010	-0.082	-0.049	-0.085	-0.040
OMG.l1	-0.012	0.095*	0.042	0.012	0.043	-0.030	0.107	0.186*	0.016	-0.005	0.085	0.101	0.150	0.065	-0.038	0.038	0.234	0.100	0.140	0.367	0.038	0.045	0.021
DOGE.l1	-0.124*	0.081	0.121	0.184	-0.075	-0.112	0.059	-0.172	0.086	0.004	-0.005	0.045	0.090	0.012	-0.022	0.001	-0.259	0.139	-0.109	-0.282	-0.086	-0.057	-0.206*
const	0.016*	-0.012	-0.023	-0.013	-0.017	-0.026	-0.032	-0.006	-0.0003	-0.0001	-0.021	-0.0002	-0.019	-0.011	-0.015	-0.045**	-0.089*	-0.029*	-0.036**	-0.081	-0.044***	0.027	-0.029*
trend	-0.0001	0.0002	0.0003	0.0001	0.0002*	0.0003	0.0004*	0.0001	0.00003	0.00003	0.0002	0.0001	0.0003	0.0001	0.0002	0.0005**	0.001*	0.0003*	0.0003*	0.001	0.0005***	-0.0002	0.0003**
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	0.240	0.301	0.226	0.214	0.295	0.211	0.102	0.152	0.169	0.094	0.199	0.241	0.164	0.187	0.250	0.181	0.126	0.226	0.160	0.301	0.201	0.202	0.232
Adjusted R^2	0.113	0.184	0.097	0.083	0.178	0.080	-0.048	0.011	0.030	-0.056	0.065	0.115	0.025	0.052	0.125	0.045	-0.020	0.096	0.020	0.184	0.068	0.070	0.104
Residual Std. Error (df = 144)	0.054	0.054	0.103	0.131	0.065	0.113	0.127	0.101	0.077	0.080	0.079	0.094	0.148	0.075	0.088	0.108	0.270	0.084	0.099	0.315	0.090	0.104	0.086
F Statistic (df = 24; 144)	1.894**	2.578***	1.749**	1.630**	2.511***	1.608**	0.681	1.075	1.218	0.626	1.488*	1.908**	1.180	1.381	2.003***	1.328	0.865	1.747**	1.140	2.579***	1.512*	1.523*	1.812**

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

Appendix 2. Cross-correlation plot of selected series residuals for VAR(1) daily model



Appendix 3. Results of VAR(2) hourly 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	-0.086**	-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 3 (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 4. 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 4 (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: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$