



Cryptocurrencies' Internal and External Relations

A Descriptive Analysis of Cryptocurrency Dynamics and Relations to the US Equity Market

Abstract

This thesis is a descriptive statistical analysis of cryptocurrency market and its relation within cryptocurrencies and across asset classes, using correlation functions, orthogonalized impulse response functions and OLS regressions. Consistent with Wang (2014), bitcoin does not suffer from a liquidity trap, even though bitcoin is a decentralized system. This thesis concludes that bitcoin has a lead effect on only 2 out of 8 of the top cryptocurrencies, endowing diversification benefits within cryptocurrency market. This paper provides evidence on cryptocurrency market's and US equity market's impulse response dynamics which are insignificant, consistent with Gangwal's (2016) results that adding cryptocurrencies to a diversified portfolio will yield to a higher Sharpe ratio. Lastly, the study reports bitcoin momentum factor having an impact on banking and financial industries' excess returns.

Keywords:

Bitcoin, Bitcoin Liquidity, Bitcoin and Equity Market, Cryptocurrency, Descriptive Analysis, Asset Class, Market Relations

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1. Introduction

Bitcoin was introduced as an alternative currency for advanced users seeking a fully electronic currency with low transactions costs, anonymity and protection from central banks' power and their loose monetary policies (decentralization). It was launched in 2008 by an alias named Satoshi Nakamoto, and ever since, it has grown in popularity. (Nakamoto, 2008) After 2008, over 1 300 cryptocurrencies have entered for cryptocurrency users and investors. While most of them can be seen more or less insignificant, the top cryptocurrencies and the blockchain technology within them are reshaping our ways of conducting transactions – not solely with monetary transactions.¹ For example, cryptocurrencies and the blockchain technology behind it is seen as a promising alternative in contract law, in form of *smart contracts*.²

Thus, in my opinion, one of the most interesting and controversial developments in the financial environment this year has been the exponential growth in the cryptocurrency market. Bitcoin, which constitutes of over 50 % of total fiat currency³ value in the cryptocurrency market, has been on media more frequently and bitcoin searches have grown almost tenfold during the last year⁴. Additionally, the cryptocurrency market's total value is now over \$300 billion with a year-to-date growth of over 2 200 % while over 500 new cryptocurrencies have been introduced to the global market at the same time⁵.

However, even though bitcoin has been studied to some degree in the financial literature, the interconnectedness of cryptocurrencies and their relations to equity market has remained low in attention – especially in finance's perspective. To my knowledge, papers discussing the internal dynamics of this market with multiple cryptocurrencies and their market relations, have not possibly been published due to obvious data limitations which were notable even during last year.⁶

The scope of this research paper is to identify bitcoin's lead effect on other top cryptocurrencies. As the bitcoin is the most renown cryptocurrency and it continues to

¹ Internet: <https://coinmarketcap.com/all/views/all/#>, date 28.11.2017

² Internet: <https://www.forbes.com/sites/bernardmarr/2017/08/15/practical-examples-of-how-blockchains-will-be-used-in-legal-firms/#2f8f5e4a66a7>, date 28.11.2017

³ Fiat currency is money that has no intrinsic value and is controlled by government regulation or by central bank authority. For example, USD and EUR are fiat currencies.

⁴ Internet: <https://trends.google.com/trends/explore?q=bitcoin>, date 28.11.2017

⁵ Internet: <https://coinmarketcap.com/charts/>, date 28.11.2017

⁶ Most of the cryptocurrencies I use in this thesis had less than 100 days of age year ago.

dominate the market, this paper investigates how bitcoin's price development impacts other top cryptocurrencies' price development and with what delay.

Additionally, in the scope of this thesis, is to examine cryptocurrencies as an asset class and their return relations to the US equity market and financial industry. Hence, this thesis also scrutinizes US equity impulses and cryptocurrencies' responses – and vice versa. To add more depth to the cryptocurrencies market relations, I regress bitcoin returns to financial industry's returns – an industry that has been vociferously against bitcoin and cryptocurrencies.⁷ In conclusion, this thesis studies cryptocurrency market's characteristics and its relation within and across, using US equity and finance industries as benchmark assets. The motivation for this is to illustrate the nature of the cryptocurrency market.

The rest of this thesis proceeds as follows. In section 2, I go through literature related to my hypotheses after which I present my hypotheses of the interconnectedness of the cryptocurrencies and their relationship to the US equity market benchmarks. Section 3 processes the various data used and its elaboration for statistical modeling and regressions. Section 4 presents the methodology and models used in the analysis. Section 5 presents the vector autoregressive regression and its orthogonalized impulse response plots and results, as well as, the OLS regressions with bitcoin momentum factor. Section 6 briefly discusses results presented in section 5 further on. Last section, 7, concludes the thesis.

2. Literature Review and Hypotheses

Bitcoin and other cryptocurrencies have begun to attract academic research during the last years due to increasing popularity of the blockchain technology. However, analyses of cryptocurrencies as a financial asset and its internal and cross-relations have not yet generated any comprehensive research in financial literature – at least in the finance's top journals.⁸ Nevertheless, to link this thesis to published literature, I will undergo liquidity trap in decentralized systems, asset class and cryptocurrency literature related to the main themes of this thesis.

⁷ Internet: <https://www.bloomberg.com/news/articles/2017-11-26/what-the-world-s-central-banks-are-saying-about-cryptocurrencies> & <https://www.theguardian.com/technology/2017/sep/13/bitcoin-fraud-jp-morgan-cryptocurrency-drug-dealers>, date 26.11.2017

⁸ To this date, there is not a single article in *Journal of Finance*, *Journal of Financial Economics* or *Review of Financial Studies*

2.1 Cryptocurrencies as means of exchange and bitcoin's liquidity

In my opinion, one of the first questions that arise when discussing cryptocurrencies, especially bitcoin, is that can they be used as a means of exchange in the future. Or, alternatively, are they merely a speculative currency asset for speculative investors seeking for short-term profits.

Descriptive analogy against decentralized systems, like bitcoin and other cryptocurrencies, is from Sweeneys' paper (1977) which was later popularized in a column by Nobel-prize winning economist Paul Krugman (1998).⁹ In this paper, Sweeneys use an analogy of baby-sitting co-op crisis where a group of highly educated and diligent young couples with kids in the Capitol Hill decides to set up a network where couples can serve as baby-sitters and then later let their babies to be watched over in favor.¹⁰ To keep track of that everybody does their respective part, this group decides to create *scrip system* where these scrips are obtained from each baby-sitting session and then can be used in turn for leaving one's babies for other parents' care – in a 1:1 principle. Possibly imperceptibly, they had created a *decentralized currency system*, like bitcoin.

Unexpectedly, however, this currency system ran into liquidity problems. As these rationally behaving couples started to accumulate these scrips for reserve, thinking of using scrips in the future for spontaneous occasions, the whole baby-sitting co-op system started slowly collapsing as the circulation of the scrips in the system drained. This diminishing circulation of scrips naturally led to couples being reluctant to use their scripts and anxious for gathering more of them for future use. Hence, the “currency system” had fallen into recession, or to be more precise, started to suffer from a liquidity trap.¹¹

This analogy is central in bitcoin and overall in the cryptocurrency market as these cryptocurrencies suffer from a significant deflation, in relation to fiat currencies, and are decentralized as the scrip system in the Sweeneys' analogy. In addition, based on historical data, it is reasonable to hold onto the currency as its value increases daily rather than to spend it as a means of exchange. When fiat currencies face this problem, centralized authority issues new money to the circulation, something that bitcoin's decentralized source code is not able to execute – as this economic factor was not taken into necessary consideration in its creation.

⁹ Internet: http://www.slate.com/articles/business/the_dismal_science/1998/08/babysitting_the_economy.html, date 30.11.2017

¹⁰ The Sweeneys were actually part of this group, meaning that it is not a fictional story.

¹¹ Liquidity trap in this context refers to causation where people build reserves of currency because they are expecting deflation or in cryptocurrency context increasing value of the currency compared to fiat currencies.

The supply of new bitcoins is fixed and new bitcoins are issued for *miners* as a reward for verifying transactions in the bitcoin blockchain¹² – not for improving liquidity when the decentralized system faces hindrances.

In my opinion, based on the rationale above, bitcoin blockchain will eventually face this problem as the money supply is predetermined. Meaning that liquidity in the bitcoin system will collapse at some point, possibly leading even stronger deflation. However, studies so far have reported that bitcoin has not fallen into this liquidity trap (Wang, 2014). Thus, making the predominant theory such where this liquidity trap does not exist.

2.2 Cryptocurrencies as an asset class

Secondly, when addressing bitcoin and cryptocurrencies in finance's perspective, a significant question is to decide what kind of asset class cryptocurrencies are. Greer (1997) posits conceptual framework to define three asset *superclasses*.

An asset class can be a capital asset which is an ongoing source of something of value (i.e. dividends or interests); a consumable/transformable asset which can be consumed or transformed into another asset as part of a production process (i.e. commodities); a store of value asset which does not generate cash flow and is not used as an economic input (i.e. art or currency. Additionally, an asset class is “a set of assets that bear some fundamental economic similarities to each other, and that have characteristics that make them distinct from other assets that are not part of that class.” (Greer, 1997)

Smith (2016) and Baur et al. (2015) argue that bitcoins are digital gold that is used for an exchange of goods and services, though possessing some of the speculative electronic commodity attributes. Thus, using the framework of Greer, Smith and Baur et al. argument, cryptocurrencies can be pigeonholed to the third superclass like art and currencies. Lombardi and Ravazzolo (2016) posit that, for example, equity and commodity returns over the long run have displayed low correlation. Therefore, intuitively, these rather homogenous superclasses should co-move and embody higher correlations within respective asset class while cross-correlations across these superclasses should be of lower magnitude.

In my opinion, in the cryptocurrency framework, this would mean that cryptocurrencies possessing similar attributes and technology should co-move more strongly. Thus, this

¹² Website: <https://bitcoin.org/en/how-it-works>, date 30.11.2017.

cryptocurrency asset superclass should have weaker relations with the US equity market, which is used as the benchmark asset in this thesis – rather than within – as it is its own asset superclass entity. Moreover, Gangwal (2016) reports that adding bitcoin to a diversified portfolio generates higher Sharpe ratio¹³, indicating weak connection US equity returns.

