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Bitcoin as a leader of crypto-currencies: A predictability study

Bachelor thesis

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Abstract

This bachelor thesis analyzes high correlation between the monopolistic leader of crypto-currency market, Bitcoin, and its followers, so called altcoins. The first research question follows the everyday life situation of a younger brother, trying to imitate, follow, or even outrun his elder. *Do alternative crypto-currencies follow the price development of their leader?* Our thesis presents positive answer to this question, as analysis of all altcoins included in this paper (Litecoin, Ripple, Peercoin and Dogecoin) proved strong causality from the Bitcoin's point of view. Subsequently, we analyzed this relationship into deeper details for each currency, using vector autoregressive model and consecutive impulse-response function. In the second part of this thesis we build on our previous findings with the following research question. *May the price development of altcoins be effectively predicted, based on the price development of bitcoin?* In this regard, we used static forecast in combination with Diebold-Mariano test, evaluating forecasting accuracy of our preceding model, compared to alternative predictions excluding the bitcoin's price. This analysis reflected various generally insignificant results with a few exceptions, indicating predictability potential. Consequently, we claim that even though we proved significant bitcoin leadership, this effect is apparently not strong enough for development of profitable trading strategy.

Keywords

Crypto-currency, Bitcoin, Litecoin, Ripple, Peercoin, Dogecoin, altcoin, causality, predictability, forecast.

Abstrakt

Tato bakalářská práce analyzuje vysokou korelaci mezi monopolistickým vůdcem trhu kryptoměn, Bitcoinem, a jeho následovníky, takzvanými altcoiny. První výzkumná otázka pramení z běžné situace, kdy mladší bratr zkouší napodobovat, následovat, případně i předčít svého staršího bratra. *Následují alternativní kryptoměny cenový vývoj jejich vůdce?* Tato práce přináší pozitivní odpověď na tuto otázku, neboť analýzou všech altcoinů v této práci (Litecoin, Ripple, Peercoin a Dogecoin) se podařilo prokázat silnou kauzalitu ze strany Bitcoinu. Nadále jsme analyzovali tento vztah do podrobnějších detailů za použití vektorové autoregrese a navazující impulse-response funkce. Ve druhé části této práce navazujeme na naše předchozí zjištění s následující výzkumnou otázku. *Může být cenový vývoj altcoinů efektivně predikován na základě cenového vývoje bitcoinu?* V této souvislosti použijeme statickou předpověď v kombinaci s Diebold-Mariano testem, hodnotícím predikční přesnost našeho předchozího modelu v porovnání s alternativními možnostmi predikce nezahrnujícími cenový vývoj bitcoinu. Tato analýza vykázala rozličné obecně nesignifikantní výsledky s několika výjimkami, poukazujícími na predikční potenciál. Tudíž, přestože se nám podařilo prokázat signifikantní vedení Bitcoinu, tento efekt zřejmě není dostatečně silný pro vývoj ziskové obchodní strategie.

Klíčová slova

Kryptoměna, Bitcoin, Litecoin, Ripple, Peercoin, Dogecoin, altcoin, kauzalita, předvídatelnost, predikce.

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

I grant a permission to reproduce and to distribute copies of this thesis document in whole or in part.

Prague, May 15, 2015

Signature

Acknowledgment

I would like to express my sincere gratitude to PhDr. Ladislav Kristoufek Ph.D. for sharing his time, expertise and his readiness to provide continuous and highly-valued assistance at any time. I am also indebted to portal Coinwarz.com for providing me high-quality data used in this thesis. Finally, I am grateful to my family for their endless support.

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List of Abbreviations

1d	with observations measured once a day
2h	with observations measured every 2 hours
BTC	Bitcoin
D-M	Diebold-Mariano (test)
DOGE	Dogecoin
FDL	Finite distributed lag (model)
IRF	Impulse-response function
LTC	Litecoin
PPC	Peercoin
VAR	Vector autoregressive (model)
XRP	Ripple

1 Introduction

"Bitcoin gold rush is over" (Halleck 2014). Is it?

During less than 3 years, decentralized virtual currency (also referred to as crypto-currency) **bitcoin** skyrocketed from $0.30 to $1242 (Washington Post 2015; Rooney 2015). Since that time (November 2013), bitcoin has been steadily falling to current value of only about $226[1] (Coinmarketcap.com 2015). This sharp up and down movement is often compared to a modern gold rush, which appears to be over, as investors are getting bored of crypto-currencies (Halleck 2014; Schneider 2015; Desjardins 2014). However, is bitcoin the only one of its kind?

In fact, there are hundreds of other crypto-currencies, alternatives to bitcoin (often referred to as altcoins), hidden in its shadow, with smaller, but certainly not negligible impact. Some of them have experienced more or less the same story as bitcoin, e.g. **litecoin**, historically the largest altcoin as for market capitalization, reaching its maximal volume of more than one billion USD at the time of bitcoin's peaking, then steadily falling down (Coinmarketcap.com 2015). On the other hand, numerous have experienced kind of a different story. For example, consider **ripple**, currently becoming the largest altcoin, after doubling its maximal market capitalization one year after the bitcoin's peaking, showing that there is still large demand for crypto-currencies (Coinmarketcap.com 2015). Consequently, despite the fact that bitcoin gold rush may be over, we could just hardly deduce that the age of whole crypto-currency market is over.

This assumption leads us to the purpose of the thesis. First of all, we will analyze the current situation of crypto-currency market with focus on the main altcoins (except for the above mentioned, also **peercoin** and **dogecoin**). The initial motive is that there is still large demand for crypto-currencies, unsatisfied by the largest, but long-term declining bitcoin, causing investors

[1] as for 16$^{\text{th}}$ April 2015

to incline to alternatives. Because of that, we will focus on dependency of altcoins on their market leader, bitcoin. Our main research question follows the everyday life situation of a younger brother, trying to imitate, follow, or even outrun his elder. *Do alternative crypto-currencies follow the price development of their leader?* If this hypothesis would prove to be correct, showing that altcoins really follow the price development of bitcoin (and possibly with some delay), one could easily exploit this information to make effective predictions of altcoins' price, based on price of bitcoin. Consequently, we can state our second research question. *May the price development of altcoins be effectively predicted, based on the price development of bitcoin?*

This bachelor thesis is organized as follows. In the first chapter, we will state the basic properties of each currency and characterize the corresponding dataset used for further research. In the second chapter, we will describe the methodology used in our study. In the third chapter, we will present and discuss the results of our analysis. In the last chapter, we will summarize our findings and reach the conclusion.

2 Literature Review

Soar of the crypto-currency market in November 2013 and subsequent plummeting during 2014 attracted attention of thousands of websites, journals and newspapers, causing high alertness of bitcoin even among broad general public, and raising countless discussions mainly in academic environment and internet sphere. This price development of bitcoin could be characterized mainly by the three most important events of bitcoin history, i.e. FBI closing the only drug marketplace Silk Road, accepting bitcoin payments, described by Farrell in 2013, China's Central Bank banning of bitcoin transactions, discussed by Kelion in 2013, and a scandalous bankruptcy of one of the largest bitcoin exchange Mt.Gox, delineated by Peston in 2014. Joint conclusion of those papers, we shall take in note while proceeding with this thesis, is that those events and corresponding reputation changes played a significant role in the crypto-currency market development.

Overall quantitative analysis of Bitcoin transaction graph was published by Ron Dorit and Adi Shamir from The Weizmann Institute of Science in 2013. This paper reflects detailed analysis of full history of transactions, which are publicly accessible but anonymized. This study also contains list of information about the typical behavior of users, how they acquire and spend their bitcoins, the balance of bitcoins they keep in their accounts, and how they move bitcoins between their various accounts in order to better protect their privacy. This research brought enormous contribution to the field of crypto-currency market studies, by providing accurate information about how bitcoins are used in practice and a large number of statistical properties of the Bitcoin transaction graph. This paper shall serve us as a complex study, explaining the nature of Bitcoin system.

Research, quantifying the connection between the change of crypto-currency market reputation and bitcoin price, was written by Ladislav Kristoufek from Charles University in 2013. This relationship is analyzed based on search queries on Google Trends and Wikipedia, which proved to be a valuable source of information. Paper was based on vector autoregressive approach applied on the "bitcoin" search queries and price of the currency in first logarithmic differences. One of the results of this paper is a prove of high correlation between price of bitcoin and its search queries on both, Google Trends and Wikipedia. This paper will help us to understand underlying aspects of bitcoin price development, as well as a pattern of methodology suitable for application in crypto-currency price development area.

As discussed before, bitcoin grabbed most of the market attention to itself due to its dominant position. Smaller but still very important altcoins developed in the shadow of the market leader, mostly avoiding attention of general public and discussed mainly at specialized web forums. Many of those alternative currencies have or had large market capitalization, compete to keep their position in significantly demanded crypto-currency market, and show highly volatile price development providing huge trading potential. This thesis aims to provide description and general overview of current situation of those currencies, which are only rarely a subject of closer analysis. Most of the information about the alternative currencies used in thesis will be derived directly from each currency's official portal, such as Litecoin.org, Ripple.com and Dogecoin.com, or from specialized crypto-currency trading portals, such as Coinmarketcap.com, Coinwarz.com and Cryptocoincharts.info.

The whole market of crypto-currencies including altcoins was precisely described by Lawrence White from George Mason University in 2014. White points out the raise of altcoins against the monopolistic bitcoin, as in aggregate they managed to increase their market capitalization twelve-fold between March 2013 and December 2014, while bitcoin did just four-fold in the same period, resulting in fall of its market share from 95% to 84%. Moreover, White opposes a team of Bank of England economists (Ali et al. 2014), while highlighting the change of position of crypto-currencies as a commonly accepted medium of exchange. According to White, this change in status results in suppressed dependency of crypto-currency usage on its own current price. The research concludes with recommendation to policy makers, to lower restrictions levied on evolving crypto-currency market, resulting in decreased economic welfare. This paper shall provide us underlying information concerning crypto-currency market as a whole.

The purpose of this thesis is to analyze relationship between bitcoin and the rest of the market with focus on potential predictability of altcoins price based on bitcoin. As mentioned before, only a few studies were led in this direction. The most corresponding paper to the purpose of our thesis was published by Tyler Miles in 2014 and analyzes correlation between bitcoin price and price of selected stocks, precious metals and altcoins' price. Results of this research show that there is only small correlation of bitcoin with precious metals. On the other hand, Miles found that there is a mid-high correlation between bitcoin and selected stock prices, i.e. Google, Amazon and Facebook. Moreover, research states that there is very high correlation between bitcoin and selected altcoins - litecoin and darkcoin. As the explanation Miles sees the fact that altcoins can be purchased mainly by using bitcoins, therefore remain slightly intertwined. This is a very interesting conclusion for our thesis as high correlation denotes that it is reasonable to do further research concerning this relationship and analyzing, whether there is causality from one or other direction.

The contribution of our thesis is to step into inadequately analyzed market of alternative crypto-currencies. Following the previous findings of high correlation between monopolistic bitcoin and altcoins, we will investigate this connection into deeper details, analyze whether there is a causality from bitcoin's direction influencing altcoins' price, and if so, show size of the response of altcoins to bitcoin's impulse change. This shall help us to better understand the whole market situation and to perform and evaluate forecast of altcoins' price based on bitcoin's price development.

3 Currencies Characteristic and Dataset Description

Before proceeding with our analysis of correlation in price development between selected crypto-currencies with focus on impact of bitcoin's leadership, it is necessary to introduce each currency and to understand its underlying background. In the following subchapters, we will state a basic properties of all analyzed currencies, including description of their price development, resulting in better understanding of current crypto-currency market situation.

Moreover, in the second part of each subchapter, we will briefly discuss range, quality and statistical properties of datasets used in this thesis. For our analysis, we will use two separate datasets for each crypto-currency, with data measured daily and every two hours, respectively. First dataset will help us to analyze long-term correlation between bitcoin and its followers on daily basis, without going into closer details. Second dataset will complement the first one with focus on short-term time period in detail.

Fortunately, it is not difficult to find high quality data for popular bitcoin. However, it is not that easy for less popular altcoins. Because of that, I would like express my special thanks to administrators of Coinwarz.com portal for sharing most of the data that will be used in our further analysis.

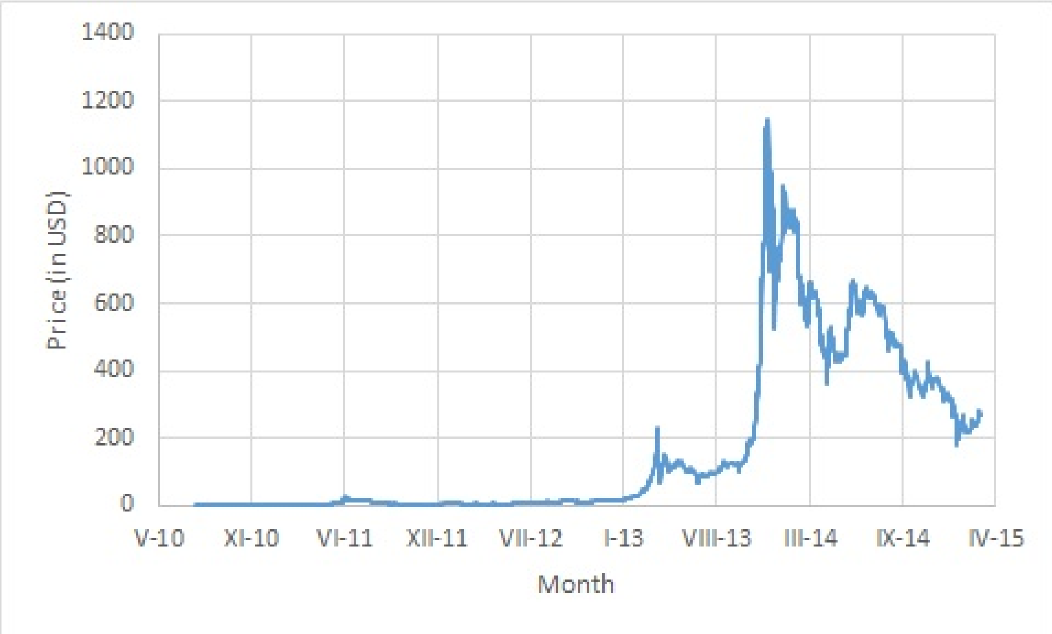
3.1 Bitcoin

General Characteristic

Bitcoin (BTC) is an online payment system invented by Satoshi Nakamoto, who published his invention in 2008, and released it as open-source software in 2009 (Davis 2011). This system introduced an innovative concept of a decentralized, peer-to-peer virtual currency, autonomous from influence of centralized authority (Piasecki 2012). Even though similar concepts existed prior bitcoin's introduction (e.g. OpenCoin, now known as Ripple, 2004 (Deng 2007)), bitcoin was the first decentralized digital currency (Brito 2013). Bitcoin is in long-term the largest crypto-currency in terms of total market volume (Espinoza 2014).

There are two possible ways how to obtain bitcoin: exchanging or mining. While exchange for fiat money (i.e. currency with value derived by government regulation or law), products or services is a common thing in a world of finance, mining is something special. In the mining process, bitcoins are provided as a reward for payment processing work in which users offer their computing power to verify and record payments into the public ledger (Brito 2013). In this way new bitcoins are created and released to the market. However, amount of this reward is set by formula with no possible external influence, is sharply decreasing and will become zero in 2140, when all 21 million bitcoins will be issued (Dorit and Shamir 2012). Consequently, total supply of bitcoins in circulation is steadily increasing and reached 14 million at the beginning of 2015.

Figure 1: Bitcoin price development



As we can see from Figure 1, showing development of bitcoin close price, bitcoin had almost zero value for a long time after its invention, until firstly crossed the line of 0.1 USD in October 2010 (Coinmarketcap.com 2015). From that time, bitcoin went through several periods of appreciation and depreciation (also referred to as bubbles and busts) (Colombo 2013). During 2011, bitcoin rose to $32 just to fall back again to $2. From 2012 to mid-2013, bitcoin did one more cycle, while rising to $266 in April 2013 and crashing to less than one fifth of this value in next 3 months. Afterwards, bitcoin rebounded and reached its all-time peak of $1242 (with market volume of more than $13.5 billion) on November 29, 2013 (Rooney 2015; Coinmarketcap.com 2015). Since that time, bitcoin has been steadily falling down to current price slightly above $225[2] and market volume of $3.5 billion (Coinmarketcap.com 2015).

To make conclusion from what has been written above, we should remember that bitcoin's price history consists of series of repeating cycles, resulting in incredibly large volatility (18 times higher than USD (Williams 2014)). As we will see on next pages, this feature is common for majority of cryptocurrencies.

3.1.1 Dataset Description

Our first dataset contains 1691 observations with daily measurements of bitcoin closing price in USD (Coindesk.com 2015). The first observation was measured on 18$^{\text{th}}$ July 2010, the last one on 4$^{\text{th}}$ March 2015, and there are no observations missing in the sample. As this dataset will be included in each model on daily basis in this thesis, its wide range covering whole bitcoin price history (and consequently all altcoins price history), combined with its perfection, are more than welcomed.

The second dataset (let us call it BTC 2h dataset) contains 8176 obser-

[2] as for 16$^{\text{th}}$ April 2015

vations of bitcoin price in USD, measured every 2 hours (i.e. each odd hour)(Coinwarz.com 2015). The first observation was measured on 3rd May 2013 17:00, the last one on 15th March 2015 23:00, and once again, there are no observations missing in the sample. Even though this dataset covers only shorter time period than daily dataset, the whole important bitcoin price development has been captured, and consequently whole relevant life period of all altcoins as well. This dataset will serve as a stepping stone for all further analysis on 2h basis.

In Table 1 we can find a brief summary of statistical properties of both datasets.

Table 1: Bitcoin summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
BTC-1d	393.016	278.651	34.5	1,147.246	1,691
BTC-2h	398.548	236.706	64.894	1,229.572	8,176

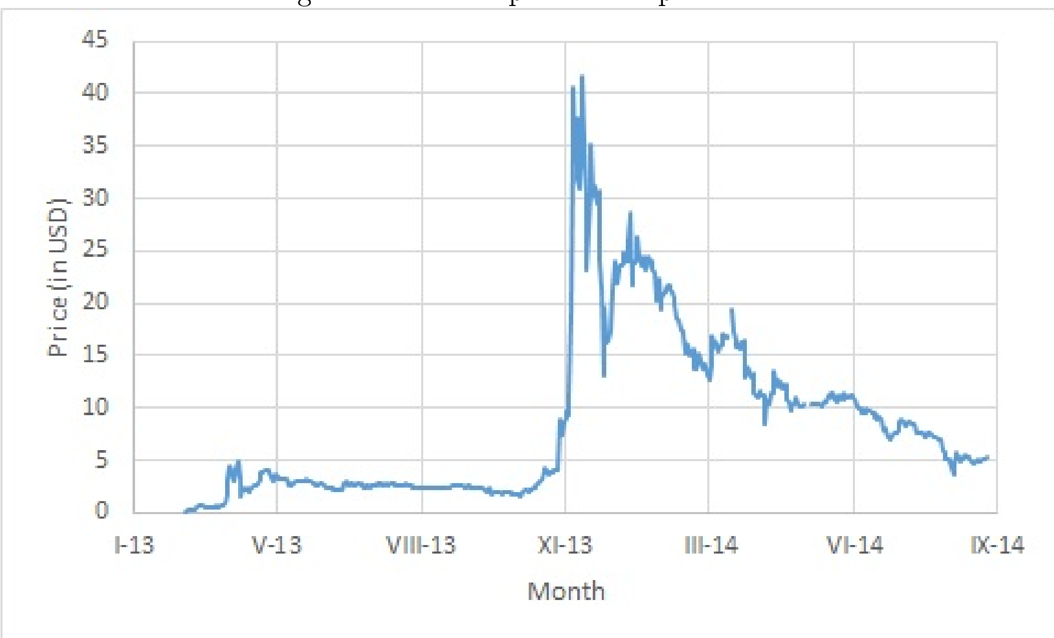
In the second column of Table 1 we see incredibly large standard deviation, almost as big as mean value, stated in the first column. This corresponds to the fast up and down movement and subsequent high volatility of bitcoin price over time. From maximum and minimum values of our datasets we see that we managed to capture almost whole lifetime of bitcoin in our dataset. These two values also represents steepness in bitcoin's price movement, as the maximal price is more than 30 times higher than the minimal one. Higher maximum value for 2h dataset corresponds to more precisely described price development, reaching above daily closing values during the peak time period.

3.2 Litecoin

General Characteristic

Litecoin (LTC) is another peer-to-peer internet currency based on an open source protocol with decentralized network without supervision of any central authority, released on 7^{th} October 2011 by Charles Lee (Litecoin.org 2015). Litecoin creation and transaction system is strongly inspired by and technologically nearly identical to Bitcoin. On the other hand, litecoin has a few improvements which helped it to gain its popularity, such as decreased block generation time, increased maximum number of coins, and different hashing algorithm (Litecoin.org 2015). It is historically the second largest crypto-currency (as for market capitalization) and the only altcoin that achieved to pass the limit of $1 billion (Coinmarketcap.com 2015). However, because of its long-term fall, litecoin has been outrun by ripple and is currently holding the third position.

Figure 2: Litecoin price development



As Litecoin system is very similar to Bitcoin, it is not a big surprise that we can find many common features in its price development, stated in Figure 2, as well. Since its release in October 2011, litecoin had a long period of having almost zero price, too. Moreover, in October 2013, litecoin also experienced massive growth which included a 100% leap within 24 hours (Charlton 2013). Litecoin reached its all time maximum of almost $60 in 28$^{\text{th}}$ November 2013, just one day before bitcoin did (Coinmarketcap.com 2015). Since that time, litecoin price is steadily falling, even more rapidly than bitcoin (litecoin market capitalization currently refers to $52 million, just about 5% of the maximum, while bitcoin is stabilizing around $3.4 million, which refers to 25% of its maximum capitalization).

3.2.1 Dataset Description

Litecoin daily dataset contains 558 observations with daily measurements of litecoin closing price in USD (Quandl.com 2015). The first observation was measured on 3$^{\text{rd}}$ March 2013, the last one on 11$^{\text{th}}$ September 2014, and there are 6 observations missing in the sample. As all those unavailable measurements are in the early period of low prices and they reflects to just about 1% of a sample, we can assume that they were very likely unmeasured with no bias and no significant impact on our analysis. Dataset has a sufficient size and covers whole relevant litecoin's lifetime.

The second dataset (let us call it LTC 2h dataset) contains 8176 observations of litecoin price in USD, measured every 2 hours (i.e. each odd hour)(Coinwarz.com 2015). The first observation was measured on 3$^{\text{rd}}$ May 2013 17:00, the last one on 15$^{\text{th}}$ March 2015 23:00, and there are no observations missing in the sample. This dataset covers almost the same time period as the previous one with much more details, and is therefore more than sufficient for our analysis.

In Table 2, we can find a brief summary of statistical properties of both datasets.

Table 2: Litecoin summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
LTC-1d	8.557	8.003	0.105	41.689	552
LTC-2h	7.734	7.592	1.185	58.961	8,176

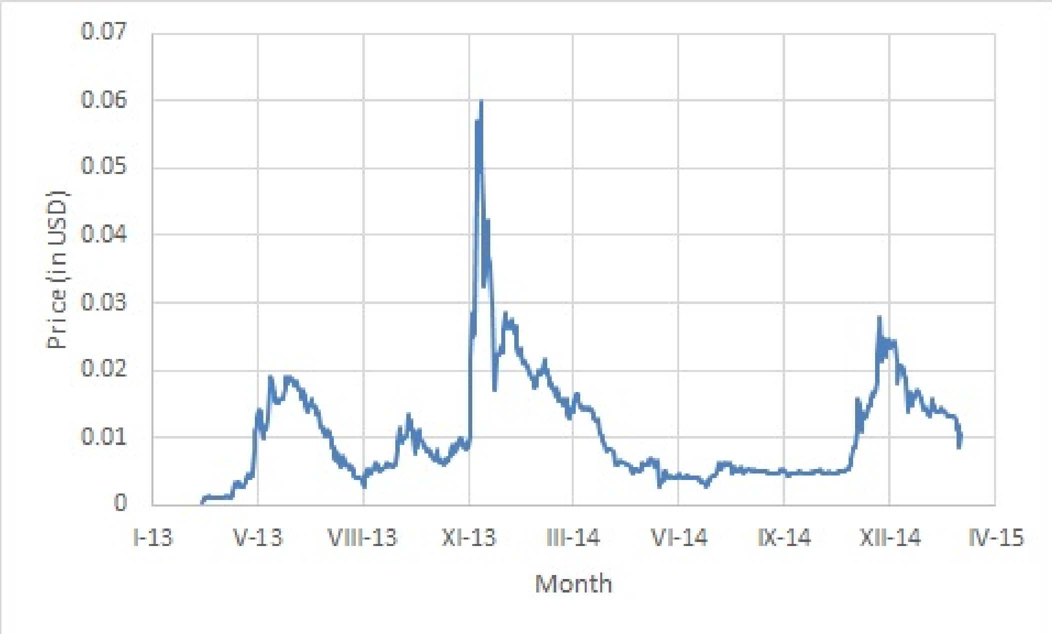
In Table 2, we see proportionally very similar numbers to what we saw in bitcoin case. This corresponds to almost identical price development, therefore the same conclusion as for Table 1 applies here.

3.3 Ripple

General Characteristic

Ripple (XRP) payment system (firstly implemented already in 2004, renamed from OpenCoin and change to open source in September 2013 (Buterin 2013)) is very different from our previous two systems, both technologically and as for its price development. It was designed to suppress Bitcoin's reliance on centralized exchanges, use less electricity than Bitcoin, and perform transactions much faster than Bitcoin (Peck 2013). To do so, unlike Bitcoin or Litecoin, Ripple is non-POW (i.e. proof-of-work) system, has no possibility of mining, can send or automatically exchange any other currency and fully confirms transaction in a second (Ripple.com 2015). Ripple could be therefore defined as a payment system, providing an independent mean of direct exchange of fiat currency (dollars, yens, etc.), crypto-currency (bitcoin, litecoin, etc.), commodity or any other unit of value. Because of that, Ripple positions itself more as a complement to, rather than competitor with Bitcoin (Coindesk.com 2015). Today, Ripple is the second largest crypto-currency by market capitalization, after outrunning Litecoin during 2014 (Cryptocoincharts.info 2015; Coinmarketcap 2015).

Figure 3: Ripple price development



From Figure 3 we see that ripple price development is not so similar to bitcoin, as in case of litecoin, although, there are a few similarities, such as high volatility, fast rocketing and then slow falling down after a crash of speculative bubble. As ripple prices are very low, because of 100 billion premined coins, we will state them in USD cents (i.e. multiplied by 100). There were three major booms in the history of ripple. Starting at less than 0.04 cents in March 2013, ripple managed to reach values of 1.9 cents at the beginning of June 2013 (Ripplecharts.com 2015). Afterwards, ripple dropped back to 0.26 cents just to follow the cryptocurrency market boom in November 2013, reaching its all time maximum of 6 cents per ripple on 4$^{\text{th}}$ December 2013 (not more than a week after bitcoin's peak)(Ripplecharts.com 2015). However, this is not the end of the story, yet, as in the previous cases. After rapid fall back to 0.28 cents in July 2014, ripple, unlike bitcoin and litecoin, managed to grow back to 2.5 cents at the end of December 2014, while reaching its market capitalization maximum (thanks to more ripples in circulation) to $853 million (Coinmarketcap 2015). That is almost 9 times more than litecoin at that time and almost doubled capitalization compared to its own in November 2013 peak value. Since that time, ripple is steadily falling with the market, while still holding position of number one altcoin.

3.3.1 Dataset Description

Our daily dataset for ripple contains 721 observations with daily measurements of ripple closing price in USD (Ripplecharts.com 2015). The first observation was measured on 14$^{\text{th}}$ March 2013, the last one on 4$^{\text{th}}$ March 2015, and there are no observations missing in the sample. Dataset covers almost two years period and also a whole relevant ripple's price history.

The second dataset (let us call it XRP 2h dataset) contains 7914 observations of ripple price in USD, measured every 2 hours (i.e. each odd hour)(Ripplecharts.com 2015). The first observation was measured on 3$^{\text{rd}}$ May 2013 17:00, the last one on 15$^{\text{th}}$ March 2015 13:00. Unfortunately, there are 254 observations missing in the sample. This inaccuracy was caused by occasionally slightly different time periods between two measurements at source dataset and consecutive transformation and pairing. However, as this process is obviously unbiased and missing observations reflects to just about 3%, this should not have any significant impact on our analysis. Dataset covers whole relevant period of ripple's lifetime.

In Table 3, we can find a brief summary of statistical properties of both datasets.

Table 3: Ripple summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
XRP-1d	0.0108	0.0081	0.00036	0.06	721
XRP-2h	0.0116	0.0081	0.0025	0.0659	7,914

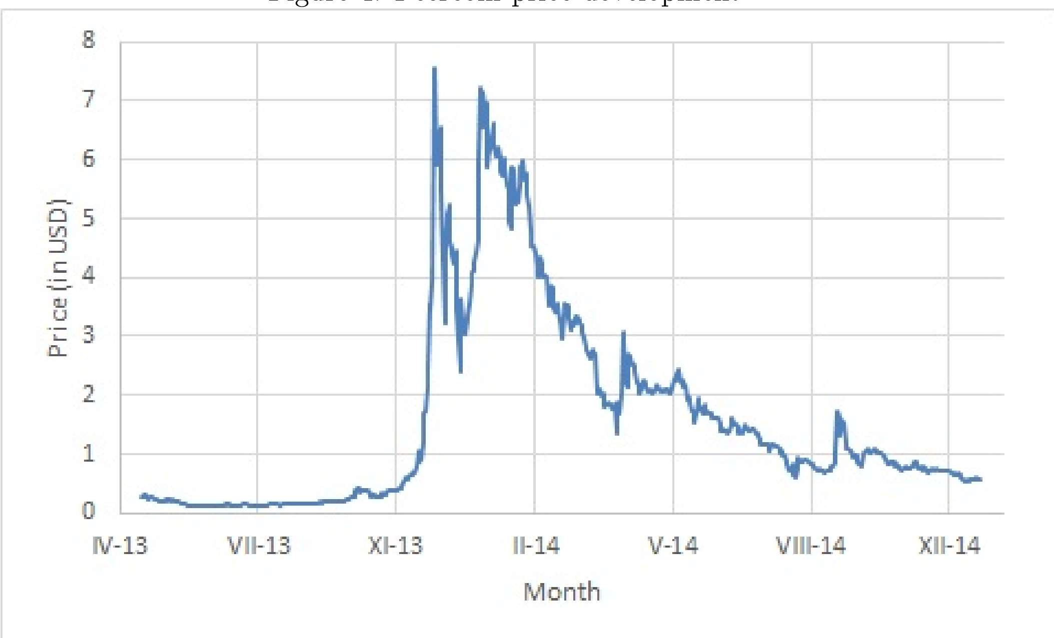
Numbers in Table 3 are once again proportionally similar to those, stated in bitcoin and litecoin cases. Much lower, almost zero values, correspond to huge number of ripples in circulation. Besides proportionally slightly lower, but still very large standard deviation, same conclusion as in Table 1 can be applied here.

3.4 Peercoin

General Characteristic

Peercoin (PPC) is peer-to-peer crypto-currency, based on paper of Scott Nadal and Sunny King from August 2012, strongly inspired by Bitcoin (Popper 2013; King 2012). Unlike Bitcoin, Peercoin was first to implement combination of POW and POS (i.e. proof-of-stake) for network securing (King 2012). Moreover, it does not have a hard limit on maximal supply of coins in circulation, but is designed to attain an annual inflation rate of 1%. This feature, along with increased energy efficiency, aims to allow for greater long-term scalability (Vega 2014). Peercoin is historically the third largest minable crypto-currency (after bitcoin and litecoin) as for market capitalization (Coinmarketcap.com 2015).

Figure 4: Peercoin price development



From Figure 4, we see that Peercoin price development was somehow different from the previous ones. It stayed at almost zero value (below \$0.5) until 7$^{\text{th}}$ November 2013 just to sharply jump up with all other crypto-currencies to its maximum of \$8.75 on 30$^{\text{th}}$ November 2013 (one day after bitcoin). Unlike litecoin but similarly to ripple, peercoin subsequently performed one more cycle. After falling to less than \$2 in mid-December, peercoin managed to come back once again, reaching \$7.55 on 2$^{\text{nd}}$ January 2014 and consequently maximal market capitalization of \$157.3 million (Coinmarketcap.com 2015). Later, after holding above \$5 till mid-February, peercoin slowly vanished to minimal value.

3.4.1 Dataset Description

Our daily dataset for peercoin contains 606 observations with daily measurements of peercoin closing price in USD, extracted from the following 2h dataset (Coinwarz.com 2015). The first observation was measured on 3$^{\text{rd}}$ May 2013, the last one on 30$^{\text{th}}$ December 2014. There are no missing observations in the sample. Dataset has a sufficient size as it contains over 600 values and covers almost whole peercoin's life period.

The second dataset (let us call it PPC 2h dataset) contains 7276 observations of peercoin price in USD, measured every 2 hours (i.e. each odd hour)(Coinwarz.com 2015). The first observation was measured on 3$^{\text{rd}}$ May 2013 17:00, the last one on 30$^{\text{th}}$ December 2014 23:00. Fortunately, there are no missing observations in the sample and the dataset has more than a sufficient size for our analysis.