2.2 Hypotheses

Motivated by Sweeneys' (1977) analogy of the decentralized liquidity trap and but noting Wang's (2014) results, I am testing whether bitcoin's liquidity affects bitcoin's and cryptocurrencies' price. To test this, bitcoin's past day's illiquidity should positively affect bitcoin's and cryptocurrencies' excess returns and vice versa, as the bitcoin dominates the market by possessing over 50 % of the total cryptocurrency market capitalization (Amihud, 2002). However, even though Sweeneys' analogy fits this situation, I hypothesize as Wang's (2014) evidence suggest, that bitcoin has not fallen into a liquidity trap meaning that bitcoin does not suffer from illiquidity. Thus:

H1: *Bitcoin's illiquidity factor does not influence bitcoin's or other top cryptocurrencies' price development (the “liquidity trap hypothesis”).*

Though it is reasonable to argue that cryptocurrencies are speculative commodity assets, I view them as currencies as Smith (2016) and Baur et al. (2015) do. As the sovereign cryptocurrency is bitcoin, I hypothesize that bitcoin price development affects other top cryptocurrencies based on the Greer's (1997) framework and bitcoin's market dominance. Meaning that bitcoin leads the price development of the whole cryptocurrency market. Thus:

H2: *Bitcoin's price development impacts other top cryptocurrencies' price development (the “internal leader effect hypothesis”).*

In relation to this internal co-moving theory, I hypothesize that cryptocurrencies as an asset class have no impacts or responses to other asset classes' impacts or responses. This is supported by Gangwal's (2016) portfolio diversification results. In this thesis, I use excess returns of US equity market and the financial industries as the benchmark assets. Thus:

H3a: *Bitcoin and excess returns on US equity market do not have an impact on each other's price development (the “no cross-impact hypothesis a”).*

¹³ Sharpe ratio *ex ante* is the expected excess average return on an asset divided by assets volatility.

H3b: *Bitcoin and excess returns of banking and financial industry do not have an impact on each other's price development (the “no cross-impact hypothesis b”).*

3. Data

3.1 Cryptocurrency data & market proxy

In this research, I am using a dataset of cryptocurrencies with over \$1 billion market value.¹⁴ The datasets are from Coinmarketcap.com and they contain the daily prices, in USD, for each cryptocurrency. This data is gathered from multiple cryptocurrency exchanges and aggregated, to indicate the average price and total market capitalization of one cryptocurrency by the Coinmarketcap.com. The reason behind this is that momentary arbitrages between cryptocurrency exchanges can be significant and last for minutes¹⁵. As Shaub (2014) concludes, based on his autocorrelation analysis, that efficient market hypothesis (EMH) does not hold among bitcoin trading exchanges, though the market does not necessarily achieve weak-form efficiency. Thus, using aggregated data set is more robust than using only one exchange's data which can be deteriorated at any given time. Further on, this data set is used for calculating the daily yields for each cryptocurrency.

Additionally, I use more comprehensive data sets from a website which track more widely variables for bitcoin which include aggregated total trade volume in dollars.¹⁶ Again, the data is gathered from multiple exchanges to tackle the cryptocurrency exchange arbitrage problem. This data is used for computing Amihud illiquidity premium for bitcoin.

Below in Table 1 is presented the initial cryptocurrencies where data for daily prices are available. This table provides descriptive basic metrics and showcases the odd and interesting nature of the cryptocurrency market compared to US equity's corresponding. The return on

¹⁴ Market value of >\$1B as of 28.11.2017. The reason for this that these cryptocurrencies can be viewed, in my opinion, as established and they've daily trading volumes of at least \$100 million. *Source:* <https://coinmarketcap.com/all/views/all/>

¹⁵ Although there is not any research report on this, it is commonly known among advanced traders. However, it is not easily exploitable as transferring money in and out of exchanges takes a lot of time and smaller exchanges suffer from illiquidity. For further information, Internet: <http://www.businessinsider.com/bitcoin-cryptocurrency-arbitrage-2017-11?r=UK&IR=T&IR=T>, date 30.11.2017

¹⁶ Internet: <https://blockchain.info/>, date 28.11.2017

equity in the US constitutes of value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ.¹⁷

In addition to cryptocurrency and value-weighted US equity data, I use Kenneth French's daily US value-weighted and equal-weighted equity data to create the excess market return, risk-free rate, HML, SMB and momentum proxies, as well as, banking and finance industry's excess returns.¹⁷ This data has the same characteristics as value-weighted US equity data in the previous paragraph.

Table 1

This table is to present reader how special and controversial the cryptocurrency market is. The table shows sample sizes used in this thesis, total duration of tradeable days that the asset has (excluding US equity). In total duration (days) where the end date is 28.11.2017. Averages are arithmetic and variances are sample variances.

Name	Sample size (days)	Total duration (days)	Mean (daily)	Total return (sample)	σ^2 (daily)
<i>Bitcoin</i>	2 599	3 195	0.307 %	3 117 %	0.186 %
<i>Ethereum</i>	789	796	0.953 %	10 458 %	0.675 %
<i>Ripple</i>	1 522	2 102	0.550 %	3 357 %	0.785 %
<i>Litecoin</i>	1 620	2 188	0.399 %	1 103 %	0.574 %
<i>Dash</i>	1 328	1 354	0.925 %	79 103 %	1.220 %
<i>Ethereum Classic</i>	437	796	1.329 %	1 236 %	3.060 %
<i>Monero</i>	1 231	1 264	0.644 %	5 710 %	0.674 %
<i>NEO</i>	390	389	1.939 %	5 918 %	2.114 %
<i>NEM</i>	917	917	1.155 %	91 941 %	0.908 %
<i>US equity market value-weighted</i>	1620	1620	0.055 %	78.321 %	0.006 %

3.2 Sample & data generating process

After downloading necessary data for statistical analysis, I calculate the daily yields r_{it} by dividing t and $t - 1$ price p_{it} subtraction with $t - 1$ price p_{it-1} :

¹⁷ Internet: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research, date 30.11.2017. More information of the data set from the Kenneth French's website.

$$r_{it} = (p_{it} - p_{it-1}) / p_{it-1} \quad (1)$$

After computing daily yields, I construct Amihud illiquidity variable to measure bitcoin's liquidity. The illiquidity premium A_{iy} is computed by dividing the absolute value of the daily yield $|r_{it}|$ with the total USD trading value ($Dvol_{it}$) (Amihud, 2002)¹⁸:

$$A_{iy} = \frac{1}{Diy} \sum_{t=1}^{Diy} \frac{|r_{it}|}{Dvol_{it}} \quad (2)$$

After constructing necessary variables for analysis, I omit cryptocurrencies with less than \$1 billion of market value, lower than \$100 million of daily trade volume and less than a year of active trading in global cryptocurrency exchanges from the initial data set to ensure reliability and sufficiently large n . Thus, in the final analysis, I have a total of 9 cryptocurrencies, including bitcoin, as presented in Table 1.¹⁹

4. Methodology

In this thesis, I use various statistical methods to capture bitcoin's leading effect on the other 8 cryptocurrencies (**H1&H2**) {Ethereum, Dash, Litecoin, Ripple, Monero, NEM, Ethereum Classic, NEO}²⁰ and to test their relations to US equity market benchmark assets (**H3a&b**).

Firstly, I compute the *autocorrelation function* (ACF) and *partial autocorrelation function* (PACF) for bitcoin. These are to capture possible autocorrelation effect in bitcoin's daily yields. Secondly, I construct *cross-correlation function* (CCF) between bitcoin and the other 8 cryptocurrencies. This is to demonstrate lead-lag correlations of two cryptocurrencies and is merely for descriptive purposes.

Thirdly, I calculate the *vector autoregressive regression* ($VAR(p)$)²¹ for each cryptocurrency which then is used for plotting the *orthogonalized impulse response function*. This method allows adding more factors to our autoregressive regression to control for illiquidity and market condition, as well as, visually seeing the shocks that one variable has on another variable in the system.

¹⁸ Note that this formula is its general form for e.g. annual or monthly illiquidity premium.

¹⁹ From now on term "the cryptocurrencies" means the 9 cryptocurrencies chosen for the analysis.

²⁰ Abbreviations used in for these cryptocurrencies: btc = bitcoin, eth = ethereum, dash = dash, litecoin = litecoin, ripple = ripple, monero = monero, nem = NEM, eth_classic = ethereum classic.

²¹ p stands for the order of optimal lag and lag factors.

Lastly, I regress various *ordinary least squares* (OLS) regressions using Fama and French’s 3–factor model, Carhart’s 4–factor model and my own Carhart’s 4–factor model with additional bitcoin momentum factor (see e.g. Sharpe, 1964; Lintner, 1965; Fama and French, 1993; Carhart, 1995) to research further the cryptocurrency and US equity market and financial industry relations.

4.1 ACF, PACF & CCF

The autocorrelation and partial autocorrelation functions (ACF, PACF) for bitcoin are to demonstrate the autocorrelation of bitcoin’s own lagged values and its signaling process. Stochastic processes’ autocorrelation is the Pearson’s correlation between the processes’ values at given time (Usono, 2015). Assuming, that the process is not wide-sense stationary, ACF (3) and PACF (4) are, as illustrated by Venables and Ripley (2002), Box and Jenkins (1976) and Usono (2015):

$$\rho(s, t) = \frac{E[(X_t - \mu_t)(X_s - \mu_s)]}{\sigma_t \sigma_s} \quad (3)$$

$$\vartheta(\varphi) = \text{Cor}[z_{t+\varphi} - P_{t,\varphi}(z_{t+\varphi}), z_t - P_{t,\varphi}(z_t)], \text{ for } \varphi \geq 2 \quad (4)$$

, where $\rho(s, t)$ and $\vartheta(\varphi)$ are the autocorrelation function and partial autocorrelation function, respectively, E is the expected value operator for the covariance between times s and t , σ is the standard deviation, $P_{t,\varphi}(x)$ marks the projection of x onto the space by $x_{t+1}, \dots, x_{t+\varphi-1}$.

To showcase the interdependence and auto– and cross–correlations with bitcoin and prominent cryptocurrencies, I use cross-correlation function (CCF) (5), in its simplified stochastic form, defined by Venables and Ripley (2002), Box and Jenkins (1976) and Usono (2015):

$$\rho_{xy}(\tau) = \frac{\gamma_{xy}(\tau)}{\sigma_x \sigma_Y} \quad (5)$$

, where ρ_{xy} is the cross-correlation function, $\gamma_{xy}(\tau)$ is the cross-covariance between bitcoin and said cryptocurrency, σ_x is the standard deviation of bitcoin and σ_Y is the standard deviation of said cryptocurrency.

4.2 VAR(p) model & Orthogonalized Impulse Response Function

To fully capture the interdependencies between bitcoin and the cryptocurrencies yields (1) while adding their optimal lag factors (p), bitcoin's illiquidity premium (2) and US equity market returns (1) to the equation, I compute vector autoregressive regression with p lags (VAR(p)) for each cryptocurrency. After Lütkepohl (2005), the vector autoregressive regression equation using constant and trend factor with endogenous variables (6a & 6b), the OLS regression with the VAR(p) and AIC^{22} as the information criteria and the estimation of the covariance matrix of the errors (7) (simplified examples):

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{k,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_k \end{bmatrix} + \begin{bmatrix} a_{1,1}^1 & a_{1,2}^1 & \cdots & a_{1,k}^1 \\ a_{2,1}^1 & a_{2,2}^1 & \cdots & a_{2,k}^1 \\ \vdots & \vdots & \ddots & \vdots \\ a_{k,1}^1 & a_{k,2}^1 & \cdots & a_{k,k}^1 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{k,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} a_{1,1}^p & a_{1,2}^p & \cdots & a_{1,k}^p \\ a_{2,1}^p & a_{2,2}^p & \cdots & a_{2,k}^p \\ \vdots & \vdots & \ddots & \vdots \\ a_{k,1}^p & a_{k,2}^p & \cdots & a_{k,k}^p \end{bmatrix} \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{k,t-p} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ \vdots \\ e_{k,t} \end{bmatrix} \quad (6a)$$

, where each y_i is a vector of length k endogenous variables and each a_i is a $k \times k$ matrix.

$$Vec(\hat{\beta}) = [(ZZ')^{-1}Z \otimes I_k] Vec(Y) \quad (6b)$$

, where \otimes denotes the Kronecker product, the Vec stands for the vectorization of the expressed matrix and using concise matrix notations for simplification.

$$\widehat{Cov}(Vec(\hat{\beta})) = (ZZ')^{-1} \otimes \widehat{\Sigma} \quad (7)$$

, where symbols are the same as before and \widehat{Cov} stands for covariance.