In Table 4, we can find a brief summary of statistical properties of both datasets.

Table 4: Peercoin summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
PPC-1d	1.586	1.694	0.109	7.547	606
PPC-2h	1.531	1.619	0.084	8.755	7,276

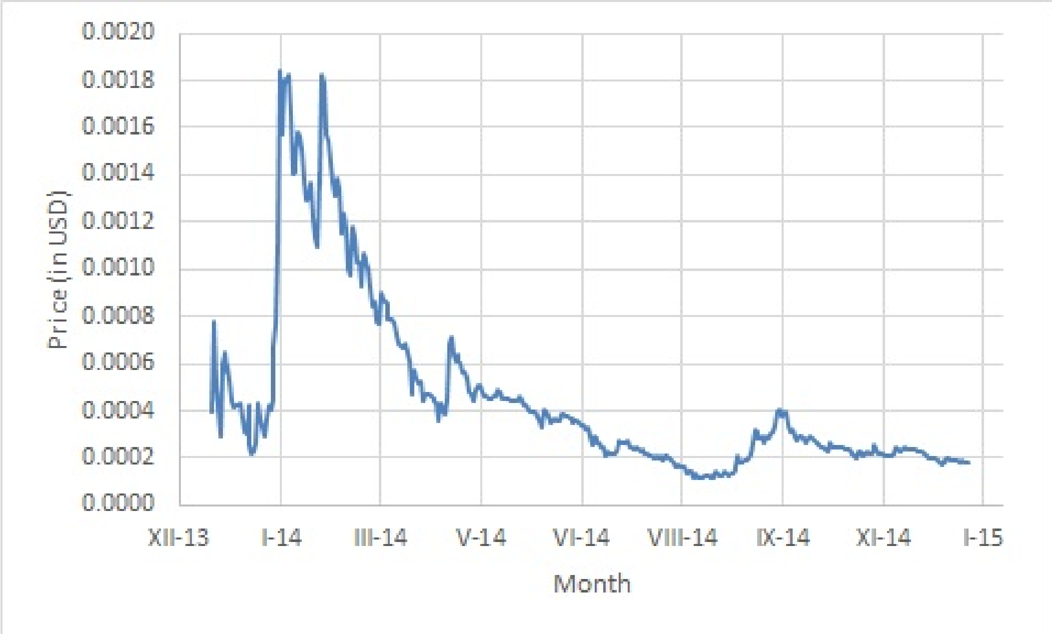
From Table 4 we can conclude that high standard deviation is also an issue for peercoin, as it is for the first time even larger than its mean value. This high volatility corresponds to even steeper growth during reference period, containing 100 times higher maximal price that the minimal one.

3.5 Dogecoin

General Characteristic

Dogecoin (DOGE) is a crypto-currency based on Litecoin, introduced by Billy Markus on 8th December 2013 (i.e. more than a week after bitcoin's peaking)(Dogecoin.com 2015). Even though it was initially meant as a "joke currency", featuring popular Shina Inu dog in its logo, and unlike Litecoin, having randomized reward for mining, Dogecoin quickly developed its own community (Dogecoin.com 2015).

Figure 5: Dogecoin price development



From Figure 5 we can see that dogecoin price development is slightly scaled compared to the previous ones. Three weeks after bitcoin's peaking, on 19th December 2013, Dogecoin jumped nearly by 300 percent in its value in 72 hours, rising from 0.026 cents to 0.095 cents[3] (Couts 2013). Dogecoin rose steadily until mid-February, while on 21st January 2014 reached its peak price of almost 0.21 cents and on 12st February 2014 maximal market capitalization of about $87.5 million (Coinmarketcap.com 2015). Since that time, dogecoin is steadily losing its value with only one minor recovery attempt in September 2014.

3.5.1 Dataset Description

The last daily dataset for dogecoin contains 374 observations with daily measurements of dogecoin closing price in USD, extracted from the following 2h dataset (Coinwarz.com 2015). The first observation was measured on 18th December 2013, the last one on 30th December 2014. There are no missing

[3] values are transferred to USD cents for better clarity

observations in the sample. Dataset is not as large as previous ones and covers only slightly more than one year period, however, this corresponds to short lifetime of dogecoin, which is whole covered in this dataset. Moreover, more than 350 observations are definitely sufficient for our analysis.

The very last dataset (let us call it DOGE 2h dataset) contains 4526 observations of dogecoin price in USD measured every 2 hours (i.e. each odd hour)(Coinwarz.com 2015). The first observation was measured on 18$^{\text{th}}$ December 2013 21:00, the last one on 30$^{\text{th}}$ December 2014 23:00. There are no missing observations in the sample and also the sufficiency assumption holds as this dataset covers the same period as the previous dataset.

In Table 5 we can find a brief summary of statistical properties of both datasets.

Table 5: Dogecoin summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
DOGE-1d	0.00045	0.00037	0.00011	0.0018	374
DOGE-2h	0.00046	0.00037	0.0001	0.0021	4,526

As the numbers in Table 5 are once again proportionally very similar to previous cases, the same conclusion applies here. Note that almost zero values correspond to a huge number of dogecoins in circulation.

3.6 Summary and current market situation

To make conclusion out of this chapter, we can see that all crypto-currencies are very similar one to each other, both technologically and as to their price development. Bitcoin was the first one to become popular and gave inspiration to many others who came with slightly improved currencies. Even though they achieved to follow up the movement of Bitcoin (and the whole market) and to multiply their values from zero to incredibly huge amounts, none of them managed neither to outrun, replace or even get close to the leader of the market, nor to stabilize at certain value.

To summarize numbers that has been written above and to better understand current situation at the crypto-currency market, we state Table 6 containing the most important historical and current data for each currency.

Table 6: Historical and current data summary

Currency	**Max. price**	**Max. market cap.**	**Current price**[4]	**Current market cap.**[4]
	USD	Mio. USD	USD	Mio. USD
BTC	1242	13500	225.6	3171.3
LTC	60	1029	1.4	53.5
XRP	0.06	853	0.00797	254.4
PPC	8.75	157	0.243	5.4
DOGE	0.00206	87	0.000106	10.5

From Table 6, we can conclude that even though price development of all previously mentioned crypto-currencies were proportionally more or less similar, there are huge size differences between each other. Even though maximal market capitalization of altcoins reached high values around 1 billion USD in litecoin and ripple case, even their sum is more than 7 times lower than market capitalization of dominant bitcoin. From the table we can also see size of current loss of market capitalization of all crypto-currencies. While ripple and bitcoin shows the highest persistence, Peercoin and Dogecoin are slowly vanishing.

[4] as for 16^{th} April 2015

4 Methodology

In the following chapter, we will state methodology used in this paper, starting from discussion about fulfillment of underlying Gauss-Markov assumptions, proceeding through definition of Finite distributed lag model and Vector autoregressive model, then describe related analytical tools such as Granger causality test and Impulse-response function, to finally elucidate combination of static forecasting and Diebold-Mariano test.

4.1 Gauss-Markov Assumptions

We want all our models to satisfy Gauss-Markov theorem and therefore our estimators to be BLUE. To do so, we need to check five underlying assumptions before starting any further analysis, i.e. linearity in parameters, no perfect collinearity, zero conditional mean, homoskedasticity and no serial correlation (Wooldridge 2009). We will focus on the last three assumptions as linearity in parameters and no perfect collinearity assumptions are obviously satisfied in our case.

TS.3 Zero Conditional Mean

"For each t, the expected value of the error u_t, given the explanatory variables for all time periods, is zero."(Wooldridge 2009, p. 347)

We can rephrase this assumption as "No important variables are omitted in the model". To satisfy this assumption we have to think about other factors which might be having impact on altcoins price changes (our dependent variable) except for bitcoin's price change. The first idea could be previous lagged price changes of altcoin itself. As we will soon find out, this intuition is correct, and therefore we will include those lags in our models. Another idea might be to include general macroeconomical factors, such as change in worldwide GDP or disposable income, or to include price development of alternative investments, such as change in stock prices,

prices of precious metals, or exchange rates of fiat currencies - alternatives to crypto-currencies. However, according to previous research in this area (Miles 2014), daily changes in those variables have negligible impact compared to bitcoin-altcoin correlation - a key focus of this paper. Therefore, to avoid unnecessary complexity, we will not include any of those little significant factors in our models. Thinking about other factors influencing current price of altcoins, we might come with probably the most important one: something like “reputation change” or “crypto-currency market popularity”, i.e. factors which are the main movers of the whole crypto-currency market. Following the same reasoning as in the previous case, we will not include this factor in our analysis either, nevertheless, we will discuss this step in the latest chapter as a possibility for further improvement.

TS.4 Homoskedasticity

"Conditional on X, the variance of u_t is the same for all t."(Wooldridge 2009, p. 349)

In other words, we need to test, whether our model contains heteroskedasticity or not. From what was stated in the previous chapter, we may already suppose that this could be an issue of our datasets. After performing Breusch-Pagan test, we got p-value of zero for at least four decimal places, meaning that we must reject the null hypothesis of homoskedasticity (Breusch and Pagan 1979). Consequently, we will run all our models with robust standard errors.

TS.5 No Serial Correlation

"Conditional on X, the errors in two different time periods are uncorrelated."(Wooldridge 2009, p. 349)

While testing for autocorrelation, one must regress lagged residuals as an explanatory variable on residuals, saved from the corresponding model. If we are not sure if there is an endogenous variable in our original model, we can put all suspicious variables into this regression as well. Fortunately, the coefficient for lagged residuals is insignificant in both cases, therefore we can assume no presence of serial correlation in our models.

Now, when we checked for all Gauss-Markov assumptions, we are ready to proceed to models used in our analysis.

4.2 Finite Distributed Lag Model

In Finite distributed lag (FDL) model, we allow one or more variables to affect dependent variable with a lag (Wooldridge 2009). The general FDL model then looks as follows:

$$y_t = \alpha_0 + \delta_0 z_t + \delta_1 z_{t-1} + \delta_2 z_{t-2} + u_t$$

Coefficient δ_0 refers to the immediate change in y due to the one-unit increase in z at time t. This coefficient is also usually called the impact propensity or **short-run elasticity** in case of logarithmic forms. Sum of all coefficients δ_0 to δ_n is called the long-run propensity, or **long-run elasticity** in case of logarithmic forms (Wooldridge 2009). The FDL model expresses exactly what we want to analyze - regression with two variables and their lags, useful for examination of significance of lagged coefficients and long-run elasticity. Consequently, we will use it as our first predictability model. On the other hand, as this model is too simple, its contribution will be mainly to help us understand the analyzed relationship in general and to serve as a stepping stone for further analysis. The key focus of our analysis concerning FDL model will be F-test for joint significance of δ coefficients corresponding to coefficients of bitcoin lags.

Before proceeding with this model, we have to solve several issues. First one is an adjustment of our variables to express what we want to analyze and to minimize imperfections. To do so, we shall adjust both our price variables to **logarithmic forms**, to make them express price elasticity rather than absolute value change, which exactly corresponds to the goal of our analysis.

Next step is to test for a **random walk**, which is a common problem of very similar stock market price data. To do so, one can generate first lag of both our variables, $logLTC_{t-1}$[5] and $logBTC_{t-1}$, and regress it back on original variables (Wooldridge 2009). Unfortunately, in both cases, 95% confidence interval includes 1, resulting in failure to reject presence of random walk in our data. To solve this issue, we have to transform our variables into the first difference forms or so called **delta forms**.

$$\Delta log(LTC_t) = log(LTC_t) - log(LTC_{t-1})^5$$
$$\Delta log(BTC_t) = log(BTC_t) - log(BTC_{t-1})$$

By performing this transformation, we not only achieved to correct our data from random walk, but also suppressed the effect of potential unobserved **time trend**, which could otherwise result in spurious regression problem (Wooldridge 2009).

Last issue is to decide how many lags we shall use in our model. There are several methods how to determine what is the optimal number of lags included in the model, which we will discuss later. Nevertheless, as this model serves only as the first step of our analysis and also because of strong insignificance of further lags, we will limit ourselves only to 3 lags for both datasets (meaning 3 days in daily set and 6 hours in 2h set) and both variables, bitcoin and altcoin itself.

4.3 Vector Autoregressive Model

Even though FDL model is a sufficient tool for getting situation overview, we will need more advanced model for analysis of causality and more sophisticated predictability. This leads us to vector autoregressive (VAR) model, which allows to model several series in terms of their own past. If we have

[5]similarly for all other altcoins

two series, y_t and z_t, a vector autoregression consists of two equations in the following form (Wooldridge 2009):

$$y_t = \delta_0 + \alpha_1 y_{t-1} + \gamma_1 z_{t-1} + \alpha_2 y_{t-2} + \gamma_2 z_{t-2} + \dots$$
$$z_t = \eta_0 + \beta_1 y_{t-1} + \rho_1 z_{t-1} + \beta_2 y_{t-2} + \rho_2 z_{t-2} + \dots$$

In our case, we are more interested in forecasting only one variable - altcoin price change, therefore we will focus ourselves mainly on the one corresponding side of the model. Unlike FDL model, VAR model does not include impact propensity and focuses on modeling dependent variables based only on the lags of both variables. This exactly matches to the goal of this thesis as the immediate effect of impact propensity may just hardly be used for making predictions.

Key issue is once again how many lags we shall include in this model. For VAR model, the easiest way is to perform Lag-order selection statistics. We intuitively limited the maximal lag order of this test to be 7 for daily data (i.e. one week) and 6 for 2h data (i.e. half a day) as further lags would not qualitatively improve the results of our analysis, but only fuzzy preceding relevant results. Afterwards, Lag-order selection statistic shows that the maximal number of lags is optimal for our model. Consequently, we will use 7 lags for all VAR models based on daily datasets and 6 lags for every VAR model based on 2h dataset.

4.4 Granger Causality Test

Building on results from VAR models, we will proceed with related Granger causality test. This test directly follows the results of corresponding VAR model and represents the main advantage of VAR model compared to preceding FDL.

The Granger causality test is a statistical hypothesis test for determining whether one time series is useful in forecasting another, first proposed in 1969 (Granger 1969). Granger causality test directly follows the VAR model and expresses p-values for both equations of the model, under the null hypothesis of no Granger causality (Wooldridge 2009). If we achieve to reject this hypothesis, we can claim that there is a causality between analyzed variables in direction corresponding to the particular side of VAR model.

4.5 Impulse-Response Function

Thanks to Granger causality test, we may examine whether there is causality present in our model or not. However, it does not help us to determine any other properties of this effect, such as its size distributed over time. We would like to know the response of one variable (i.e. altcoin) to an impulse change in another variable (i.e. bitcoin). This is exactly what impulse-response (IR) function represents (Lütkepohl 2005). As in the previous case of Granger causality test, this function directly follows the results of preceding VAR model and graphically explains the time distribution and size of relationship analyzed in previous models.

The function itself has really straightforward meaning, however, its interpretation may be troublesome. On X-axis, we can find number of steps (i.e. measurement periods - 1d or 2h) passed from the one unit change in impulse variable, while on y-axis, we see the value of response of the other variable, corresponding to the given one unit impulse change. Function itself therefore shows how price of altcoin should change over time given that otherwise stable bitcoin changed by "one unit" at step 0. Here comes a catch in definition of "one unit". To avoid mismatch of different variances of specific currencies, one shall use IR function with variables in **standardized form**, i.e. deduct mean value and divide this number by standard deviation. Used in this form, we will get the response results of IR function measured in proportion of standard deviation change in response variable, corresponding to change by one standard deviation in impulse variable.

4.6 Diebold-Mariano Test

Preceding figures shall help us to understand the relationship between bitcoin and altcoins and to answer our first research question. Now, we shall proceed to the second research question and analyze possible predictability of altcoin price change based on bitcoin price change. To do so, we will create a static forecast based on our VAR model and compare its accuracy with two sample alternative predictions via Diebold-Mariano test.

To perform static forecast, we will lower the number of observations by 100 in daily datasets and by 1000 in 2h datasets and re-estimate all our VAR models, while using only the limited sample. After that we will forecast the next value based on the corresponding limited model and repeat this process 100 times on daily basis or 1000 times on 2h basis, to fill our original sample size with one step ahead forecasts. The main advantage of using static forecasting is its usage of actual rather than forecasted values for making the next prediction, resulting in more adaptive forecast rather than rapidly averaging dynamic forecast (Klose, Pircher and Sharma 2004).

To evaluate our forecast, we will not only compare our predicted values to the real ones, but also to two sample alternative predictions. To answer our research question i.e. to analyze whether the effect of bitcoin could be leveraged for making effective predictions, we will create exactly the same forecast, while using VAR models containing only altcoin lags, but excluding effect of bitcoin. As the second alternative prediction, we will use a simple constant prediction of zero price change in any time, serving as an underlying aspect for evaluation of quality of both alternative VAR models.