To expose the shock that one estimated variable might have to another, I use orthogonalized impulse response function to capture these impulse response dynamics. In the orthogonalized impulse response function, one variable pushes or signals an impulse to another variable in the system, allowing to visually see the impulse response dynamics and its statistical significance in a clear manner. I use the orthogonalized impulse response function as described by Lütkepohl (2005). However, due to its lengthy expression, I leave the set of equations without display. In short, orthogonalized impulse response function uses the coefficients it receives from VAR(p) model, described above.

For both VAR(p) and orthogonalized impulse response function I use R programming environment and *vars* package by Bernhard (2008). Thus, the examples of the equations are

²² AIC = Akaike information criterion. Used as a standard information criterion in economical regressions.

simplified examples as I do not have access to the source code for precise deriving of the used equations here.

4.3 OLS regression for cryptocurrency and market relations

After analyzing the interdependencies with bitcoin and the cryptocurrencies and US equity market returns, I study more deeply the relations within cryptocurrencies and US equity market with emphasis on the banking and finance industry. This is done by using Fama and French's 3-factor model (9), Carhart's 4-factor model (10) and augmented 5-factor model (11) which adds my bitcoin momentum factor (8) to the Carhart's 4-factor model. The bitcoin momentum factor and regression equations are computed as follows:

$$\delta_{it} = \left[\prod_{t-2}^{t-6} (r_{it} + 1) \right] - 1 \quad (8)$$

, where r_{it} is the return on bitcoin on day t and δ_{it} is the bitcoin momentum coefficient. The bitcoin coefficient for day t is calculated from the total cumulative return between days $t - 2$ and $t - 6$. The coefficient δ_{it} is calculated as Blitz et al. (2013), taking the technical short-term reversal²³ into consideration, thus omitting the $t - 1$ return from the equation.

$$r_{it} = \beta_{Rm}(R_{m,t} - R_{f,t}) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \alpha \quad (9)$$

, where r_{it} is the portfolio's or cryptocurrency's expected return, right-hands sides' first term captures the market's excess returns' beta²⁴, the second term captures the small minus big returns' beta²⁵, the third term captures the high minus low returns' beta²⁶.

$$r_{it} = \beta_{Rm}(R_{m,t} - R_{f,t}) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{MOM}(MOM) + \alpha \quad (10)$$

, where the terms are the same as in the Fama and French's 3-factor model but now a fourth beta is added which captures the momentum effect of the market.²⁷

²³ Website: <https://quantpedia.com/Screener/Details/13>, date 30.11.2017. "Short-term reversal strategy exploits the strong tendency of stocks with strong gains or with strong losses to reverse in a short-term time frame"

²⁴ Excess returns are defined as the market return at the given t minus the risk-free rate at the given t .

²⁵ Small minus big excess returns are defined as calculating the historical excess returns by smaller capitalization firms over larger capitalization ones.

²⁶ High minus low excess returns are defined as computing historic excess returns of high book-to-market ratio (value stocks) firms' over low book-to-market ratio (growth stocks) firms'.

²⁷ Momentum excess returns are defined, in this instance, as creating 6 portfolios and classifying them based on their prior returns and then computing the return by 2 best performing portfolios (long) average returns minus 2 worst performing portfolios (short) average returns.

$$r_{it} = \beta_{Rm}(R_{m,t} - R_{f,t}) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{MOM}(MOM) + \beta_{\delta}(\delta) + \alpha \quad (11)$$

, where (8) is added as the fifth factor to the equation (10).

5. Results from the statistical analysis and regressions

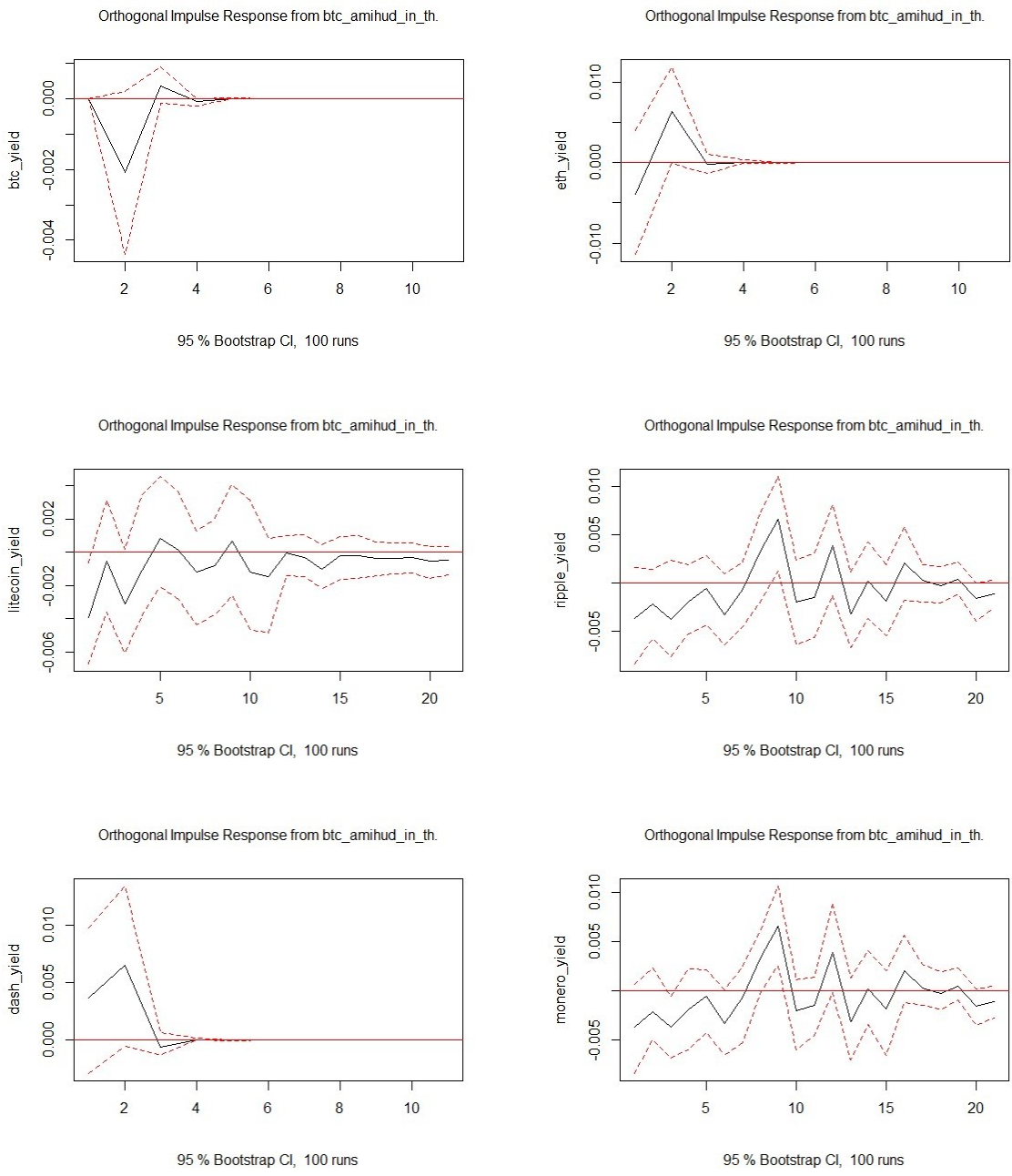
In this chapter, I present the results of the orthogonalized impulse response function and the OLS regressions. These results are to demonstrate the interconnectedness of bitcoin and cryptocurrencies, as well as, cryptocurrencies' relations with US equity market and financial sector while controlling for known market factors and bitcoin momentum factor's effect. Estimated VAR(p) coefficients are left out disclosing as they and their statistical significance can be viewed in the orthogonalized impulse response function plots. For correlation analysis, Appendix A presents the autocorrelations and cross-correlations of bitcoin and the cryptocurrencies.

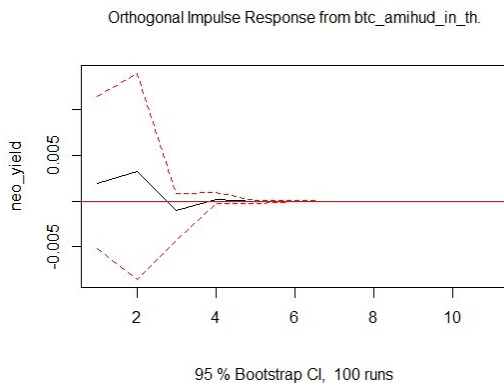
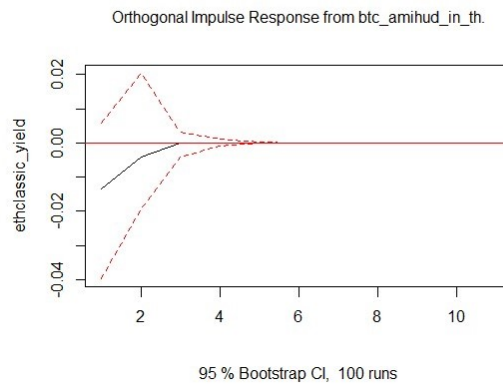
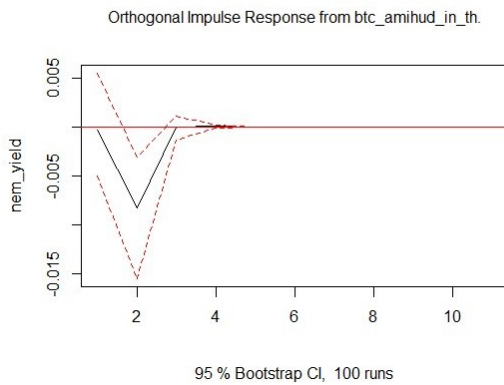
5.1 Orthogonalized impulse response functions

Figure 1 presents the orthogonalized impulse response function graphs of bitcoin's Amihud illiquidity factor (2) onto bitcoin's and the cryptocurrencies' return impulses and responses. Hence, testing the **(H1) "liquidity trap hypothesis"**.