For comparison of multiple forecasts accuracy, Diebold-Mariano test proved to be very useful (Diebold 2012). This test retrieves the Diebold-Mariano statistics for testing the null hypothesis of equal forecast accuracy in the following form (Diebold and Mariano 1994):

$$S_1 = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}}$$

where $\bar{\mathbf{d}}$ is the sample mean loss differential and $\hat{\mathbf{f}}_d(0)$ is a consistent estimate of the spectral density of the loss differential at frequency zero.[6]

Sign of this statistics reflects which of the two compared models performed better in forecasting, being negative in case of the first model supremacy and positive in the other case. Corresponding p-value indicates, whether the difference between compared models forecast accuracy is significant or not. Rejection of the null hypothesis therefore results in significantly better forecast accuracy of the model, indicated by sing of the test statistics. As this model compares forecasting accuracy of two models only, we will have to perform it three times for each pair of alternative predictions and then summarize the results, to see, which model performed the best forecasts.

[6]full details of this statistics may be found in the original paper (Diebold and Mariano 1994)

5 Discussion of Results

In the following chapter, we will discuss the results of previously described methodology, applied to the 4 selected altcoins (litecoin, ripple, peercoin, dogecoin), used as a dependent/response variable, and bitcoin, used as an explanatory/impulse variable. For each currency, both daily and 2h datasets results will be analyzed.

5.1 Litecoin

In Table 7, we can see the results of a FDL model for litecoin daily and 2h dataset, respectively.

Table 7: Litecoin FDL

	dlogLTC (1 day)	dlogLTC (2 hours)
dlogBTC	1.080***	1.017***
	(9.80)	(40.68)
dlogBTClag1	-0.0937	0.0382
	(-0.89)	(0.68)
dlogBTClag2	-0.184	0.200
	(-1.38)	(1.50)
dlogBTClag3	0.113	0.0880
	(1.12)	(1.66)
dlogLTClag1	0.190	-0.0520
	(1.95)	(-0.96)
dlogLTClag2	0.0600	-0.183
	(0.79)	(-1.45)
dlogLTClag3	-0.102	-0.0672
	(-1.68)	(-1.33)
_cons	0.00114	-0.000245
	(0.33)	(-0.94)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We will analyze the 7 coefficients included in this model, i.e. bitcoin impact propensity, and 3 lags for both, bitcoin and litecoin. Each subsequent lag represents 1 day delay in the left column and 2 hours delay in right column. Except for the value of corresponding coefficients, t-statistics are shown in brackets below for each variable. Moreover, stars by the coefficient reflect significance of the coefficient at specific significance levels, explained below the table.

As stated before, our variables are in delta-log forms, therefore their coefficients can be explained as price change elasticity. The first coefficient therefore represents short-run elasticity. We can see that this coefficient for both datasets is higher than 1, meaning that there is even slightly higher short-run elasticity than 100% between immediate price change of bitcoin and litecoin. Moreover, this coefficient is strongly significant even at 0.1% significance level. Therefore, ceteris paribus, we can conclude that there is a very strong correlation between immediate bitcoin price change and litecoin price change. This result is very intuitive and corresponds to our previous assumption of high correlation, however, this is not so much interesting for our analysis, as immediate impact could hardly be leveraged to make effective predictions.

We can see that none of the lagged coefficient are significant at 5% level. However, interpretation of each coefficient just by itself may be very misleading. We are much more interested in their joint significance and summary impact, i.e. long-run elasticity. To analyze joint significance, we run F-test for three lags of bitcoin. Its results are shown in Table 8. As long-run elasticity would be much better explained by IR function, we will leave its interpretation for later time.

Table 8: Litecoin F-test

	dlogLTC (1 day)		dlogLTC (2 hours)
F (3, 532)	1.08	F (3, 8164)	1.33
Prob >F	0.3568	Prob >F	0.2627

Unfortunately, from the results of F-test we see that p-values for both datasets are above 25%, meaning that effect of bitcoin lagged price changes is jointly very insignificant in determination of litecoin price change. Nevertheless, there is no reason for giving up with our analysis, but just for proceeding with much more powerful tool for causality detection - VAR model and related Granger causality test an IR function.

As discussed before, advantage of VAR model is that, unlike FDL model, it does not include impact propensity, which is out of our interest in our research, but only lagged price changes of both variables. Moreover, this model approaches to the result from both sides and uses lags of both variables for estimating not only litecoin, but also bitcoin price change. This both sided approach is much more useful for causality analysis. As discussed in previous chapter, we will also increase number of lags included in this model. In Table 9, we state the results of VAR model only for the litecoin side of the model, nevertheless, detailed results of both regressions are attached in appendix.

Table 9: Litecoin VAR

	dlogLTC (1 day)	dlogLTC (2 hours)
L1.dlogBTC	0.0794	-0.0735**
	(0.86)	(-3.22)
L2.dlogBTC	-0.274**	0.152***
	(-2.94)	(6.62)
L3.dlogBTC	0.0384	0.0300
	(0.41)	(1.30)

L4.dlogBTC	0.187*	0.0694**
	(2.00)	(3.01)
L5.dlogBTC	0.103	0.0199
	(1.09)	(0.87)
L6.dlogBTC	0.145	-0.0323
	(1.55)	(-1.41)
L7.dlogBTC	0.0510	
	(0.56)	
L1.dlogLTC	0.0645	-0.0531***
	(1.16)	(-3.66)
L2.dlogLTC	0.164**	-0.225***
	(2.91)	(-15.54)
L3.dlogLTC	-0.112*	-0.0616***
	(-1.98)	(-4.17)
L4.dlogLTC	-0.0605	-0.0685***
	(-1.06)	(-4.64)
L5.dlogLTC	0.113*	-0.0204
	(2.00)	(-1.40)
L6.dlogLTC	0.0163	0.0328*
	(0.29)	(2.26)
L7.dlogLTC	-0.00641	
	(-0.12)	
_cons	0.00261	-0.0000908
	(0.56)	(-0.26)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

At first sight, we see that we get much more interesting results with several significant coefficients, especially for 2h dataset, analyzing the first 12 hours of price changes. Once again, we shall not focus on interpretation of coefficients one by one, but more importantly on their joint significance. To do so, we shall proceed to Granger causality test and IR function interpretation.

Results of Granger causality test are included in Tables 10 and 11, for daily and 2h dataset, respectively. The second row of each table is the one, corresponding to the litecoin side of foregoing VAR model from Table 9. The first row corresponds to the second side of regression in VAR model, which is explaining bitcoin price change by lags of both currencies. Our key focus is the p-value in each row, related to null hypothesis of no causality. Note that both p-values (and even all p-values at follow-up models) are very low, particularly because of high number of lags included in VAR model with high explanation power. This shows that even higher number of lags included in the model could distort the results in a way that anything could be proven. As a result, we will focus ourselves more on 0.1% significance level than on other, less strict levels.

Table 10: Litecoin Granger causality test - 1 day

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogLTC	27.874	7	0.000
dlogLTC	dlogBTC	18.882	7	0.009

From Table 10 we see that p-value in the second row, corresponding to litecoin side of the model, is 0.009, meaning that we can reject the null hypothesis of no causality at 1% significance level, however, we cannot at 0.1% level. On the other hand, causality from the other side has a p-value of 0 for at least 3 decimal places, meaning we can reject the null hypothesis even at 0.1% significance level. This is not what we would like to show, as the consequence is even stronger prove of causality from litecoin to bitcoin, rather than the other way around. This could be probably caused mainly by very strong correlation of bitcoin and its long time main follower litecoin, resulting in deep co-development more than a causality in any direction, screwed by not very detailed daily data changes.

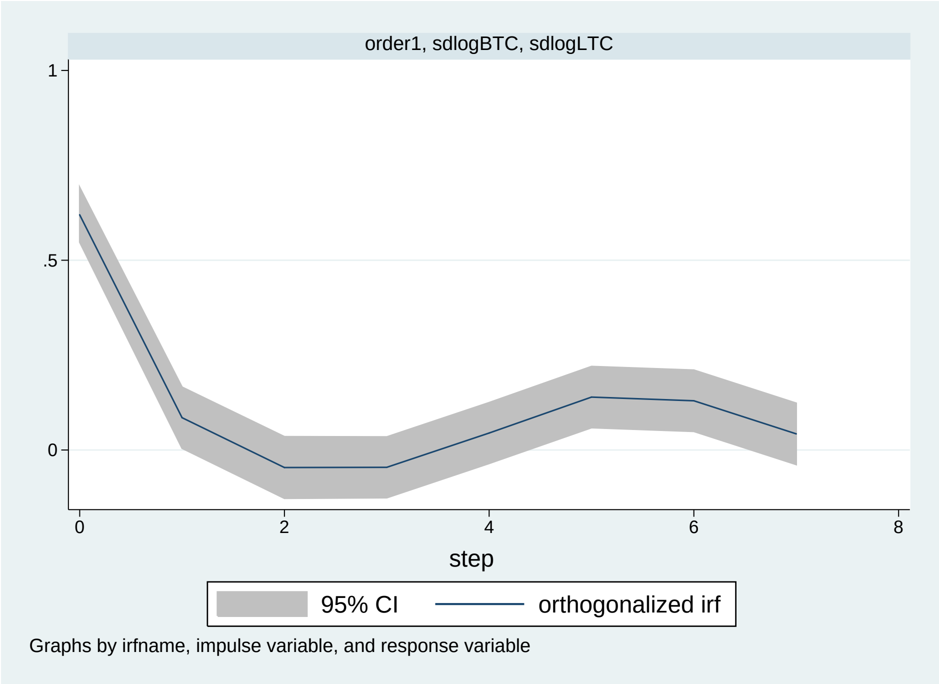
Table 11: Litecoin Granger causality test - 2 hours

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogLTC	15.387	6	0.017
dlogLTC	dlogBTC	69.426	6	0.000

We get much more intuitive results from Table 11, corresponding to more detailed 2h data. P-value of 0 for at least free decimal places in the second row means that we can reject null hypothesis of no causality at 0.1% significance level. However, in the first row, we get much larger p-value of 0.017, meaning we cannot reject the null hypothesis even at 1% significance level. Consequently, we see there is a very strong guidance from bitcoin side, which exactly corresponds to the main research question of this thesis. On the other hand, we have to be careful about less weaker, but just slightly insignificant causality from the litecoin side, which combined with the results from daily dataset, corresponds to strong correlation between bitcoin and litecoin, rather than causality from one side, and therefore lowers probability of potential usage of bitcoin's guidance for making predictions in this case.

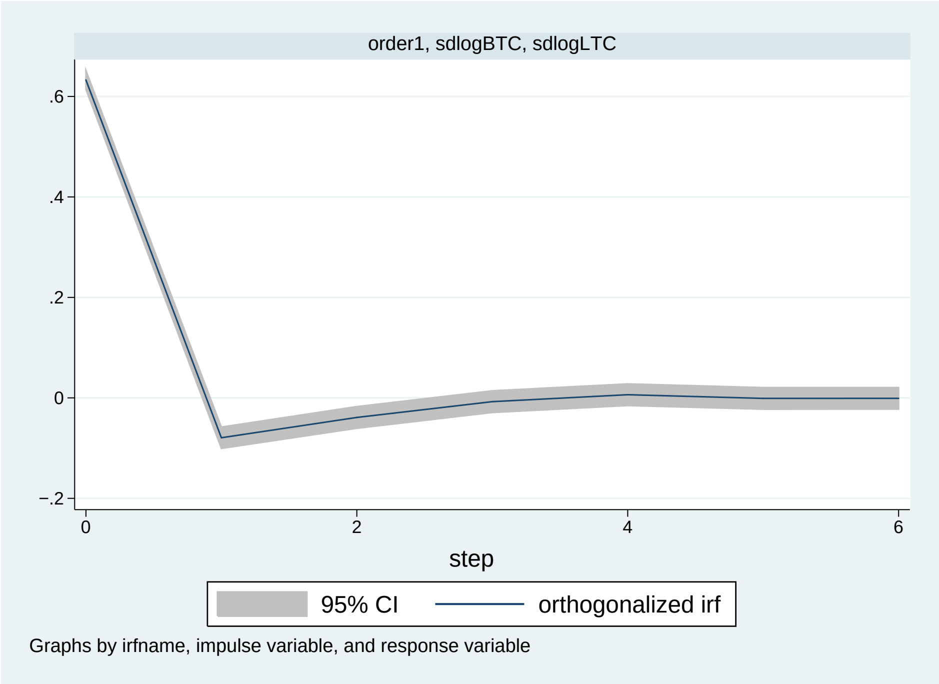
Positive results from Granger causality test show us that it is reasonable to analyze effect of bitcoin, as an impulse variable, on litecoin, as a response variable. The direction, size and development of this effect are shown as IR functions in Figures 6 and 7, for both datasets, daily and 2h, respectively. The grey area around the curve represents 95% confidence interval, useful for making conclusions about its significance. When interpreting results of IR function, we shall remember that we are using variables in their standardized forms.

Figure 6: Litecoin IRF - 1 day



Shape of IR function for daily dataset is corresponding to an overview we got from the first, FDL model. Curve starts at more than 0.5, meaning there is more than 50% immediate litecoin response, measured in standard deviation, corresponding to impulse change by one standard deviation in bitcoin price. Afterwards, function steeply falls down to slightly, but not significantly, more than zero at first lag, corresponding to one day delay. The function, representing the long-run elasticity, then settles around zero, except for a significantly positive value between the fifth and sixth day. This shift reaches about 10% positive response in this period, indicating possible predictability potential, however, one shall be careful while making decisions based on 5-6 days old data.

Figure 7: Litecoin IRF - 2 hours



In the second chart, we see the similar development, containing sharp fall from over 60% and consecutive settlement around zero. The one important difference is a significant fall below zero, showing there is significantly negative response in litecoin price 2 hours after the impulse change in bitcoin. What may be a reason for such a response will be discussed in later chapters.

This is the end of analysis corresponding to the first research question. As we proved that there is a strong causality from bitcoin side at least on 2h basis and analyzed size of this relationship through IR function, we may proceed to further evaluation of forecasting accuracy of our corresponding VAR models. In Table 12, we can find results of Diebold-Mariano test based on daily litecoin dataset. As mentioned in previous chapter, we made 3 pairs out of 3 alternative forecasts - based on our VAR model including both bitcoin and altcoin lags **(inclusive)**, based on similar VAR model excluding bitcoin's impact **(exclusive)** and a stable prediction of zero change in litecoin price **(zero)**. All daily forecasts contain 100 predicted steps.

Table 12: Litecoin Diebold-Mariano test - 1 day

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	0.8943	**zero**	0.3711
inclusive	exclusive	2.041	**exclusive**	0.0412
exclusive	zero	-0.7856	**exclusive**	0.4321

From the first row of Table 12, we can conclude that prediction of zero price change performed better than our model in forecasting last 100 values. However, p-value above 35% reflects insignificancy of this comparison and fail of rejection of the null hypothesis of equal accuracy at 5% significance level. From the second row of Table 12 we see that even the alternative model excluding effect of bitcoin performed better than our model, moreover, significantly at 5% significance level. Last row of Table 12 is resulting in insignificant superiority of the alternative VAR model, compared to zero change prediction.

To sum up the results of Diebold-Mariano test for daily forecast of litecoin price change, we state a summary ranking of our 3 alternative predictions in Table 13. In brackets behind predictions, we put a mark in case of insignificant superiority compared to the following alternative prediction.

Table 13: Litecoin forecast accuracy ranking - 1 day

1.	**exclusive**	(insign.)
2.	**zero**	(insign.)
3.	**inclusive**	

In Table 14, we can find results of Diebold-Mariano test, this time based on 2h litecoin dataset. All 2h forecasts contain 1000 predicted steps.

Table 14: Litecoin Diebold-Mariano test - 2 hours

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	1.016	**zero**	0.3095
inclusive	exclusive	0.2562	**exclusive**	0.7978
exclusive	zero	1.187	**zero**	0.2353

From the first comparison, we see that zero once again performed insignificantly better than our model. Also alternative VAR model performed better than ours again, but this time not significantly. Unlike in previous case, zero performed better than alternative VAR model, but even this result is insignificant at 5% level. Ranking for the 2h dataset follows in Table 15:

Table 15: Litecoin forecast accuracy ranking - 2 hours

1.	**zero**	(insign.)
2.	**exclusive**	(insign.)
3.	**inclusive**	

From Tables 13 and 15 we can conclude that our model is not very efficient in forecasting litecoin price change, either with daily or 2h data. However, we shall note that 5 out of 6 D-M test results were insignificant, causing failure in rejection of the null hypothesis of equal accuracy. Therefore, we can conclude there is almost no difference between particular predictions.

To make overall conclusion of litecoin analysis, we can see that litecoin and bitcoin are strongly positively correlated, particularly because of litecoin's long-term position of number one altcoin and main bitcoin's follower with very similar features. Even though we proved a strong causality from bitcoin side on 2h basis, and also almost perfect elasticity in immediate price change, size of this effect is large only at a time lower than 2 hours, then sharply settling around zero, threatening potential of predictability. This intuition proved to be correct, as our model performed worse than the two prediction alternatives, even though the difference was generally very insignificant. This corresponds to our previous hypothesis of immediate co-development, rather than lagged guidance, which would eliminate potential for predictability based on bitcoin price change.

5.2 Ripple

In Table 16, we can see the results of a FDL model for ripple daily and 2h dataset, respectively.

Table 16: Ripple FDL

	dlogXRP (1 day)	dlogXRP (2 hours)
dlogBTC	0.327***	0.0261
	(3.51)	(1.38)
dlogBTClag1	-0.178*	-0.00918
	(-2.10)	(-0.54)
dlogBTClag2	-0.110	-0.000938
	(-1.24)	(-0.05)
dlogBTClag3	-0.0776	0.0495**
	(-0.81)	(2.58)
dlogXRPlag1	0.0592	0.0264
	(0.89)	(0.73)
dlogXRPlag2	0.00444	-0.0148
	(0.09)	(-0.50)
dlogXRPlag3	-0.0457	0.00380
	(-1.08)	(0.12)
_cons	0.00342	-0.0000512
	(0.92)	(-0.18)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of FDL model for ripple are very different from those we saw for litecoin. Short-run elasticity has much lower impact than it had for litecoin, reaching only slightly more than 30% for daily data and only 2% (compared to more than 100% in previous case) with no significance for 2h dataset. This is a shocking change, pointing out lower immediate correlation of ripple and bitcoin, possibly because of much lower technological similarity and overall vision of currency than in litecoin case.

Table 17: Ripple F-test

	dlogXRP (1 day)		dlogXRP (2 hours)
F (3, 709)	1.58	F (3, 7277)	2.44
Prob >F	0.1928	Prob >F	0.0628

Even F-tests for joint significance of lagged coefficients has changed from the previous ones. In daily set, p-value is slightly below 20%, which is much lower value than in litecoin case, but still very insignificant. Nevertheless, for the 2h set, we get p-value of only 6%, reflecting slight insignificance at 5% level and significance at 10% level. This shall direct our focus on the first 6 hours of bitcoin price change, indicating they may have a significant impact on current price change of ripple.

Table 18: Ripple VAR

	dlogXRP (1 day)	dlogXRP (2 hours)
L1.dlogBTC	-0.192**	-0.00667
	(-3.04)	(-0.51)
L2.dlogBTC	-0.136*	0.00510
	(-2.14)	(0.39)
L3.dlogBTC	-0.0966	0.0728***
	(-1.53)	(5.48)
L4.dlogBTC	0.0984	0.134***
	(1.56)	(10.13)
L5.dlogBTC	0.131*	0.102***
	(2.08)	(7.68)
L6.dlogBTC	-0.0227	-0.0227

	(-0.36)	(-1.71)
L7.dlogBTC	0.156*	
	(2.46)	
L1.dlogXRP	0.0724	0.0395***
	(1.93)	(3.31)
L2.dlogXRP	0.0193	-0.0247*
	(0.51)	(-2.08)
L3.dlogXRP	-0.0545	0.0273*
	(-1.45)	(2.33)
L4.dlogXRP	0.0590	0.0388***
	(1.57)	(3.42)
L5.dlogXRP	0.0591	0.0128
	(1.57)	(1.13)
L6.dlogXRP	-0.0855*	-0.00160
	(-2.31)	(-0.14)
L7.dlogXRP	0.00206	
	(0.06)	
_cons	0.00265	0.0000677
	(0.71)	(0.24)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From the VAR results in Table 18, we can see once again several significance stars at 2h data column, especially for the period between the 3$^{\text{rd}}$ and the 5$^{\text{th}}$ lag, i.e. from 6 to 10 hours after bitcoin price change, all of them with p-values below 0.1%. Note also high significance of lags of ripple itself, which shall be also counted for in one's prediction model. As the interpretation of separated coefficient may be misleading, we will proceed directly to their joint interpretation.

Table 19: Ripple Granger causality test - 1 day

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogXRP	7.4642	7	0.382
dlogXRP	dlogBTC	28.837	7	0.000

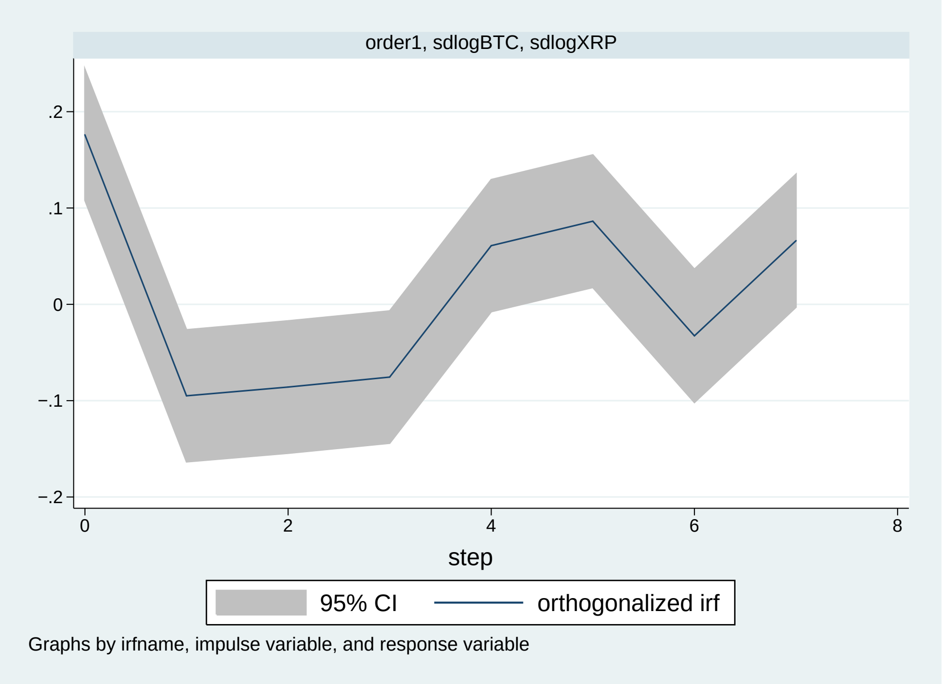
Unlike partly disappointing Granger causality test results for daily litecoin data, we get much more interesting results of the test for ripple daily set. P-value of 0 for at least 3 decimal places leads to strong rejection of no causality caused by bitcoin. On the other hand, p-value of almost 40% leads to failure to reject no causality hypothesis from ripple's side, even at 10% significance level. This is a very powerful prove of causality only in the direction, we were expecting.

Table 20: Ripple Granger causality test - 2 hours

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogXRP	4.4958	6	0.610
dlogXRP	dlogBTC	173.41	6	0.000

For the 2h dataset, we get even more significant results, comparing p-value of 0 for at least 3 decimal places to p-value over 60%. This leads to strong rejection of no causality caused by bitcoin, and furthermore, complete failure to reject causality from the other side. Consequently on this enormous imbalance, we can conclude that ripple is under the strong guidance of bitcoin with no visible impact of ripple at bitcoin price change. The measurement of this impact, follows in Figures 8 and 9.

Figure 8: Ripple IRF - 1 day



From Figure 8, we can see much lower immediate impact of bitcoin price change, corresponding to only less than 20% response of ripple. Afterwards, function is sharply falling significantly below zero in first two days, then growing back to positive values in day 5, and subsequently oscillating around zero.

Figure 9: Ripple IRF - 2 hours

For 2h dataset, we see a completely different story. The function is starting at value insignificantly different from zero, then steadily growing to more than 10% after 8 hours, just to plummet below zero in next 4 hours. This significant delayed response indicates predictability potential which will be now analyzed in detail.

In Table 21, we can find results of Diebold-Mariano test based on daily ripple dataset.

Table 21: Ripple Diebold-Mariano test - 1 day

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	1.481	**zero**	0.1386
inclusive	exclusive	3.454	**exclusive**	0.0006
exclusive	zero	-0.4357	**exclusive**	0.663

From the results of Table 21, we see that our VAR model is significantly worse than alternative VAR model and also insignificantly worse than zero.

Lower significance of zero compared to exclusive model in first two rows also corresponds to better accuracy of exclusive model with comparison to zero in the third row. On the other hand, this result is once again insignificant. Summary ranking of our 3 alternative predictions from Table 21 is shown in the following Table 22.

Table 22: Ripple forecast accuracy ranking - 1 day

1.	**exclusive**	(insign.)
2.	**zero**	(insign.)
3.	**inclusive**	

In Table 23, we can find results of Diebold-Mariano test, this time based on 2h ripple dataset.

Table 23: Ripple Diebold-Mariano test - 2 hours

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	0.3231	**zero**	0.7466
inclusive	exclusive	-0.7336	**inclusive**	0.4632
exclusive	zero	2.818	**zero**	0.0048

In the first row of Table 23, we see that zero is once again better than our model, however, with p-value of almost 75%, resulting in almost equal forecast accuracy. Moreover, our model is performing better than exclusive model for the first time, unfortunately with high p-value as well. Those two results corresponds to strongly significant superior accuracy of zero compared to exclusive model. Ranking for the 2h dataset follows in Table 24:

Table 24: Ripple forecast accuracy ranking - 2 hours

1.	**zero**	(insign.)
2.	**inclusive**	(insign.)
3.	**exclusive**	

From Tables 22 and 24 we can conclude that our model is not very efficient in forecasting ripple price change on daily basis, similarly to litecoin case. On the other hand, we got slightly but not significantly better results on 2h basis, where predictability potential was already seen from IR function. Even though slightly better performance of inclusive model corresponds to significant causality of bitcoin, which shall be included in the model while making forecasts, predictions based on our model did not achieve to significantly outrun constant prediction of zero price change.

To make overall conclusion, ripple results were something completely different from litecoin. From the very beginning we saw that short-run elasticity is almost zero compared to perfect litecoin elasticity. Also the lagged coefficients for first few hours were significant even in FDL model. Later on, we proved a very strong bitcoin one-sided guidance, corresponding especially to high significance of bitcoin lags in VAR model while using 2h dataset. IR function helped us to analyze the size and direction of this effect, showing significantly positive response of ripple to bitcoin price change in a period between 2^{nd} and 5^{th} lag, peaking 8 hours after the impulse, resulting in possible predictability potential. However, our model performed worse forecasts than both alternatives on daily basis, and only slightly better than exclusive model on 2h basis. Effectiveness of predictions based on our model was therefore questioned.

5.3 Peercoin

In Table 25, we can see the results of a FDL model for peercoin daily and 2h dataset, respectively.

Table 25: Peercoin FDL

	dlogPPC (1 day)	dlogPPC (2 hours)
dlogBTC	1.062***	0.922***
	(14.80)	(9.08)
dlogBTClag1	-0.112	0.386
	(-1.19)	(1.41)
dlogBTClag2	-0.0811	0.320
	(-0.77)	(1.82)
dlogBTClag3	0.0159	0.101
	(0.20)	(0.67)
dlogPPClag1	0.130*	-0.472
	(2.16)	(-1.45)
dlogPPClag2	-0.0584	-0.459*
	(-0.88)	(-2.23)
dlogPPClag3	0.0341	-0.197
	(0.46)	(-1.19)
_cons	-0.000451	-0.0000464
	(-0.17)	(-0.03)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Peercoin results of FDL model remind the litecoin case a lot, having strongly significant impact propensity of more or less 100% in both cases and almost no significance throughout lagged coefficients. However, we shall once again rather interpret their joint significance, following in Table 26.

Table 26: Peercoin F-test

	dlogPPC (1 day)		dlogPPC (2 hours)
F (3, 596)	0.60	F (3, 7264)	1.17
Prob >F	0.6139	Prob >F	0.3180

Corresponding F-test for joint significance of first 3 lags of bitcoin price change for both datasets, shows even higher p-values than in litecoin case, reaching above 60% for daily and 30% for 2h data. Therefore, we cannot conclude anything in respect to our research question from the results of FDL model and shall proceed to VAR model analysis.

Table 27: Peercoin VAR

	dlogPPC (1 day)	dlogPPC (2 hours)
L1.dlogBTC	-0.186*	0.285***
	(-2.19)	(3.93)
L2.dlogBTC	-0.0195	0.304***
	(-0.23)	(4.17)
L3.dlogBTC	0.00653	0.112
	(0.08)	(1.54)
L4.dlogBTC	-0.0113	0.101
	(-0.13)	(1.38)
L5.dlogBTC	0.0280	-0.0456
	(0.33)	(-0.63)
L6.dlogBTC	0.292***	0.0304
	(3.45)	(0.42)
L7.dlogBTC	0.0699	
	(0.82)	
L1.dlogPPC	0.143**	-0.495***
	(2.71)	(-41.65)
L2.dlogPPC	-0.106*	-0.521***
	(-2.01)	(-39.29)
L3.dlogPPC	0.00932	-0.264***

	(0.18)	(-18.16)
L4.dlogPPC	0.236***	-0.142***
	(4.57)	(-9.75)
L5.dlogPPC	0.0389	-0.0151
	(0.74)	(-1.14)
L6.dlogPPC	-0.0531	-0.0449***
	(-1.02)	(-3.77)
L7.dlogPPC	-0.00987	
	(-0.19)	
_cons	0.000522	0.000137
	(0.15)	(0.09)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We can see several significant coefficients in VAR model, especially for more detailed 2h sets and lags of peercoin itself. This may correspond to lower correlation of peercoin and bitcoin, compared to litecoin's case, however, the results are quite fuzzy and their direct interpretation may be misleading, therefore further analysis is necessary.

Table 28: Peercoin Granger causality test - 1 day

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogPPC	11.417	7	0.121
dlogPPC	dlogBTC	16.416	7	0.022

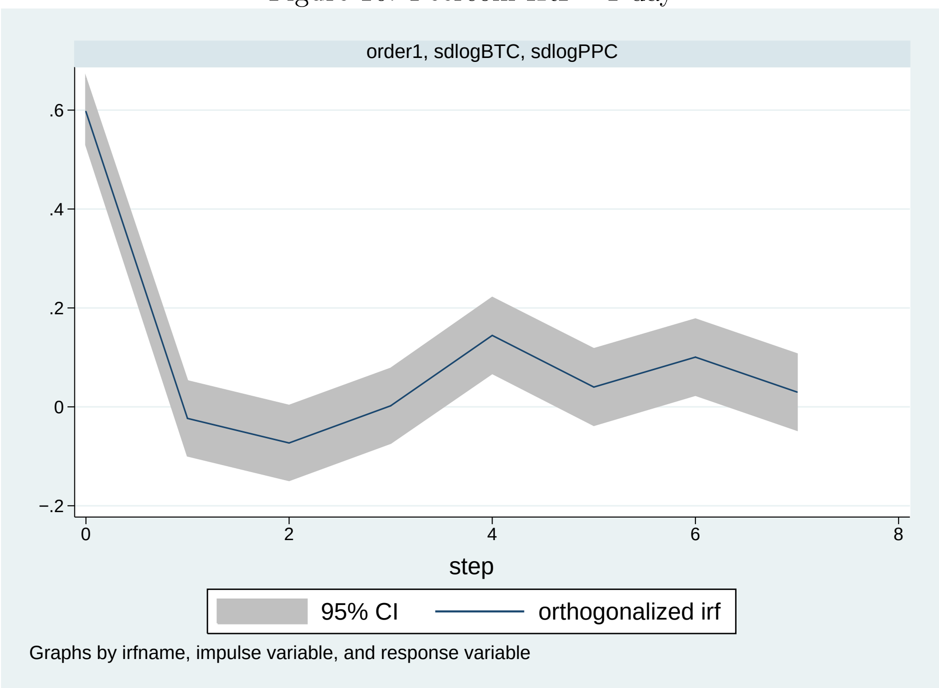
In daily case of Granger causality test, we may reject the null hypothesis of no causality from bitcoin side at 5% significance level, however, we cannot do it at level of 1% or lower. Causality is therefore weakened compared to litecoin case. Furthermore, we cannot reject causality from the other side even at 10% significance level, which was an issue in litecoin case, resulting in only one direction, but weaker guidance of bitcoin on daily basis.