Figures 1

These plots are to show the impulse of a variable and another variable's response to it the system. In this case, it is the impulse from bitcoin's Amihud illiquidity factor (*btc_amihud_in_th*) and response to cryptocurrency's daily yield in percentage (decimal numbers) (y-axis). The x-axis shows the future estimation (lead effect) in days ranging from 10 to 20 days. The black line is daily yield response for the said cryptocurrency and the dotted red lines display the statistical significance at $\alpha = 5\%$. If the confidence interval (or band), bootstrap confidence level, does not contain zero (horizontal axis) then it is statistically significant.



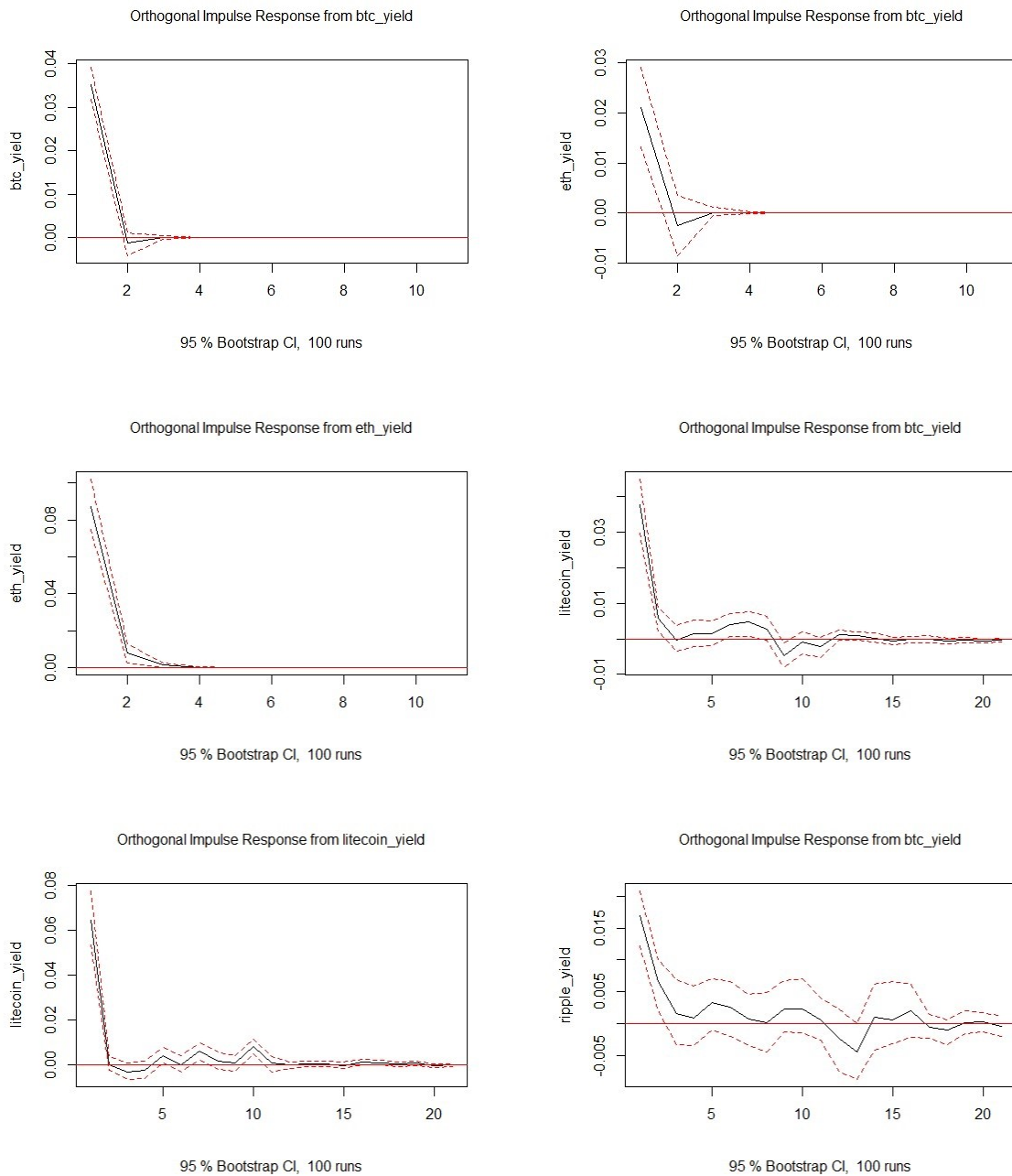


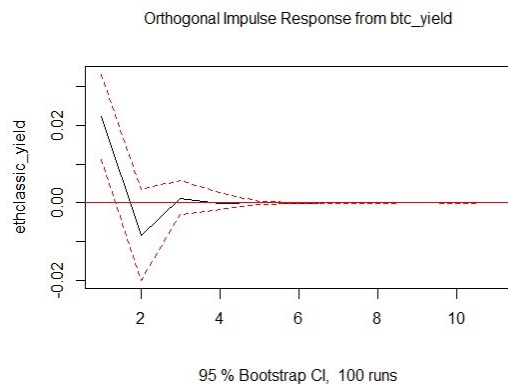
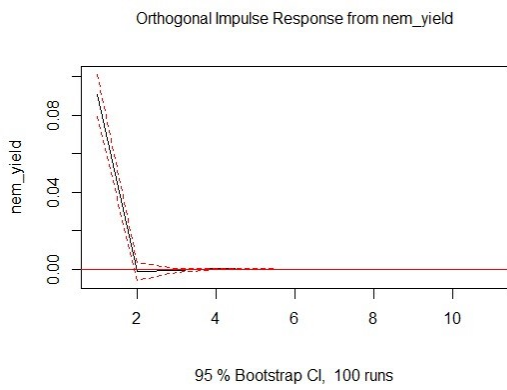
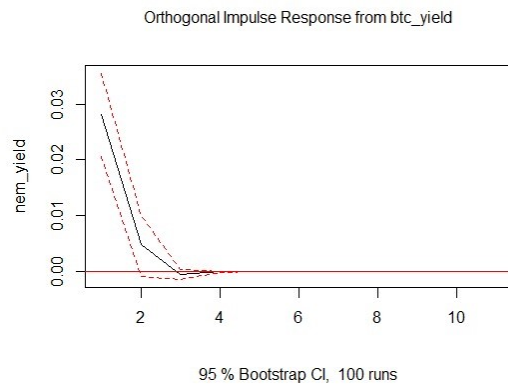
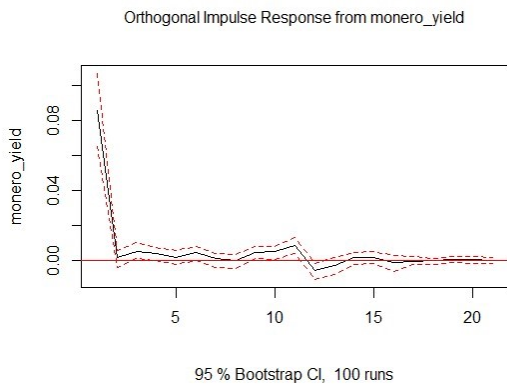
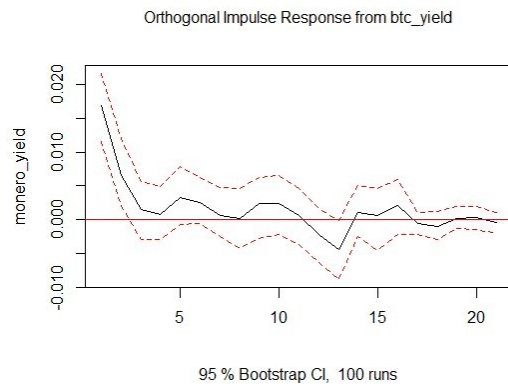
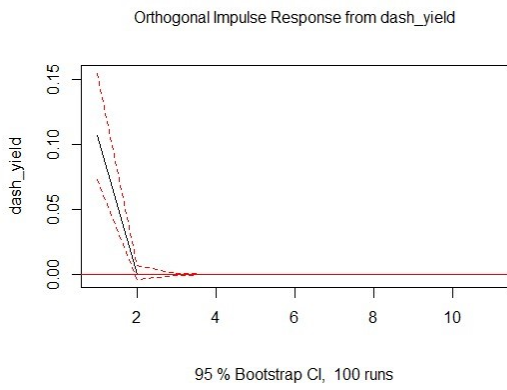
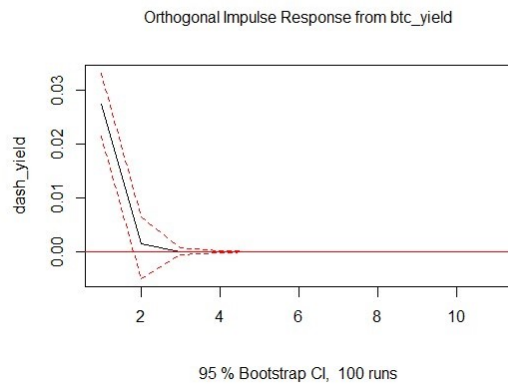
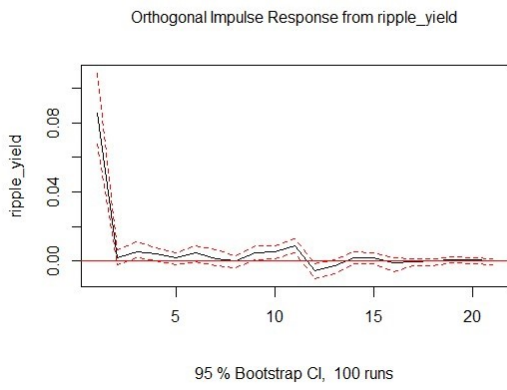
As can be seen in these plots, the bitcoin illiquidity factor does not have a statistically significant shock to the cryptocurrencies. In other words, bitcoin’s illiquidity factor at t does not estimate cryptocurrencies’ yields well in $t+1$ and onwards. Hence, based on this evidence, **(H1) “liquidity trap hypothesis”** is not rejected at 5 % significance level. This finding is in line with Wang’s (2014) results and provides evidence that bitcoin market is liquid and does not suffer from a liquidity trap.