Table 29: Peercoin Granger causality test - 2 hours

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogPPC	56.881	6	0.000
dlogPPC	dlogBTC	31.718	6	0.000

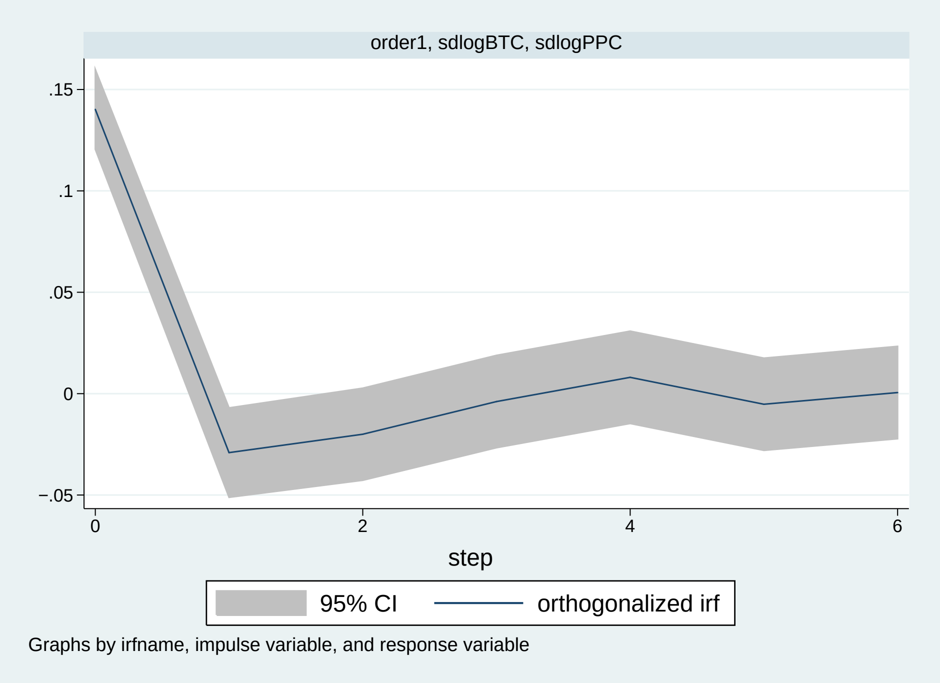
On 2h basis, causality is very strong from both sides, having 0 p-value for at least 3 decimal places, and (with respect to χ^2 statistics) even slightly stronger from peercoin's point of view. This shows some inconsistency between first 12 hours short-run analysis and one week long-run analysis. We shall therefore treat the results of both datasets separately.

Figure 10: Peercoin IRF - 1 day



In Figure 10, we can see the IR function starting at a very high immediate response level of about 60%, sharply falling down to zero after first day and oscillating slightly above zero with a significant peak of almost 20% on day 4.

Figure 11: Peercoin IRF - 2 hours



In Figure 11, we see similar movement, but with much lower values, starting at immediate response of only 15% and after sharply falling to slightly negative numbers, and rapidly stabilizing at zero level. Both IR functions provided inconclusive results so we will proceed to forecasting capability evaluation.

In Table 30, we can find results of Diebold-Mariano test based on daily peercoin dataset.

Table 30: Peercoin Diebold-Mariano test - 1 day

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	-0.1407	**inclusive**	0.8881
inclusive	exclusive	-0.8485	**inclusive**	0.3961
exclusive	zero	1.987	**zero**	0.0470

From the results of Table 30, we see that our VAR model performed better than both, exclusive VAR model and zero change prediction. Unfortunately, this supremacy is insignificant in both cases at 5% significance level. On the other hand, we get significantly better forecast accuracy from zero than from exclusive VAR model. Ranking of 3 alternative predictions is therefore as follows in Table 31.

Table 31: Peercoin forecast accuracy ranking - 1 day

1.	**inclusive**	(insign.)
2.	**zero**	(sign.)
3.	**exclusive**	

In Table 32, we can find results of Diebold-Mariano test, this time based on 2h peercoin dataset.

Table 32: Peercoin Diebold-Mariano test - 2 hours

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	2.319	**zero**	0.0204
inclusive	exclusive	-4.047	**inclusive**	0.0001
exclusive	zero	3.328	**zero**	0.0009

From Table 32, we see three significant results for the very fist time. Zero performed significantly better than both models, while our model had also significantly better accuracy than exclusive VAR model. Ranking for the 2h dataset follows in Table 33:

Table 33: Peercoin forecast accuracy ranking - 2 hours

1.	**zero**	(sign.)
2.	**inclusive**	(sign.)
3.	**exclusive**	

From Tables 31 and 33 we can conclude that our model performed much better in peercoin case than in previous two cases, reaching insignificant first place on daily basis and strongly significant second place on 2h basis. Even though we cannot conclude that our model was better in forecasting peercoin price than alternative predictions, we shall note that its accuracy was significantly better than exclusive model on 2h basis.

As the results were different for our datasets, we will do the final conclusion for each dataset separately. While for the first 12 hours, we saw a strong inter-correlation between peercoin and bitcoin from both sides, it diminished in the long-run, resulting only in a weaker guidance from bitcoin's side. However, response to bitcoin price change on 2h basis was not very high, corresponding to more significant coefficients for peercoin itself in VAR model. On the other hand, on daily basis, peercoin is much more reactive, leading to highly positive response especially in the fourth day. This effect shows potential for making predictions of peercoin based on bitcoin price change on daily basis, which we analyzed in detail through D-M test. We actually found out that our model performed better than both alternatives on daily basis, however, the result was not significant. On 2h basis, our model reached only second place, but significantly better than exclusive model. Because of that, including bitcoin lags in prediction model of peercoin price change shall be seen as a significant improvement.

5.4 Dogecoin

In Table 34, we can see the results of a FDL model for dogecoin daily and 2h dataset, respectively.

Table 34: Dogecoin FDL

	dlogDOGE (1 day)	dlogDOGE (2 hours)
dlogBTC	1.170***	1.051***

	(7.81)	(24.25)
dlogBTClag1	-0.238	0.259**
	(-1.63)	(3.19)
dlogBTClag2	-0.230	0.0407
	(-1.44)	(0.73)
dlogBTClag3	-0.461*	-0.0765
	(-2.35)	(-1.32)
dlogDOGElag1	-0.0142	-0.198**
	(-0.13)	(-2.95)
dlogDOGElag2	0.0376	0.0133
	(0.47)	(0.31)
dlogDOGElag3	-0.0264	0.0556
	(-0.29)	(1.55)
_cons	-0.00158	-0.0000899
	(-0.31)	(-0.16)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For dogecoin, we can see so far the highest short-run elasticity, reaching about 110% and statistically very significant in both cases. Moreover, the first lag in 2h dataset is also significant at 1% significance level. We shall keep this in our focus during further analysis.

Table 35: Dogecoin F-test

	dlogDOGE (1 day)		dlogDOGE (2 hours)
F (3, 366)	3.31	F (3, 4514)	4.60
Prob >F	0.0201	Prob >F	0.0032

F-test give us a very interesting p-values, resulting in joint statistical significance of bitcoin lagged price changes at 5% significance level on daily basis, and even at 1% significance level on 2h basis. This is completely different compared to e.g. litecoin.

Table 36: Dogecoin VAR

	dlogDOGE (1 day)	dlogDOGE (2 hours)
L1.dlogBTC	-0.323*	0.109**
	(-2.26)	(2.76)
L2.dlogBTC	-0.310*	-0.0241
	(-2.16)	(-0.60)
L3.dlogBTC	-0.249	-0.149***
	(-1.73)	(-3.72)
L4.dlogBTC	0.100	0.0105
	(0.69)	(0.26)
L5.dlogBTC	-0.320*	-0.0125
	(-2.25)	(-0.31)
L6.dlogBTC	0.0395	-0.0174
	(0.28)	(-0.44)
L7.dlogBTC	0.0107	
	(0.08)	
L1.dlogDOGE	0.0527	-0.239***
	(0.91)	(-14.56)
L2.dlogDOGE	0.0204	-0.0614***
	(0.35)	(-3.69)
L3.dlogDOGE	0.0492	0.0209
	(0.89)	(1.27)
L4.dlogDOGE	0.0107	-0.0319*
	(0.20)	(-1.96)
L5.dlogDOGE	0.0811	0.000347
	(1.54)	(0.02)
L6.dlogDOGE	0.00198	-0.0148
	(0.04)	(-0.94)
L7.dlogDOGE	-0.0152	
	(-0.30)	
_cons	-0.00465	-0.000584
	(-0.94)	(-0.96)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of VAR model are corresponding to FDL model, showing significance for a first few bitcoin and dogecoin lags, especially for 2h dataset. To analyze the effect jointly, we shall proceed to further steps.

Table 37: Dogecoin Granger causality test - 1 day

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogDOGE	14.324	7	0.046
dlogDOGE	dlogBTC	19.421	7	0.007

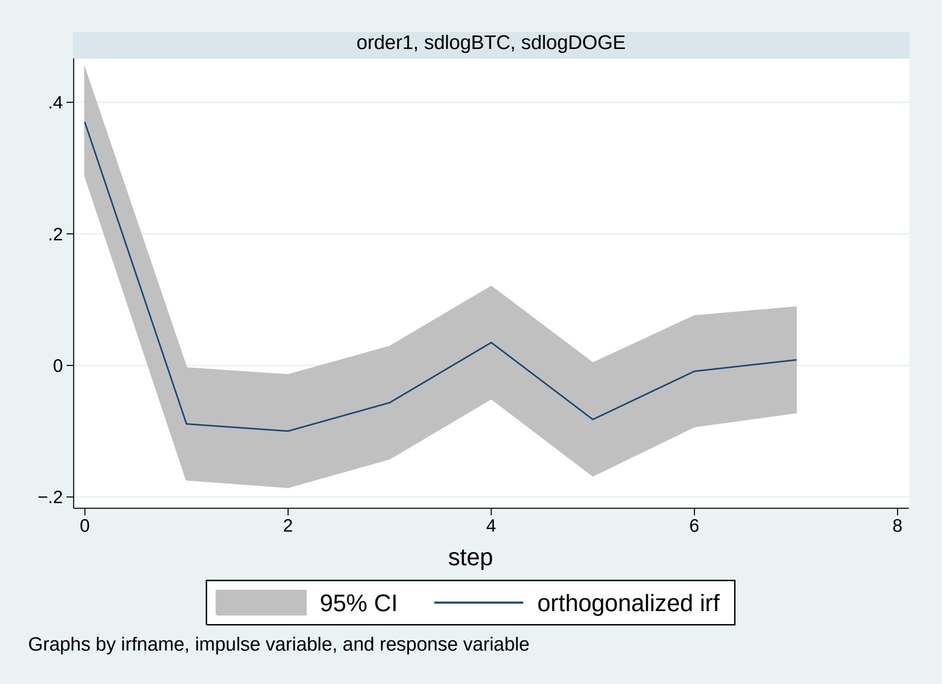
Granger causality test for daily data proves guidance of bitcoin at 1% significance level and consequent fail to reject no causality from dogecoin point of view at the same level.

Table 38: Dogecoin Granger causality test - 2 hours

Equation	Excluded	chi2	df	Prob >chi2
dlogBTC	dlogDOGE	11.283	6	0.080
dlogDOGE	dlogBTC	24.3	6	0.000

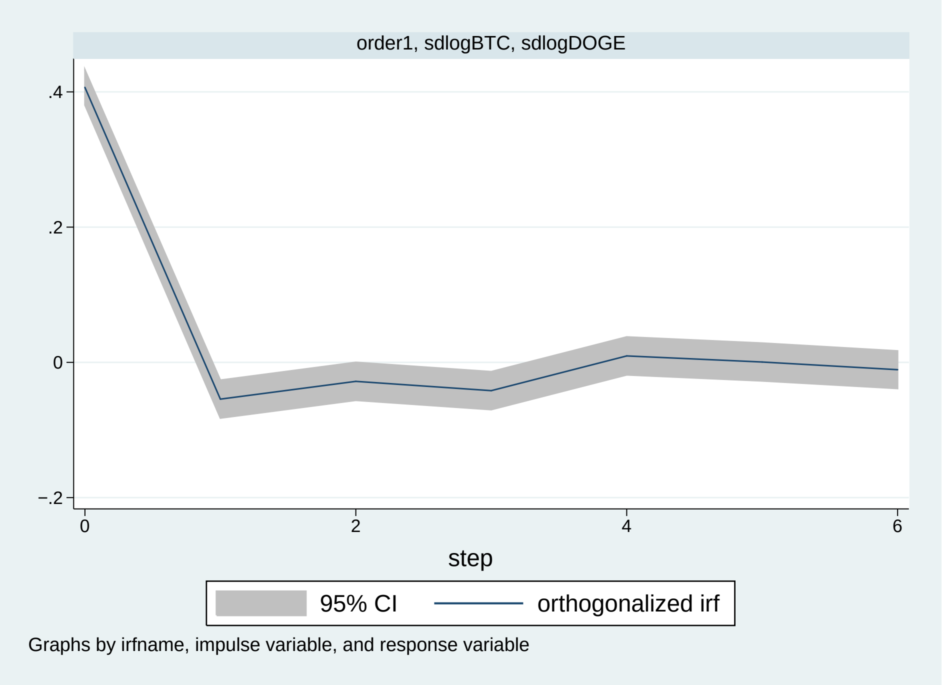
For the 2h data, results are even more significant, while comparing p-value of zero for at least 3 decimal places, to p-value of 8%. This supports the hypothesis of bitcoin guidance of dogecoin price changes. The size of this effect and its development is shown in following IR functions.

Figure 12: Dogecoin IRF - 1 day



The first function has a shape common for all the others, while sharply falling from 40% response significantly below zero in day 1 and then steadily oscillating around or slightly below zero.

Figure 13: Dogecoin IRF - 2 hours



The second chart has a very similar development to the daily one, showing rapid fall from about 40% response to values significantly below zero for about 4 hours, then stabilizing at zero response value.

In Table 39, we can find results of Diebold-Mariano test based on daily dogecoin dataset.

Table 39: Dogecoin Diebold-Mariano test - 1 day

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	1.146	**zero**	0.2519
inclusive	exclusive	1.095	**exclusive**	0.2737
exclusive	zero	2.432	**zero**	0.015

In Table 39 we see similar results to what we saw in litecoin and ripple case, i.e. insignificantly worse performance of our model compared to alternative predictions. On the other hand, zero prediction showed to be significantly more accurate than exclusive model. Overall ranking of our 3 predictions is stated in Table 40.

Table 40: Dogecoin forecast accuracy ranking - 1 day

1.	**zero**	(sign.)
2.	**exclusive**	(insign.)
3.	**inclusive**	

In Table 41, we can find results of Diebold-Mariano test, this time based on 2h dogecoin dataset.

Table 41: Dogecoin Diebold-Mariano test - 2 hours

Forecast 1	Forecast 2	Statistics	Better	P-value
inclusive	zero	-1.697	**inclusive**	0.0897
inclusive	exclusive	-0.4914	**inclusive**	0.6232
exclusive	zero	-1.717	**exclusive**	0.0861

Results from Table 41 are different from what we saw in previous cases. Our model performed the best results, significantly better than zero at least at 10% significance level. Its accuracy was also higher compared to exclusive model, however, this result is very insignificant. Interesting finding is that this time zero performed significantly worse than both VAR models at 10% significance level. Ranking for the 2h dataset follows in Table 42.

Table 42: Dogecoin forecast accuracy ranking - 2 hours

1.	**inclusive**	(insign.)
2.	**exclusive**	(sign.)
3.	**zero**	

From Tables 40 and 42 we can conclude that on daily basis, both VAR models has poor performance as zero proved to be significantly more accurate. On contrary, on 2h basis both VAR models performed significantly better than zero, showing potential for effective predictability. Even though including bitcoin lags enhanced our model compared to the exclusive one, the null hypothesis of better accuracy could not be rejected.

To summarize the last currency analysis, we saw, especially from FDL model and consecutive F-test, a significant impact of bitcoin on dogecoin price change. As a necessary prerequisite, we showed that causality from bitcoin side is much stronger than the other way around. From the IR functions we saw that this lagged effect has mainly negative direction, which goes against our initial assumption of high bitcoin price development correlation, most probably expressing the substitutability of crypto-currencies and subsequent demand switching as a response to success or fail of any other given currency. Even though our model performed below average on daily basis, we got sufficient result on 2h basis. Significantly better performance of both VAR models compared to zero indicates high potential for predictability of dogecoin price change on 2h basis.

6 Conclusion

To reach the final conclusion, we shall first summarize the results from the previous chapter. Afterwards, based on this summary, we will return to the beginning of our thesis and try to answer the initial research questions. Subsequently, we will make a final comment on several issues of our analysis and state recommendations for further research.

We have seen in preceding chapter that there are several features which are common (at least to some extent) for each analyzed currency. The first one was almost perfect short-run elasticity between altcoin and its leader, resulting in large immediate response to a bitcoin's price change. The second feature was a steep diminishing of this positive response effect, most of the times exceeding beyond zero into negative numbers, and subsequently settling around zero response level. The last common feature was a strong rejection of no causality hypothesis, especially for 2h datasets, and most of the times much stronger from the bitcoin's point of view.

This leads us to our initial research question: "Do alternative crypto-currencies follow the price development of their leader?" From what have been stated above, we could answer: "Yes, they do." However, we have to be very careful about several drawbacks of our analysis, having impact on plausibility of our response.

The first thing we shall discuss is the interesting part of majority of the IR functions, we saw in previous chapter, i.e. the response in negative direction, usually present between the first and the second lag of 2h datasets and sometimes after a longer period in daily datasets. Even though this is still a valid response, the direction does not correspond to our initial idea of younger brother following and imitating his elder. To understand this effect, we have to realize that all currencies are to some extent very similar and that investors usually treat them as substitutes.[7] Therefore in the

[7]also previously discussed in general description of Ripple

short-run, this response may be explained as an almost immediate switching from the declining currency to the growing one (or the other way around), caused mainly by "stag" investors. In the long-run, the effect has the same explanation, but is probably caused by "bulls" losing its faith to currency and becoming "bears" (and vice versa).

Another issue limiting potential predictability is rapidly diminishing immediate response, reaching almost zero value before the first lag, i.e. before 2 hours for the 2h dataset. From our analysis, we cannot say when exactly this response is happening, as it may happen any time before the first lag. Therefore, even if we react to the bitcoin price changes in a few seconds, we cannot be sure if the positive response effect is already gone or not, especially in the world of virtual currencies, where majority of trades are performed instantly by trading algorithms. This would mean that efficient market hypothesis is valid even for crypto-currency market, and therefore no effective predictions based on other participants may take a place on this market. To analyze this effect more precisely, one would have to use even more detailed data, e.g. measured every minute. We leave this as a potential area for further improvement of this paper.

We can suppose that this will most probably be the issue of litecoin, where we have seen almost perfect bitcoin price co-development, but minimal delayed response. On the other hand, this shall not be such a deal for much less elastic ripple. Moreover, the strongest and the most significant delayed response we found particularly for ripple. Strong delayed response has been also seen for peercoin, 4 days after the impulse, supported by above average accuracy of predictions by our model. Dogecoin behaved very similarly to litecoin with immediate response fading before the first lag and stabilizing around zero, so this also may be an issue in this case. On the other hand, predictions of our dogecoin VAR model on 2h basis had the best performance out of all analyzed currencies, indicating potential for effective predictability.

As discussed before, to develop an effective trading tool, this model shall be also enhanced by other factors having impact on the certain currency's value, as omitting an important variable may cause our model to be biased. Examples of those factors may be e.g. change in major stock prices, value of precious metals, or exchange rate development of main fiat currencies, as an alternatives to crypto-currencies.

When thinking about the other factors influencing crypto-currency market, we also have to state the most important one - overall reputation of the market. After a quick glance at chart of bitcoin price development, we can see the huge impact of the most important events discussed previously. All of those events caused enormous media attention while consequently changing overall comprehension of the whole crypto-currency market and turning its future price development by 180 degrees. Those turning points resulted in incredible volatility of the whole market. Not including this factor in our model may mist over our judgment by finding correlation somewhere just because of the unobserved common 3$^{\text{th}}$ factor. On the other hand, we managed to suppress the impact of any external time trend by using variables in delta forms throughout our analysis. Yet, we think that it would be very interesting to perform analysis of a predictability model, also containing e.g. frequency of "bitcoin" searches executed by Google Trends or Wikipedia, separated into positive and negative meaning. This proved to be a good measure of interest in the currency with a good explanatory power (Kristoufek 2013). We will also leave this issue as a recommendation for further research.

This was a final comment evaluating our analysis and highlighting the main areas suitable for further research. Now, we may try to answer the second research question: "May the price development of altcoins be effectively predicted, based on the price development of bitcoin?" With respect to results of our forecasting accuracy analysis and previously discussed issues we claim that even though we proved significant bitcoin leadership, it is apparently not strong enough for development of profitable trading strategy.

References

Ali, R.; Barrdear J.; Clews R.; Southgate J. (2014). “The Economics of Digital Currencies,” Bank of England Quarterly Bulletin (Q3).

Breusch, T. and Pagan, A. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. Econometrica.

Brito, J.; Castillo, A. (2013). Bitcoin: A Primer for Policymakers. Mercatus Center. George Mason University.

Buterin, V. (2013). Introducing Ripple. Bitcoin Magazine.

Charlton, A. (2013). Litecoin value leaps 100% in a day as market cap passes $1bn. International Business Times, UK Edition.

Coindesk.com, (2015). Bitcoin Price Index - Real-time Bitcoin Price Charts. [online] Available at: http://www.coindesk.com/price/ [Accessed 30 Mar. 2015].

Coinmarketcap.com, (2015). Crypto-Currency Market Capitalizations. [online] Available at: http://coinmarketcap.com/ [Accessed 16 Apr. 2015].

Coinwarz.com, (2015). Cryptocurrency Mining vs. Bitcoin Mining Profitability. [online] Available at: http://www.coinwarz.com/cryptocurrency [Accessed 30 Mar. 2015].

Colombo, J. (2013). Bitcoin May Be Following This Classic Bubble Stages Chart. Forbes.

Couts, A. (2013). To the moon! DogeCoin fetches 300 percent jump in value in 24 hours. Digital Trends.

Cryptocoincharts.info, (2015). Bitcoin and Altcoin price charts / graphs. [online] Available at: http://www.cryptocoincharts.info/ [Accessed 16 Apr. 2015].

Davis, J. (2011). The Crypto-Currency: Bitcoin and its mysterious inventor. The New Yorker.

Deng, X. (2007). Internet and Network Economics: Third International Workshop, WINE 2007. Germany: Springer. p. 268. ISBN 978-3-540-77104-3.

Desjardins, J. (2014). Bitcoin: A Modern Day Gold Rush?. [online] Visual Capitalist. Available at: http://www.visualcapitalist.com/bitcoin-modern-gold-rush/ [Accessed 28 Apr. 2015].

Diebold, F. (2012). Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold-Mariano Tests. Cambridge, Mass.: National Bureau of Economic Research.

Diebold, F. and Mariano, R. (1994). Comparing predictive accuracy. Cambridge, MA: National Bureau of Economic Research.

Dogecoin.com, (2015). Dogecoin. [online] Available at: http://dogecoin.com/ [Accessed 17 Apr. 2015].

Dorit, R.; Shamir, A. (2012). Quantitative Analysis of the Full Bitcoin Transaction Graph. Cryptology ePrint Archive.

Espinoza, J. (2014). Is It Time to Invest in Bitcoin? Cryptocurrencies Are Highly Volatile, but Some Say They Are Worth It. Journal Reports (The Wall Street Journal). Retrieved 3 November 2014.

Farrell, G. (2013). FBI Snags Silk Road Boss With Own Methods. [online] Bloomberg.com. Available at: http://www.bloomberg.com/news/articles/2013-10-03/fbi-snags-silk-road-boss-with-own-methods [Accessed 29 Apr. 2015].

Halleck, T. (2014). Bitcoin Gold Rush Is Over As Investors Get Bored Of Cryptocurrency. [online] International Business Times. Available at: http://www.ibtimes.com/bitcoin-gold-rush-over-investors-get-bored-cryptocurrency-1699969 [Accessed 28 Apr. 2015].

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica.

Kelion, L. (2013). Bitcoin sinks after China restricts yuan exchanges - BBC News. [online] BBC News. Available at: http://www.bbc.com/news/technology-25428866 [Accessed 29 Apr. 2015].

King, S. (2012). PPCoin: Peer-to-Peer Crypto-Currency with Proof-of-Stake.

Klose, C., Pircher, M. and Sharma, S. (2004). Univariate time series forecasting. Term Paper. University of Vienna, Department of Economics.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. Charles University in Prague.

Litecoin.org, (2015). Litecoin - Open source P2P digital currency. [online] Available at: https://litecoin.org/ [Accessed 16 Apr. 2015].

Lütkepohl, H. (2005). New introduction to multiple time series analysis. Berlin: New York.

Miles, T. (2014). Bitcoin Price Correlation with Stocks, Precious Metals, Altcoins. [online] 1CoinPool | Dogecoin Mining Pool. Available at: http://www.1coinpool.com/blog/bitcoin-price-correlation-with-stocks-precious-metals-altcoins [Accessed 19 Apr. 2015].

Peck, M. (January 14, 2013). Ripple Could Help or Harm Bitcoin. IEEE Spectrum. Institute of Electrical and Electronics Engineers.

Peston, R. (2014). Top Bitcoin exchange MtGox goes offline - BBC News. [online] BBC News. Available at: http://www.bbc.com/news/technology-26333661 [Accessed 29 Apr. 2015].

Piasecki, P. (2012). Design and security analysis of Bitcoin infrastructure using application deployed on Google Apps Engine. Master Thesis.

Popper, N. (2013). In Bitcoin's orbit: Rival virtual currencies vie for acceptance. The New York Times.

Quandl.com, (2015). Litecoin (LTC) vs US Dollar (USD), BTC-e (TAMMER1) - Data and Charts from Quandl. [online] Available at: https://www.quandl.com/data/TAMMER1/LTCUSD-Litecoin-LTC-vs-US-Dollar-USD-BTC-e [Accessed 6 Apr. 2015].

Ripple.com, (2015). Introduction to Ripple for Bitcoiners. [online] Available at: https://ripple.com/ [Accessed 16 Apr. 2015].

Ripplecharts.com, (2015). XRP/USD Bitstamp charts. [online] Available at: https://www.ripplecharts.com/#/markets [Accessed 6 Apr. 2015].

Rooney, B. (2015). Bitcoin worth almost as much as gold. [online] CNNMoney. Available at: http://money.cnn.com/2013/11/29/investing/bitcoin-gold/index.html [Accessed 28 Apr. 2015].

Schneider, N. (2015). After the Bitcoin Gold Rush. [online] The New Republic. Available at: http://www.newrepublic.com/article/121089/how-small-bitcoin-miners-lose-crypto-currency-boom-bust-cycle [Accessed 28 Apr. 2015].

Vega, D. (2014). Peercoin: 5 Fast Facts You Need to Know. Heavy.com. Heavy, Inc.

Washington Post, (2015). When will the people who called Bitcoin a bubble admit they were wrong?. [online] Available at: http://www.washingtonpost.com/blogs/the-switch/wp/2013/11/05/when-will-the-people-who-called-bitcoin-a-bubble-admit-they-were-wrong [Accessed 28 Apr. 2015].

White, L. (2014). The Market for Cryptocurrencies. George Mason University - Department of Economics.

Williams, M. (2014). Virtual Currencies – Bitcoin Risk. World Bank Conference Washington DC. Boston University.

Wooldridge, J. (2009). Introductory econometrics. Mason, OH: South Western, Cengage Learning.

Appendix - List of full VAR models

In the following chapter, we reports a list of full VAR models for both datasets and all currencies, including both sides of the model with all corresponding properties.

Figure 14: Litecoin VAR 1d model

Vector autoregression

Sample: 9 - 558, but with gaps		No. of obs	= 528
Log likelihood =	1297.638	AIC	= -4.80166
FPE =	.0000282	HQIC	= -4.706702
Det(Sigma_ml) =	.0000251	SBIC	= -4.559098

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogLTC	15	.106604	0.0801	45.95659	0.0000
dlogBTC	15	.063783	0.0805	46.22195	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogLTC						
dlogLTC						
L1.	.0644976	.0554031	1.16	0.244	-.0440904	.1730857
L2.	.164096	.056439	2.91	0.004	.0534775	.2747145
L3.	-.112249	.056704	-1.98	0.048	-.2233868	-.0011111
L4.	-.0605486	.0568548	-1.06	0.287	-.1719818	.0508847
L5.	.1131542	.0565621	2.00	0.045	.0022946	.2240138
L6.	.0162701	.056465	0.29	0.773	-.0943994	.1269395
L7.	-.0064076	.0549327	-0.12	0.907	-.1140738	.1012586
dlogBTC						
L1.	.0794085	.092445	0.86	0.390	-.1017803	.2605973
L2.	-.2743277	.0933454	-2.94	0.003	-.4572813	-.0913741
L3.	.038423	.0937991	0.41	0.682	-.1454198	.2222659
L4.	.1874221	.0939405	2.00	0.046	.003302	.3715421
L5.	.1025259	.0940843	1.09	0.276	-.0818759	.2869278
L6.	.1454403	.0938369	1.55	0.121	-.0384766	.3293572
L7.	.0510388	.0916642	0.56	0.578	-.1286197	.2306973
_cons	.002609	.0046436	0.56	0.574	-.0064924	.0117103
dlogBTC						
dlogLTC						
L1.	-.0942499	.0331488	-2.84	0.004	-.1592203	-.0292795
L2.	.0997215	.0337686	2.95	0.003	.0335362	.1659068
L3.	-.0047637	.0339272	-0.14	0.888	-.0712597	.0617324
L4.	-.0156908	.0340174	-0.46	0.645	-.0823636	.0509821
L5.	.0829043	.0338422	2.45	0.014	.0165747	.1492339
L6.	.0003221	.0337842	0.01	0.992	-.0658937	.0665379
L7.	.0818025	.0328674	2.49	0.013	.0173836	.1462213
dlogBTC						
L1.	.1672248	.0553117	3.02	0.003	.0588158	.2756338
L2.	-.0791437	.0558505	-1.42	0.156	-.1886086	.0303211
L3.	-.0549159	.0561219	-0.98	0.328	-.1649128	.055081
L4.	.0761529	.0562065	1.35	0.175	-.0340098	.1863157
L5.	.010597	.0562926	0.19	0.851	-.0997345	.1209284
L6.	.0664771	.0561445	1.18	0.236	-.0435641	.1765183
L7.	-.1850055	.0548446	-3.37	0.001	-.2924988	-.0775121
_cons	.0036131	.0027784	1.30	0.193	-.0018324	.0090586

Figure 15: Litecoin VAR 2h model

Vector autoregression

Sample: 8 - 8176		No. of obs	= 8169
Log likelihood =	39050.97	AIC	= -9.554406
FPE =	2.43e-07	HQIC	= -9.54678
Det(Sigma_ml) =	2.41e-07	SBIC	= -9.532101

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogLTC	13	.031857	0.0400	340.616	0.0000
dlogBTC	13	.020239	0.0212	177.073	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogLTC						
dlogLTC						
L1.	-.0531037	.0144897	-3.66	0.000	-.0815031	-.0247044
L2.	-.2254122	.0145093	-15.54	0.000	-.2538499	-.1969744
L3.	-.0615918	.0147582	-4.17	0.000	-.0905173	-.0326662
L4.	-.0685309	.0147581	-4.64	0.000	-.0974563	-.0396056
L5.	-.0203811	.0145157	-1.40	0.160	-.0488313	.0080692
L6.	.0327533	.0144956	2.26	0.024	.0043424	.0611642
dlogBTC						
L1.	-.0734932	.0228077	-3.22	0.001	-.1181955	-.0287909
L2.	.1516275	.0229025	6.62	0.000	.1067395	.1965155
L3.	.0300289	.0230995	1.30	0.194	-.0152453	.0753031
L4.	.0694405	.0231022	3.01	0.003	.0241611	.11472
L5.	.019906	.0229541	0.87	0.386	-.0250832	.0648953
L6.	-.0323017	.0228653	-1.41	0.158	-.0771168	.0125134
_cons	-.0000908	.0003523	-0.26	0.797	-.0007814	.0005998
dlogBTC						
dlogLTC						
L1.	.0052725	.0092054	0.57	0.567	-.0127697	.0233147
L2.	-.0274748	.0092178	-2.98	0.003	-.0455414	-.0094082
L3.	.0133281	.0093759	1.42	0.155	-.0050484	.0317046
L4.	.0048433	.0093759	0.52	0.605	-.013533	.0232197
L5.	.0054845	.0092219	0.59	0.552	-.01259	.0235591
L6.	.0148391	.0092091	1.61	0.107	-.0032104	.0328887
dlogBTC						
L1.	-.1175803	.0144898	-8.11	0.000	-.1459799	-.0891808
L2.	-.0589031	.01455	-4.05	0.000	-.0874206	-.0303855
L3.	-.0644497	.0146752	-4.39	0.000	-.0932125	-.0356868
L4.	-.0115935	.0146769	-0.79	0.430	-.0403596	.0171727
L5.	.0002008	.0145828	0.01	0.989	-.028381	.0287826
L6.	-.0312017	.0145264	-2.15	0.032	-.0596728	-.0027305
_cons	.0001757	.0002238	0.79	0.432	-.000263	.0006145

Figure 16: Ripple VAR 1d model

Vector autoregression

Sample: 9 - 721		No. of obs	= 713
Log likelihood =	1657.508	AIC	= -4.56524
FPE =	.0000357	HQIC	= -4.490982
Det(Sigma_ml) =	.0000328	SBIC	= -4.372976