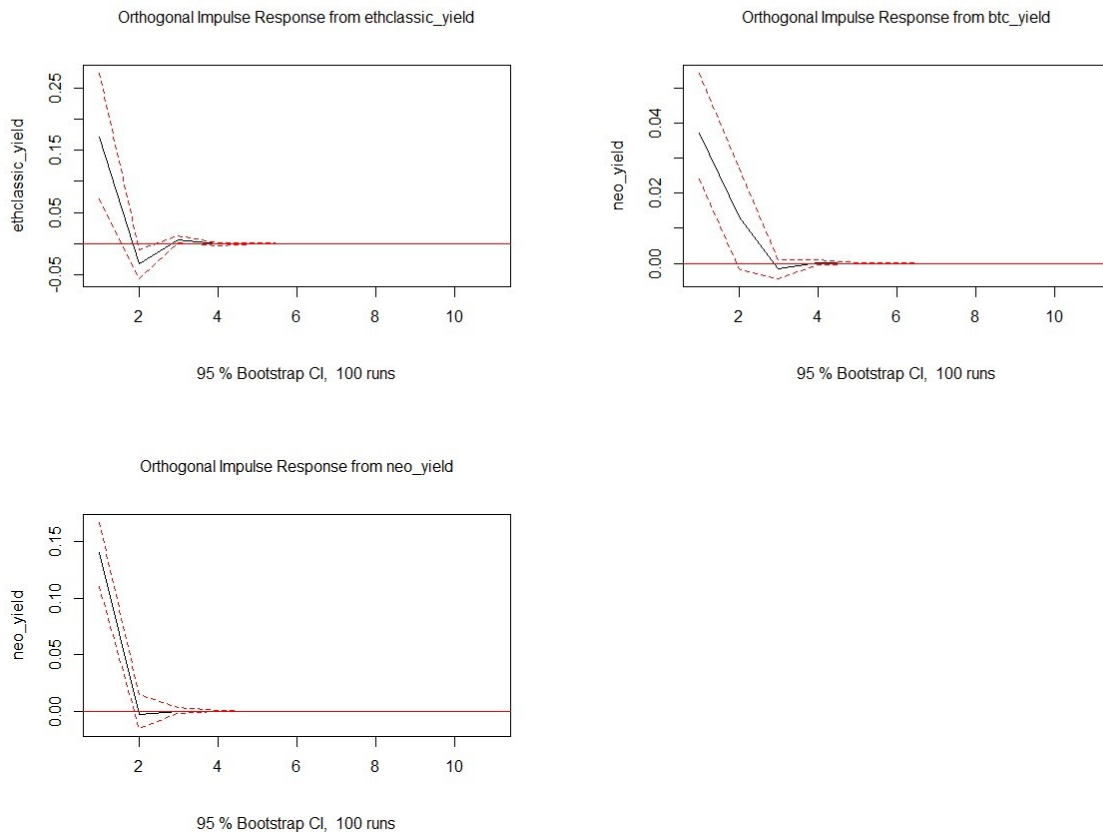
Figure 2 presents the orthogonalized impulse response function graphs of bitcoin and the cryptocurrencies returns’ impulses and responses to each other and themselves. Thus, testing the **(H2) “internal leader effect hypothesis”** in which bitcoin’s price development’s impulses should affect other top cryptocurrencies’ price development responses.

Figures 2

These plots are to show the impulse of a variable and another variable's response to it the system. In this case, it is the impulse from cryptocurrency's daily yield and response to cryptocurrency's daily yield in percentage (decimal numbers) (y-axis). The x-axis shows the future estimation (lead effect) in days ranging from 10 to 20 days. The black line is daily yield (%) response, for the said cryptocurrency and the dotted red lines display the statistical significance at $\alpha = 5\%$. If the confidence interval (or band), bootstrap confidence level, does not contain zero (horizontal axis) then it is statistically significant.





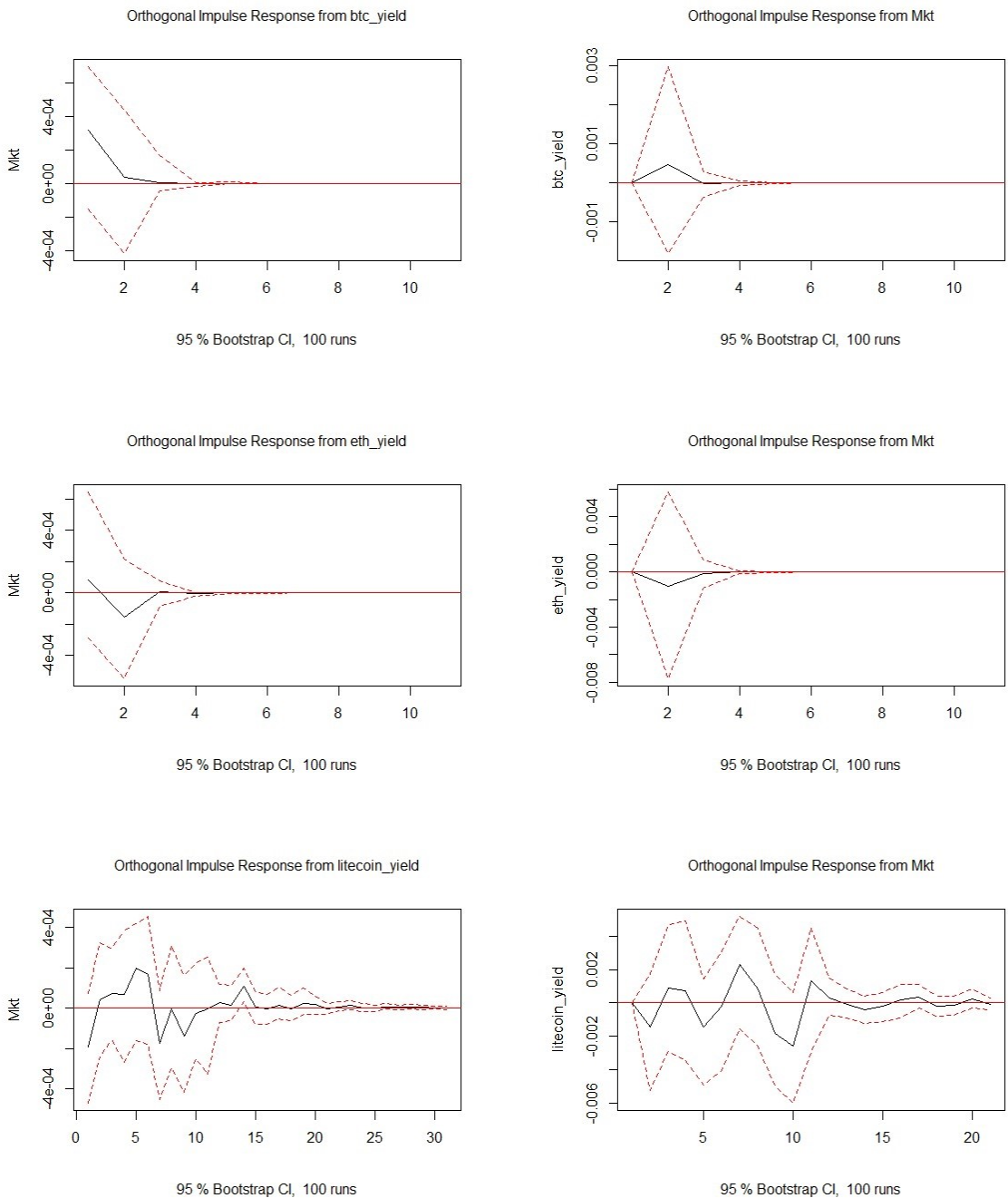


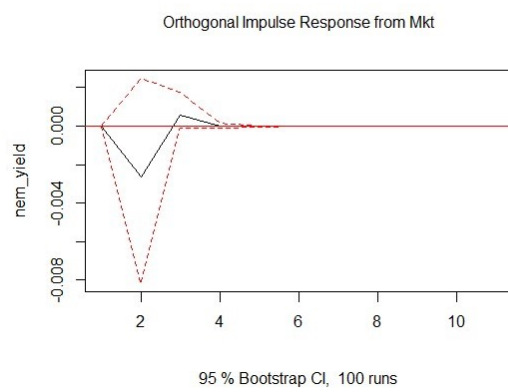
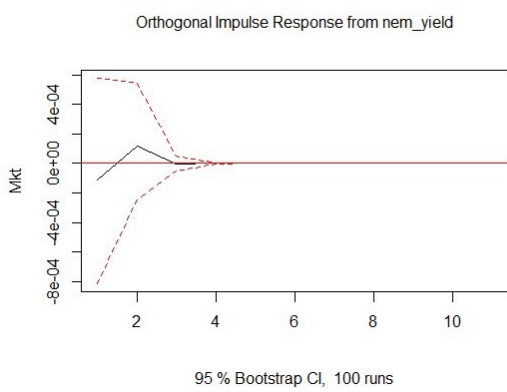
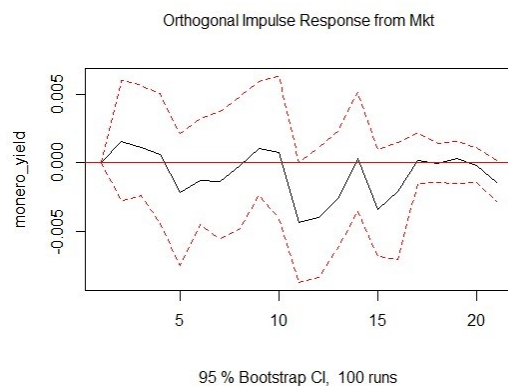
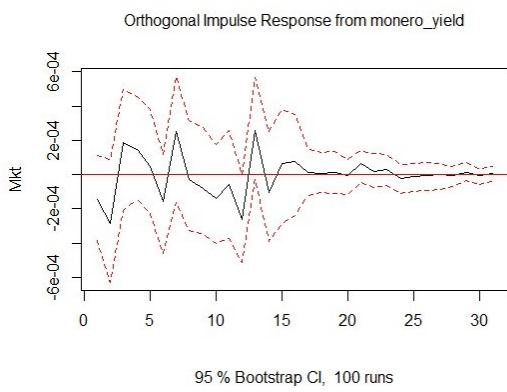
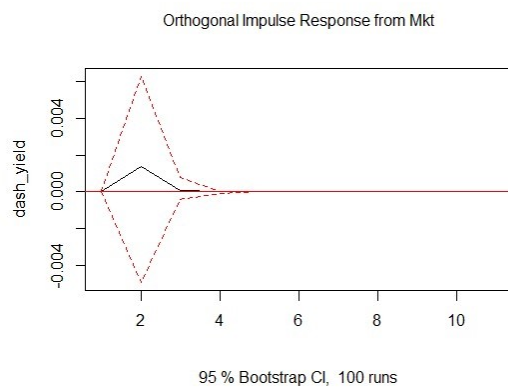
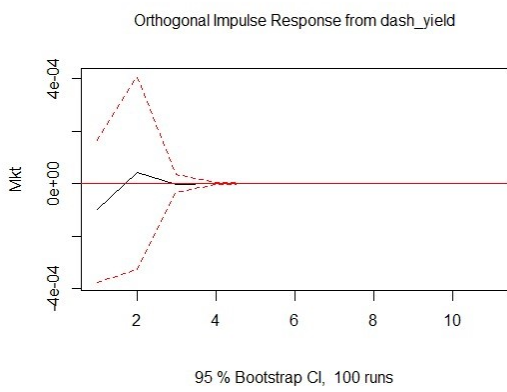
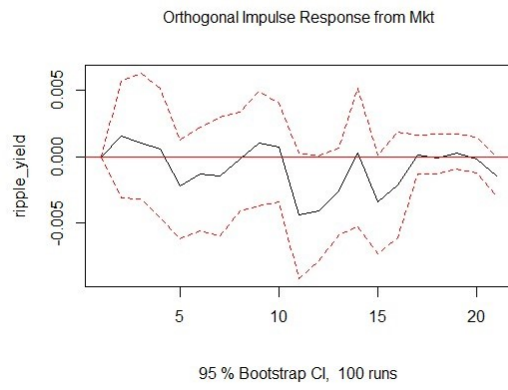
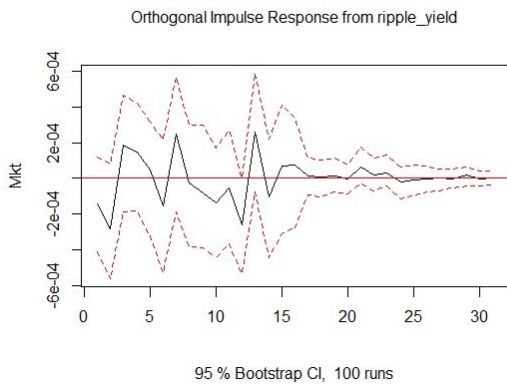
Firstly, as seen in the plots, all the cryptocurrencies have, mostly short-term, autocorrelations. Meaning that past days' returns seem to predict well future returns. Secondly, bitcoin only seems to have a lead effect on litecoin and ripple but the rest of the responses in these systems are statistically insignificant. Thus, hypothesis (H2) “**internal leader effect hypothesis**” receives mixed results. However, it is fair to say that bitcoin is not a sovereign estimator for the cryptocurrency market, excluding its statistically significant shocks onto litecoin and ripple. The (H2) hypothesis is rejected at 5 % significance level.

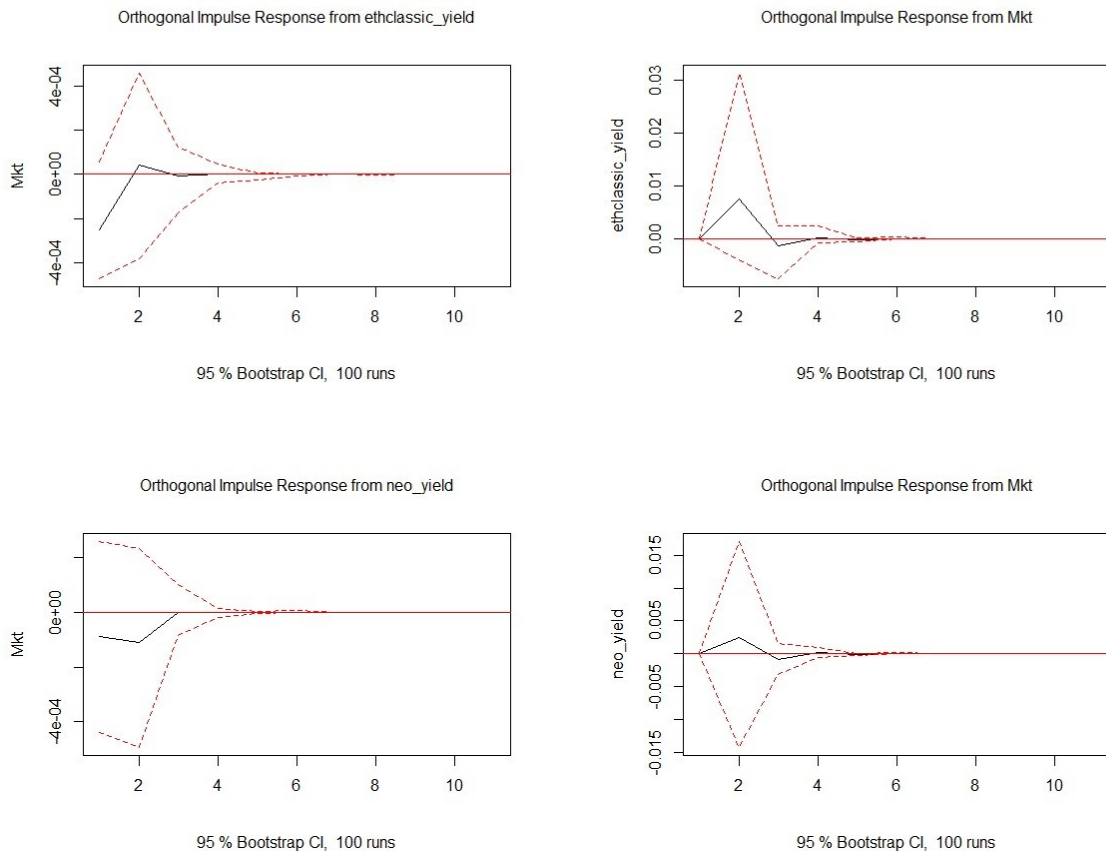
Figures 3 presents the orthogonalized impulse response function graphs of bitcoin's and the cryptocurrencies' return impulses and responses onto US equity market's returns. Hence, testing the (H3a) “**no cross-impact hypothesis a**” in which these different asset classes should not have shocks onto each other.

Figures 3

These plots are to show the impulse of a variable and another variable's response to it the system. In this case, it is the impulse from cryptocurrency's daily yield and response to US equity market's daily yield in percentage (decimal numbers) (y-axis) and vice versa. The x-axis shows the future estimation (lead effect) in days ranging from 10 to 20 days. The black line is daily yield (%) response to the said cryptocurrency or the equity and the dotted red lines display the statistical significance at $\alpha = 5\%$. If the confidence interval (or band), bootstrap confidence level, does not contain zero (horizontal axis) then it is statistically significant.







From the plots can be deduced that cryptocurrencies and US equity market have no impulse response dynamics for estimation. This finding is in line with the **(H3a) “no cross-impact hypothesis a”** when addressing US equity market returns. Hence, based on US equity returns, the **(H3a)** hypothesis is not rejected at 5 % significance level.

5.2 OLS regressions

To further research the market relations **(H3a&b)** I construct various regressions while controlling for Fama and French’s 3–factors (9), Carhart’s 4–factors (10) and using 5–factor model which includes the additional bitcoin momentum (11).

Table 2 presents regression where dependent variables (y) are bitcoin and the cryptocurrencies and explanatory variables are Fama and French’s 3–factors (9). Table 3 adds stock market momentum as an explanatory variable (10). Table 4 adds the bitcoin momentum to the 4–factor model (11).

Table 2

This table shows OLS regressions on cryptocurrencies (y) and their estimated coefficients explained in the methodology, in decimal numbers. On the same line with a coefficient name is the estimated decimal number values for it. Values inside parentheses are *t*-values. Significance codes (α): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'.

	Bitcoin	Ethereum	Dash	Litecoin	Ripple	Monero	NEM	Ethereum Classic	NEO
α	0.006*** (4.445)	0.009** (2.608)	0.010** (3.160)	0.004* (2.172)	0.005* (2.401)	0.006** (2.705)	0.012*** (3.766)	0.015. (1.704)	0.020** (2.704)
β_{RM}	0.067 (0.398)	0.102 (0.265)	0.040 (0.105)	-0.008 (-0.035)	-0.066 (-0.225)	-0.021 (-0.071)	-0.661. (-1.726)	-1.053 (-0.557)	-0.019 (-0.012)
β_{SMB}	-0.060 (-0.201)	-0.259 (-0.409)	-1.230* (-2.044)	-0.353 (-0.910)	-0.177 (-0.383)	0.114 (0.245)	-0.131 (-0.209)	-0.840 (-0.434)	-1.500 (-0.914)
β_{HML}	-0.527. (-1.677)	0.438 (0.752)	0.318 (0.520)	0.053 (0.131)	-0.372 (-0.772)	-0.254 (-0.542)	0.519 (0.887)	-0.769 (-0.471)	0.140 (0.100)
<i>Mult.</i>	0.001	0.001	0.004	0.001	0.000	0.000	0.004	0.003	0.003
R^2									
<i>Adj.</i>	-0.000	-0.003	0.002	-0.001	-0.001	-0.002	0.001	-0.004	-0.005
R^2									

Using formula (9), the results suggest that cryptocurrencies have no market relations as expected. Alpha is positive and significant and R^2 is low as they should. The (H3a) is not rejected. The next Table 3 adds the market momentum factor as an additional explanatory variable.

Table 3

This table shows OLS regressions on cryptocurrencies (y) and their estimated coefficients explained in the methodology, in decimal numbers. On the same line with a coefficient name is the estimated decimal numbers values for it. Values inside parentheses are *t*-values. Significance codes (α): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'.

	Bitcoin	Ethereum	Dash	Litecoin	Ripple	Monero	NEM	Ethereum Classic	NEO
α	0.006*** (4.446)	0.008** (2.591)	0.010** (3.128)	0.004* (2.156)	0.005* (2.399)	0.006** (2.698)	0.012*** (3.761)	0.014. (1.691)	0.020** (2.710)
β_{RM}	0.066 (0.395)	0.059 (0.152)	0.002 (0.005)	-0.008 (-0.031)	-0.066 (-0.266)	-0.049 (-0.168)	-0.703. (-1.806)	-1.021 (-0.548)	-0.112 (-0.070)
β_{SMB}	-0.068 (-0.225)	-0.347 (-0.531)	-1.355* (-2.224)	-0.402 (-1.028)	-0.180 (-0.387)	0.034 (0.072)	-0.213 (-0.331)	-0.861 (-0.441)	-1.460 (-0.884)
β_{HML}	-0.561 (-1.639)	0.314 (0.503)	-0.036 (-0.054)	-0.117 (-0.267)	-0.383 (-0.732)	-0.419 (-0.821)	0.369 (0.581)	-0.792 (-0.479)	0.191 (0.135)
β_{MOM}	-0.059 (-0.253)	-0.249 (-0.565)	-0.577 (-1.298)	-0.298 (-1.034)	-0.019 (-0.055)	-0.280 (-0.816)	(-0.265) (-0.607)	-0.152 (-0.089)	0.395 (0.260)
<i>Mult.</i>	0.001	0.002	0.005	0.001	0.000	0.001	0.005	0.003	0.003
R^2									
<i>Adj.</i>	-0.000	-0.004	0.002	-0.001	-0.002	-0.002	0.000	-0.006	-0.007
R^2									

The results are the almost identical with Table 3, which some weakening of alpha and improvement in R^2 . The **(H3a)** is not rejected. In the last Tables 4, 5 & 6 the bitcoin momentum factor is added to the equation.

Table 4

This table shows OLS regressions on cryptocurrencies (y) and their estimated coefficients explained in the methodology, in decimal numbers. On the same line with a coefficient name is the estimated decimal number values for it. Values inside parentheses are *t*-values. Significance codes (α): 0 ‘****’ 0.001 ‘***’ 0.01 ‘**’ 0.05 ‘.’.