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogXRP	15	.099559	0.0620	47.14259	0.0000
dlogBTC	15	.059831	0.0312	22.93954	0.0613

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogXRP						
dlogXRP						
L1.	.0723518	.037526	1.93	0.054	-.0011977	.1459013
L2.	.0192862	.037748	0.51	0.609	-.0546986	.093271
L3.	-.0545053	.0375556	-1.45	0.147	-.128113	.0191024
L4.	.0589823	.0375198	1.57	0.116	-.0145551	.1325198
L5.	.0590756	.0375561	1.57	0.116	-.0145329	.1326841
L6.	-.0854614	.0369898	-2.31	0.021	-.15796	-.0129629
L7.	.0020643	.0364559	0.06	0.955	-.0693879	.0735165
dlogBTC						
L1.	-.1918569	.0631288	-3.04	0.002	-.315587	-.0681268
L2.	-.1359362	.0634624	-2.14	0.032	-.2603203	-.0115521
L3.	-.0965971	.0633276	-1.53	0.127	-.2207169	.0275227
L4.	.0983738	.063157	1.56	0.119	-.0254117	.2221592
L5.	.1312385	.0632411	2.08	0.038	.0072883	.2551888
L6.	-.0226849	.0634777	-0.36	0.721	-.147099	.1017292
L7.	.1560387	.063484	2.46	0.014	.0316124	.2804649
_cons	.0026457	.0037168	0.71	0.477	-.0046391	.0099305
dlogBTC						
dlogXRP						
L1.	-.0131381	.0225516	-0.58	0.560	-.0573384	.0310622
L2.	.0265315	.0226851	1.17	0.242	-.0179304	.0709934
L3.	.0032424	.0225694	0.14	0.886	-.0409928	.0474777
L4.	.0471476	.0225479	2.09	0.037	.0029545	.0913406
L5.	-.0116612	.0225697	-0.52	0.605	-.0558969	.0325746
L6.	-.0174007	.0222294	-0.78	0.434	-.0609695	.026168
L7.	-.0102841	.0219085	-0.47	0.639	-.053224	.0326558
dlogBTC						
L1.	.0607438	.0379378	1.60	0.109	-.013613	.1351006
L2.	-.020095	.0381384	-0.53	0.598	-.0948449	.0546548
L3.	.003852	.0380573	0.10	0.919	-.070739	.078443
L4.	.0169643	.0379548	0.45	0.655	-.0574257	.0913544
L5.	.0825264	.0380054	2.17	0.030	.0080372	.1570155
L6.	.0813835	.0381476	2.13	0.033	.0066157	.1561514
L7.	-.0832365	.0381513	-2.18	0.029	-.1580117	-.0084613
_cons	.0015093	.0022336	0.68	0.499	-.0028685	.0058872

Figure 17: Ripple VAR 2h model

Vector autoregression

Sample: 8 - 8165, but with gaps		No. of obs	= 6947
Log likelihood = 33307.71		AIC	= -9.581605
FPE = 2.36e-07		HQIC	= -9.572773
Det(Sigma_ml) = 2.35e-07		SBIC	= -9.555983

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogXRP	13	.023064	0.0301	215.5112	0.0000
dlogBTC	13	.021053	0.0215	152.6241	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogXRP						
dlogXRP						
L1.	.0394532	.0119219	3.31	0.001	.0160868	.0628197
L2.	-.0246701	.0118506	-2.08	0.037	-.0478968	-.0014434
L3.	.0272631	.011692	2.33	0.020	.0043472	.0501789
L4.	.0387861	.0113539	3.42	0.001	.0165328	.0610393
L5.	.0128032	.0113399	1.13	0.259	-.0094227	.0350291
L6.	-.0016005	.0112163	-0.14	0.887	-.0235842	.0203831
dlogBTC						
L1.	-.0066681	.0131529	-0.51	0.612	-.0324472	.0191111
L2.	.0050961	.0132349	0.39	0.700	-.0208439	.0310361
L3.	.072824	.0132964	5.48	0.000	.0467635	.0988845
L4.	.1340306	.0132334	10.13	0.000	.1080936	.1599676
L5.	.1023651	.0133207	7.68	0.000	.076257	.1284732
L6.	-.0226843	.0132322	-1.71	0.086	-.0486189	.0032503
_cons	.0000677	.0002765	0.24	0.807	-.0004742	.0006096
dlogBTC						
dlogXRP						
L1.	-.0134263	.0108822	-1.23	0.217	-.0347551	.0079025
L2.	-.007163	.0108172	-0.66	0.508	-.0283643	.0140382
L3.	-.0118297	.0106724	-1.11	0.268	-.0327473	.0090878
L4.	-.0017157	.0103638	-0.17	0.869	-.0220284	.018597
L5.	-.0070755	.0103511	-0.68	0.494	-.0273632	.0132122
L6.	-.0075792	.0102382	-0.74	0.459	-.0276457	.0124874
dlogBTC						
L1.	-.1199651	.0120059	-9.99	0.000	-.1434962	-.096434
L2.	-.0884566	.0120808	-7.32	0.000	-.1121345	-.0647787
L3.	-.0507888	.0121369	-4.18	0.000	-.0745767	-.0270009
L4.	-.0080578	.0120794	-0.67	0.505	-.031733	.0156174
L5.	.005064	.0121591	0.42	0.677	-.0187674	.0288953
L6.	-.0159392	.0120783	-1.32	0.187	-.0396122	.0077338
_cons	.0001057	.0002524	0.42	0.675	-.0003889	.0006003

Figure 18: Peercoin VAR 1d model

Vector autoregression

Sample: 9 - 608		No. of obs	= 600
Log likelihood =	1736.741	AIC	= -5.689135
FPE =	.0000116	HQIC	= -5.603554
Det(Sigma_ml) =	.0000105	SBIC	= -5.469289

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogPPC	15	.08324	0.1037	69.45019	0.0000
dlogBTC	15	.051587	0.0504	31.8564	0.0042

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogPPC						
dlogPPC						
L1.	.1429582	.0527113	2.71	0.007	.039646	.2462704
L2.	-.1058041	.0525205	-2.01	0.044	-.2087424	-.0028658
L3.	.0093227	.0526489	0.18	0.859	-.0938674	.1125127
L4.	.2355205	.0515079	4.57	0.000	.1345669	.3364742
L5.	.0389493	.0524825	0.74	0.458	-.0639145	.1418132
L6.	-.0530507	.0520922	-1.02	0.308	-.1551495	.049048
L7.	-.0098653	.051878	-0.19	0.849	-.1115444	.0918138
dlogBTC						
L1.	-.1860643	.0849469	-2.19	0.028	-.3525572	-.0195714
L2.	-.0195164	.0850458	-0.23	0.818	-.1862031	.1471703
L3.	.006528	.0848282	0.08	0.939	-.1597323	.1727883
L4.	-.0112935	.0846911	-0.13	0.894	-.1772851	.1546981
L5.	.0279735	.0847584	0.33	0.741	-.13815	.1940969
L6.	.2915292	.0845026	3.45	0.001	.1259072	.4571512
L7.	.0698548	.0851542	0.82	0.412	-.0970443	.2367539
_cons	.0005217	.0033693	0.15	0.877	-.006082	.0071255
dlogBTC						
dlogPPC						
L1.	.0184917	.0326671	0.57	0.571	-.0455346	.082518
L2.	-.069026	.0325488	-2.12	0.034	-.1328206	-.0052314
L3.	.0116948	.0326284	0.36	0.720	-.0522558	.0756453
L4.	.0644804	.0319213	2.02	0.043	.0019158	.127045
L5.	-.010047	.0325253	-0.31	0.757	-.0737954	.0537015
L6.	.0247231	.0322834	0.77	0.444	-.0385512	.0879974
L7.	-.0454694	.0321507	-1.41	0.157	-.1084836	.0175448
dlogBTC						
L1.	-.0641432	.0526447	-1.22	0.223	-.1673249	.0390384
L2.	.0662113	.0527059	1.26	0.209	-.0370904	.1695131
L3.	-.034764	.0525711	-0.66	0.508	-.1378015	.0682735
L4.	.0553062	.0524862	1.05	0.292	-.0475647	.1581772
L5.	.0969001	.0525278	1.84	0.065	-.0060526	.1998527
L6.	.0662112	.0523693	1.26	0.206	-.0364307	.1688532
L7.	.0767051	.0527731	1.45	0.146	-.0267283	.1801384
_cons	.0012136	.0020881	0.58	0.561	-.002879	.0053061

Figure 19: Peercoin VAR 2h model

Vector autoregression

Sample:	8 - 7276	No. of obs	= 7269
Log likelihood =	22814.52	AIC	= -6.270057
FPE =	6.49e-06	HQIC	= -6.26158
Det(Sigma_ml) =	6.44e-06	SBIC	= -6.245408

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogPPC	13	.125324	0.2561	2502.089	0.0000
dlogBTC	13	.020559	0.0276	206.5282	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogPPC						
dlogPPC						
L1.	-.4946427	.0118758	-41.65	0.000	-.5179188	-.4713665
L2.	-.5211663	.0132643	-39.29	0.000	-.5471638	-.4951688
L3.	-.2641398	.0145446	-18.16	0.000	-.2926467	-.235633
L4.	-.1417519	.0145442	-9.75	0.000	-.170258	-.1132457
L5.	-.0150932	.0132935	-1.14	0.256	-.041148	.0109615
L6.	-.0449263	.0119179	-3.77	0.000	-.068285	-.0215676
dlogBTC						
L1.	.2845076	.0724364	3.93	0.000	.1425348	.4264803
L2.	.3042206	.0730086	4.17	0.000	.1611264	.4473148
L3.	.1123103	.0730541	1.54	0.124	-.030873	.2554936
L4.	.1009469	.0730519	1.38	0.167	-.0422321	.244126
L5.	-.0456227	.072627	-0.63	0.530	-.1879691	.0967237
L6.	.0304021	.0719763	0.42	0.673	-.1106689	.171473
_cons	.0001369	.001469	0.09	0.926	-.0027422	.0030161
dlogBTC						
dlogPPC						
L1.	.0024216	.0019482	1.24	0.214	-.0013968	.00624
L2.	.0029364	.002176	1.35	0.177	-.0013284	.0072012
L3.	.0022979	.002386	0.96	0.335	-.0023785	.0069744
L4.	.0110474	.0023859	4.63	0.000	.006371	.0157237
L5.	-.0045129	.0021807	-2.07	0.039	-.0087871	-.0002387
L6.	-.0014762	.0019551	-0.76	0.450	-.0053081	.0023558
dlogBTC						
L1.	-.1114306	.0118829	-9.38	0.000	-.1347206	-.0881405
L2.	-.0920197	.0119768	-7.68	0.000	-.1154938	-.0685457
L3.	-.0529103	.0119842	-4.41	0.000	-.076399	-.0294217
L4.	-.0239823	.0119839	-2.00	0.045	-.0474703	-.0004943
L5.	.0140089	.0119142	1.18	0.240	-.0093425	.0373603
L6.	-.0190777	.0118074	-1.62	0.106	-.0422199	.0040644
_cons	.0001989	.000241	0.83	0.409	-.0002734	.0006712

Figure 20: Dogecoin VAR 1d model

Vector autoregression

Sample: 9 - 378		No. of obs	= 370
Log likelihood =	1071.064	AIC	= -5.627375
FPE =	.0000123	HQIC	= -5.501336
Det(Sigma_ml) =	.0000105	SBIC	= -5.310064

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogDOGE	15	.096731	0.0563	22.07024	0.0772
dlogBTC	15	.038917	0.0620	24.45557	0.0403

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogDOGE						
dlogDOGE						
L1.	.0527025	.0576352	0.91	0.360	-.0602604	.1656655
L2.	.0204313	.057612	0.35	0.723	-.092486	.1333487
L3.	.0492481	.0552691	0.89	0.373	-.0590774	.1575736
L4.	.010722	.054013	0.20	0.843	-.0951415	.1165855
L5.	.0810551	.0525941	1.54	0.123	-.0220275	.1841377
L6.	.0019842	.0520633	0.04	0.970	-.100058	.1040264
L7.	-.0151798	.0512858	-0.30	0.767	-.1156982	.0853386
dlogBTC						
L1.	-.3229365	.142761	-2.26	0.024	-.602743	-.04313
L2.	-.3095239	.1432794	-2.16	0.031	-.5903464	-.0287015
L3.	-.248643	.1437945	-1.73	0.084	-.5304751	.0331891
L4.	.1000562	.1442707	0.69	0.488	-.182709	.3828215
L5.	-.3196378	.1422037	-2.25	0.025	-.5983519	-.0409236
L6.	.0395323	.141633	0.28	0.780	-.2380632	.3171278
L7.	.0106789	.1395402	0.08	0.939	-.2628149	.2841728
_cons	-.0046527	.0049761	-0.94	0.350	-.0144057	.0051003
dlogBTC						
dlogDOGE						
L1.	.0329089	.0231875	1.42	0.156	-.0125378	.0783556
L2.	-.0681595	.0231782	-2.94	0.003	-.1135878	-.0227311
L3.	.0187647	.0222356	0.84	0.399	-.0248163	.0623457
L4.	-.0288881	.0217302	-1.33	0.184	-.0714786	.0137024
L5.	.0091006	.0211594	0.43	0.667	-.0323711	.0505723
L6.	-.0155906	.0209458	-0.74	0.457	-.0566437	.0254625
L7.	-.0077136	.0206331	-0.37	0.709	-.0481537	.0327264
dlogBTC						
L1.	-.0470788	.0574349	-0.82	0.412	-.1596492	.0654916
L2.	-.0516531	.0576435	-0.90	0.370	-.1646322	.0613261
L3.	.0401364	.0578507	0.69	0.488	-.0732489	.1535217
L4.	.0433728	.0580423	0.75	0.455	-.0703879	.1571336
L5.	-.0533737	.0572107	-0.93	0.351	-.1655047	.0587572
L6.	.0214027	.0569811	0.38	0.707	-.0902782	.1330836
L7.	.0325827	.0561392	0.58	0.562	-.077448	.1426134
_cons	-.002412	.002002	-1.20	0.228	-.0063358	.0015118

Figure 21: Dogecoin VAR 2h model

Vector autoregression

Sample:	8 - 4526	No. of obs	= 4519
Log likelihood =	20449.74	AIC	= -9.039051
FPE =	4.07e-07	HQIC	= -9.026046
Det(Sigma_ml) =	4.02e-07	SBIC	= -9.002136

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dlogDOGE	13	.041117	0.0536	255.7734	0.0000
dlogBTC	13	.01715	0.0334	156.0767	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dlogDOGE						
dlogDOGE						
L1.	-.2390329	.0164147	-14.56	0.000	-.2712052	-.2068607
L2.	-.0614353	.0166375	-3.69	0.000	-.0940443	-.0288264
L3.	.0209202	.016419	1.27	0.203	-.0112604	.0531008
L4.	-.0318892	.0162489	-1.96	0.050	-.0637364	-.000042
L5.	.0003474	.01611	0.02	0.983	-.0312277	.0319225
L6.	-.0148329	.0157489	-0.94	0.346	-.0457002	.0160344
dlogBTC						
L1.	.1091726	.0395	2.76	0.006	.031754	.1865911
L2.	-.0240714	.0400886	-0.60	0.548	-.1026436	.0545009
L3.	-.1493821	.0401502	-3.72	0.000	-.2280751	-.0706891
L4.	.0105108	.0401573	0.26	0.794	-.0681961	.0892177
L5.	-.0124962	.0399614	-0.31	0.755	-.0908191	.0658267
L6.	-.0173876	.0391787	-0.44	0.657	-.0941765	.0594013
_cons	-.0005842	.000611	-0.96	0.339	-.0017818	.0006134
dlogBTC						
dlogDOGE						
L1.	.0104173	.0068469	1.52	0.128	-.0030022	.0238369
L2.	-.0168059	.0069398	-2.42	0.015	-.0304076	-.0032041
L3.	-.0026628	.0068486	-0.39	0.697	-.0160858	.0107603
L4.	-.002144	.0067777	-0.32	0.752	-.0154281	.01114
L5.	.0052811	.0067198	0.79	0.432	-.0078894	.0184516
L6.	-.0033017	.0065691	-0.50	0.615	-.016177	.0095736
dlogBTC						
L1.	-.1647222	.0164761	-10.00	0.000	-.1970148	-.1324296
L2.	-.079413	.0167216	-4.75	0.000	-.1121868	-.0466392
L3.	-.067508	.0167473	-4.03	0.000	-.1003322	-.0346838
L4.	-.0259297	.0167503	-1.55	0.122	-.0587597	.0069003
L5.	-.0291679	.0166686	-1.75	0.080	-.0618377	.0035019
L6.	-.0255615	.0163421	-1.56	0.118	-.0575915	.0064684
_cons	-.000234	.0002549	-0.92	0.359	-.0007335	.0002656