	Bitcoin	Ethereum	Dash	Litecoin	Ripple	Monero	NEM	Ethereum Classic	NEO
α	0.006*** (3.862)	0.009* (2.528)	0.010** (3.168)	0.003 (1.536)	0.004 (1.927)	0.006* (2.534)	0.012*** (3.701)	0.016 (1.736)	0.022** (2.702)
β_{RM}	0.054 (0.321)	0.063 (0.160)	0.012 (0.030)	-0.042 (-0.174)	-0.105 (-0.361)	-0.061 (-0.207)	-0.694 (-1.772)	-1.036 (-0.556)	-0.120 (-0.075)
β_{SMB}	-0.069 (-0.230)	-0.349 (-0.535)	-1.345* (-2.204)	-0.423 (-1.088)	-0.215 (-0.461)	0.027 (0.056)	-0.220 (-0.342)	-0.911 (-0.466)	-1.506 (-0.910)
β_{HML}	-0.555 (-1.624)	0.314 (0.503)	-0.034 (-0.050)	-0.135 (-0.310)	-0.415 (-0.795)	-0.424 (-0.830)	0.369 (0.581)	-0.775 (-0.468)	0.213 (0.150)
β_{MOM}	-0.061 (-0.262)	-0.247 (-0.560)	-0.562 (-1.260)	-0.366 (-1.274)	-0.080 (-0.234)	-0.297 (-0.862)	(-0.260) (-0.594)	-0.046 (-0.027)	0.482 (0.314)
β_{δ}	0.024** (2.685)	-0.004 (-0.089)	-0.021 (-0.530)	0.079*** (4.040)	0.064** (2.633)	0.028 (0.905)	-0.009 (-0.213)	-0.043 (-0.414)	-0.039 (-0.439)
<i>Mult.</i>	0.004	0.002	0.005	0.011	0.005	0.002	0.005	0.003	0.003
R^2									
<i>Adj.</i>	0.002	-0.005	0.001	0.008	0.002	-0.003	-0.001	-0.008	-0.010
R^2									

The bitcoin momentum factor is significant when fitting bitcoin, litecoin, and ripple, which is the conclusion as in the orthogonalized impulse response function results. However, alphas diminish and lose their significance compared to Tables 2 and 3. Still, the **(H3a)** is not rejected.

Results for testing **(H3b)** “no cross-impact hypothesis b”, are found in Table 5 and 6. Table 5 has value-weighted and equal-weighted regression coefficients for the full period and for subsamples for the banking industry (SIC code 45). Table 6 has the corresponding for the financial industry (SIC code 48).

Table 5

Value-weighted (VW) and equal-weighted (EW) regressions where dependent variable (y) is *banking industry's excess returns* and explanatory variables are as in Table 4.²⁸ Full period constitutes the total 2599 trading days. Additionally, the data set is divided into 2 different periods (50/50) where the earlier period is the earlier data set timewise and the later period is the data set further away from today. On the same line with a coefficient name is the estimated decimal number values for it. Values inside parentheses are t -values. Significance codes (α): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'.

BANKS [45]	VW full period	EW full period	VW earlier period	EW earlier period	VW later period	EW later period
α	-0.001 (-1.435)	0.001*** (10.017)	0.000 (0.011)	0.001*** (6.818)	-0.000 (-1.571)	0.001*** (8.774)
β_{Rm}	1.186*** (112.591)	0.601*** (85.664)	1.200*** (73.972)	0.664*** (60.161)	1.162*** (87.070)	0.569*** (64.150)
β_{SMB}	0.139*** (7.293)	0.579*** (45.682)	0.190*** (7.322)	0.647*** (36.766)	0.082** (3.085)	0.538*** (30.586)
β_{HML}	0.983*** (45.661)	0.626*** (43.663)	0.837*** (29.466)	0.688*** (35.609)	1.231*** (39.633)	0.573*** (27.743)
β_{MOM}	0.051*** (3.537)	0.088*** (9.043)	0.128*** (6.766)	0.167*** (13.025)	-0.070** (-3.256)	-0.027. (-1.908)
β_{δ}	0.002*** (3.396)	0.001 (1.056)	0.004* (2.528)	0.002 (1.607)	0.002** (2.864)	0.000 (0.102)
$Mult. R^2$	0.880	0.880	0.837	0.834	0.923	0.903
$Adj. R^2$	0.880	0.880	0.836	0.833	0.923	0.902

²⁸ Detailed information about the classification of banking industry's excess returns used is found in the Appendix B.

Firstly, the commonly accepted Carhart’s 4-factor coefficients are expectedly all significant across the table. Secondly, the interesting part is that in estimating banking industry’s value-weighted returns shows higher bitcoin momentum β_{δ} coefficient comparing to equal-weighted returns. This implies that bitcoin momentum has a stronger effect on larger banks and institutions and weaker on smaller ones. Thirdly, the bitcoin momentum effect has grown over time and is stronger today than years ago.

Table 6

Value-weighted (VW) and equal-weighted (EW) regressions where dependent variable (y) is *financial industry’s excess returns* and explanatory variables are as in Table 4.²⁹ Full period constitutes the total 2599 trading days. Additionally, the data set is divided into 2 different periods where the earlier period is the earlier data set timewise and the later period is the data set further away from today. On the same line with a coefficient name is the estimated decimal number values for it. Values inside parentheses are t -values. Significance codes (α): 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’.

FIN [48]	VW full period	EW full period	VW early period	EW early period	VW later period	EW later period
α	-0.000 (-0.577)	-0.000 (-0.004)	-0.000 (-0.263)	-0.000 (-0.070)	0.000 (0.158)	0.000 (0.224)
β_{Rm}	1.267*** (114.619)	0.960*** (110.803)	1.287*** (77.780)	0.947*** (69.753)	1.244*** (82.628)	0.958*** (81.790)
β_{SMB}	0.152*** (7.618)	0.634*** (40.487)	0.174*** (6.588)	0.608*** (28.109)	0.148*** (4.962)	0.660*** (28.418)
β_{HML}	0.698*** (30.886)	0.390*** (21.973)	0.663*** (22.918)	0.350*** (14.735)	0.760*** (21.625)	0.436*** (16.003)
β_{MOM}	-0.020 (-1.296)	-0.037** (-3.064)	0.088*** (4.586)	-0.018 (-1.112)	-0.209*** (-8.625)	-0.084*** (-4.480)
β_{δ}	0.001* (2.145)	0.001 (1.639)	0.006*** (3.846)	0.005*** (3.867)	0.001 (0.584)	0.000 (0.198)

²⁹ Detailed information about the classification of banking industry’s excess returns used is found in the Appendix B.

Table 6 continues on this page.

<i>Mult. R²</i>	0.874	0.890	0.843	0.838	0.906	0.921
<i>Adj. R²</i>	0.874	0.890	0.842	0.838	0.906	0.921

Firstly, the commonly accepted Carhart’s 4–factor coefficients are expectedly all significant across the table as in Table 5. Secondly, the interesting part is that in estimating financial industry’s value-weighted returns shows lower bitcoin momentum β_δ coefficient comparing to equal-weighted returns. This implies that bitcoin momentum has a stronger effect on smaller financial institutions and weaker on larger ones, and is the opposite as with the banks. Thirdly, the bitcoin momentum effect has weakened from the beginning, which again, is completely opposite than with the banking industry.

These results (Table 5 and 6) provide evidence that bitcoin, and possibly the cryptocurrency market, influences banking and financial industries’ excess returns. Thus, **(H3b) “no cross-impact hypothesis b”**, is rejected on 5 % significance level.

6. Discussion and Further Analysis

In this section, I undergo the results for main hypotheses in a descriptive manner and provide my own analysis of the results.

6.1 The liquidity trap

As hypothesized, my results are aligned with Wang’s (2014) that bitcoin does not suffer from a liquidity trap. Even though in my opinion, bitcoin will eventually fall into liquidity trap due to its fundamentals discussed in Section 2, it seems to enjoy relatively good liquidity today. This might stem from the increasing number of traders in the bitcoin and cryptocurrency market. However, in the future when the pace of bitcoin supply slows down, the Sweeneys’ analogy might become more realistic.

6.2 Internal impulse response dynamics of the cryptocurrencies

Notable about the orthogonalized impulse response function plots is the high autocorrelation amongst the cryptocurrencies. Past day’s returns seem to estimate well future price development, especially $t + 1$ returns. However, bitcoin impulse has only statistical significance on litecoin’s and ripple’s responses in the system. Table 1 shows the number of

days where daily price data is available. Notable is that these two cryptocurrencies have the most days of data, after bitcoin, which might explain these results. Another reason is that litecoin and ripple, as older cryptocurrencies, are technologically more related to bitcoin³⁰ compared to e.g. ethereum which represents new and more sophisticated blockchain technology. Nevertheless, this result provides evidence that traders can reduce their idiosyncratic volatility³¹ within the cryptocurrency market, something that has not been studied with various cryptocurrencies to my knowledge.

6.3 Cryptocurrencies' relation to the US equity market

As the results from orthogonalized impulse response functions suggest, bitcoin and the cryptocurrencies have no relations with the US equity market which is consistent with Gangwal's (2016) paper reporting that between 2012 and 2016 adding bitcoin to international investors' portfolio yields a higher Sharpe ratio. This result is robust even with regressions utilizing Fama and French's 3-factor model as well as adding to it Carhart's momentum component. When adding bitcoin momentum factor to the Carhart's model, the results converge with the orthogonalized impulse response function's, providing evidence that bitcoin affects on litecoin's and ripple's returns but not on the other top 6 cryptocurrencies.

6.4 Cryptocurrencies' relation to the financial industry

The most interesting result from this thesis is that the bitcoin momentum explains both banking and financial industry's returns, even when controlling with Carhart's 4-factors. With banking industry, the value-weighted regression is statistically significant compared to equal-weighted implying that bitcoin momentum affects larger institutions more. In addition, this effect has grown stronger during the last years, as the subsample regression suggest. With financial industry, based on the regressions, the direction points the opposite. Bitcoin effect is stronger with smaller institutions but it has diminished over the years.

These findings raise questions. Intuitively, financial industry's smaller players, such as security and commodity brokers, would have been more quickly aboard in the cryptocurrency market but now are reducing risks from this high volatility market which would explain the change in the subsamples. On the other hand, larger banking institutions which have been strongly against

³⁰ Website: <http://www.businessinsider.com/bitcoin-price-ethereum-and-other-cryptocurrencies-compare-2017-9?r=US&IR=T&IR=T>, date 30.11.2017

³¹ Idiosyncratic risk is risk that can be diversified by allocating resources (e.g. money) to multiple assets if they have less than 1 of correlation.

bitcoin³² and the cryptocurrencies in general, have realized that the market has grown so big that they must commit to it.³³

7. Conclusion

In this thesis, I have analyzed if bitcoin suffers from illiquidity, bitcoin's leading effect among the top cryptocurrencies and cross-asset dynamics between cryptocurrencies and US equity market and financial sector. In my study, I use daily data of 9 cryptocurrencies, including bitcoin, and daily data of US equity market, banking and financial industry with both value-weighted and equal-weighted excess returns.

Firstly, I calculated Amihud illiquidity premium for bitcoin and constructed bitcoin momentum factor. Secondly, I computed ACF, PACF, CCF and VAR(p) models which I used for plotting orthogonalized impulse response functions to view bitcoin's illiquidity, bitcoin's leading effect among cryptocurrencies and cryptocurrencies shocks to US equity market, and vice versa. Thirdly, I regressed 3, 4 and 5-factor models (fifth factor as the bitcoin momentum) to add robustness to US equity market relation analysis. Finally, I regressed the 5-factor model on banking and financial industries' excess returns.

My findings on bitcoin's liquidity are consistent with Wang's (2014) paper where he argues that bitcoin market is liquid and does not suffer from a liquidity trap. However, this paper is inconsistent with Sweeneys' analogy that decentralized currency systems are prone to failure. Also, my thesis is consistent with Smith (2016), Baur et al. (2015) that cryptocurrencies can be classified as currencies based on their characteristics and have weak relations with another asset classes. In this study, I use US equity market as a benchmark to show that cryptocurrencies, as an asset class belonging to currencies, have no impulse response dynamics with each other. In addition, this paper is aligned with Gangwal's (2016) study where he reports that between 2012 and 2016, adding bitcoin to international investor's portfolio yield a higher ratio. My thesis confirms this and adds more cryptocurrencies to this list.

Moreover, this paper provides interesting findings of bitcoin momentum factor's effect, controlling with Carhart's (1995) 4-factors, on banking and financial industry's excess returns. The bitcoin momentum's effect has grown over time as a statistically significant estimator for

³² Website: <https://www.forbes.com/sites/panosmourdukoutas/2017/09/14/why-big-banks-attacked-bitcoin/#6dd45fa06c53>, date 1.5.2017.

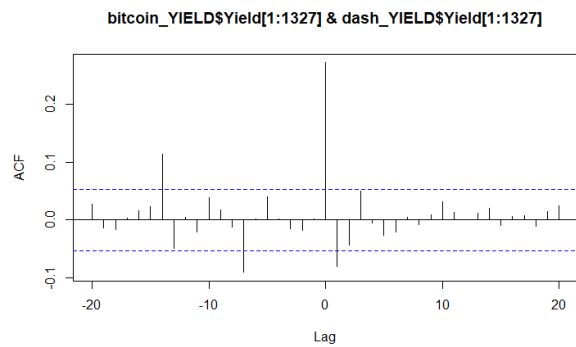
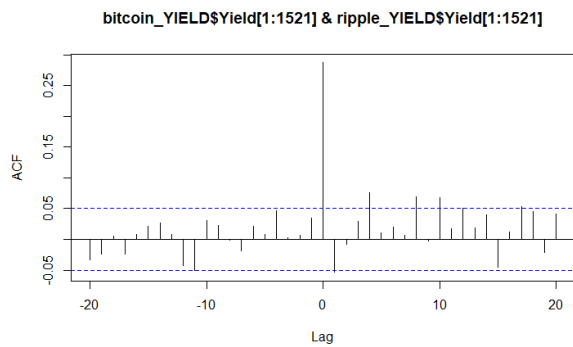
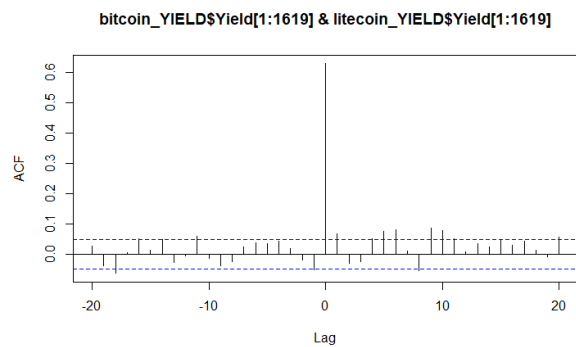
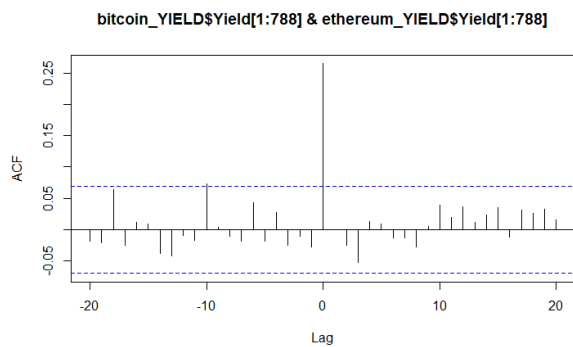
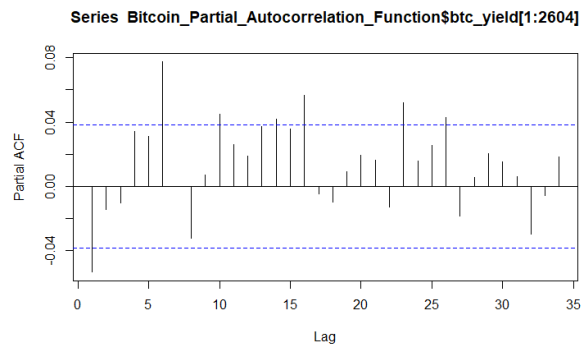
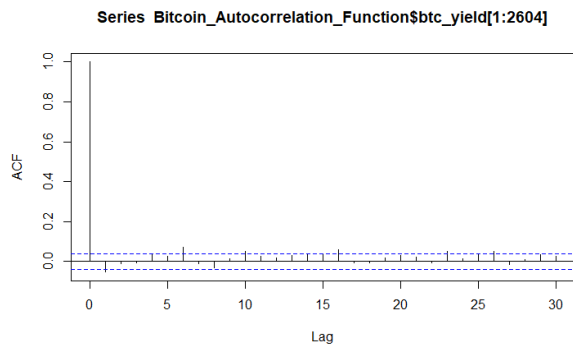
³³ Website: <http://www.zerohedge.com/news/2017-10-05/big-banks-are-coming-bitcoin>, date 1.5.2017.

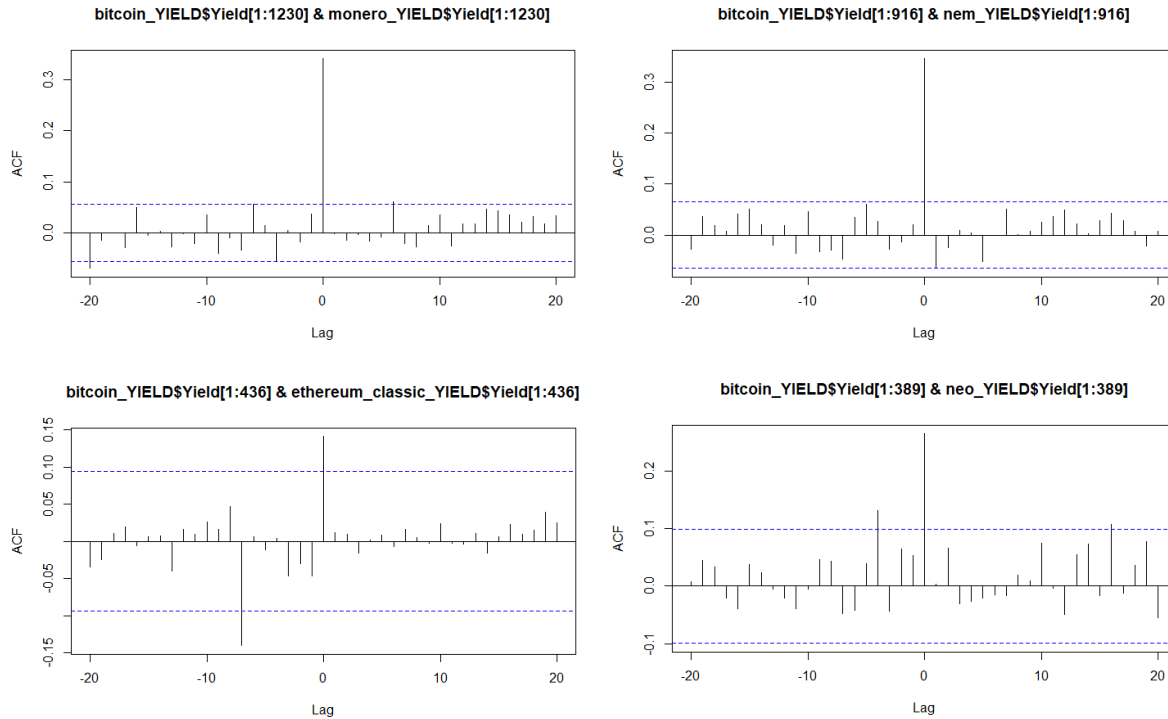
big banks' and institutions' excess returns. On the other hand, the bitcoin momentum has an opposite impact on financial industry's excess returns. Meaning that the bitcoin momentum has a stronger effect on smaller institutions and it has weakened during the last years. I leave this finding for further studies, as this thesis focuses more on the descriptive analysis of the cryptocurrency market relations within and outside.

The results of this study offer three practical implications. Firstly, it provides evidence that the bitcoin does not suffer from a liquidity trap and the market is liquid enough for investors and cryptocurrency users. Secondly, only two of the 8 other cryptocurrencies analyzed in this study are under bitcoin's lead effect, making it possible to reduce idiosyncratic risk within cryptocurrency portfolio. Finally, as the cryptocurrency market and US equity excess returns do not have significant impulse response dynamics, the cryptocurrencies make an interesting asset diversification class for investors seeking for diversification benefits.

APPENDIX A: ACF, PACF & CCF of bitcoin and cryptocurrencies

The interpretation of the graphs is the following, the x-axis illustrates the lead or lag in days. The y-axis shows the function and its result. The heading elaborates in 1–2 what function and series is in question, in 3–10 the said cryptocurrency's CCF between bitcoin, the numbers inside the bracket show with how many days of data it is calculated (end date 29.09.2017) and the dotted blue line are the significance level (5%). These plots present the following: number 1 is the ACF of bitcoin, number 2 is the PACF of bitcoin and 3–10 are CCFs between bitcoin and the said cryptocurrency.





APPENDIX B: Industry variable definitions

This Appendix presents the *banking industry's* BANKS [45] and *financial industry's* FIN [48] SIC codes and the sub-industry's belonging to the accumulating classification in the United States of America.

BANKS [45]	FIN [48]
6000-6000 Depository institutions	6200-6299 Security and commodity brokers
6010-6019 Federal reserve banks	6700-6700 Holding, other investment offices
6020-6020 Commercial banks	6710-6719 Holding offices
6021-6021 National commercial banks	6720-6722 Investment offices
6022-6022 State banks - Fed Res System	6723-6723 Management investment, closed-end
6023-6024 State banks - not Fed Res System	6724-6724 Unit investment trusts
6025-6025 National banks - Fed Res System	6725-6725 Face-amount certificate office
6026-6026 National banks - not Fed Res System	6726-6726 Unit inv trusts, closed-end
6027-6027 National banks, not FDIC	6730-6733 Trusts
6028-6029 Banks	6740-6779 Investment offices
6030-6036 Savings institutions	6790-6791 Miscellaneous investing
6040-6059 Banks (?)	6792-6792 Oil royalty traders
6060-6062 Credit unions	6793-6793 Commodity traders
6080-6082 Foreign banks	6794-6794 Patent owners & lessors
6090-6099 Functions related to deposit banking	6795-6795 Mineral royalty traders
6100-6100 Nondepository credit institutions	6798-6798 REIT
6110-6111 Federal credit agencies	6799-6799 Investors, NEC
6112-6113 FNM	
6120-6129 S&Ls	
6130-6139 Agricultural credit institutions	
6140-6149 Personal credit institutions (Beneficial)	
6150-6159 Business credit institutions	
6160-6169 Mortgage bankers	
6170-6179 Finance lessors	
6190-6199 Financial services	

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