CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
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Interplay between Bitcoin price and its mining difficulty

Bachelor thesis

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Declaration of Authorship

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Prague, May 10, 2019

Daniel Ondruška

Abstract

Cryptocurrencies are well known asset that almost everyone at least heard of. Some of these cryptocurrencies have all of its supply already in circulation, while others do not. Two biggest cryptocurrencies, Ethereum and Bitcoin, have their supply being increased every day through the process known as mining, which many never even heard of. This process and its interaction with price are the main topic of this thesis. Price and hash rate, which is good and flexible index of difficulty of mining, of Bitcoin and Ethereum are studied and it is shown, that there is an interplay among both currencies but also withing the currency itself.

Keywords	Bitcoin, Ethereum, Cryptocurrency, Cointegration, Mining, Price, Difficulty, Hash Rate
Title	Interplay between Bitcoin price and its mining difficulty

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Abstrakt

Kryptoměny jsou dobře známé aktivum, o kterém slyšel prakticky každý. Některé z těchto kryptoměn již mají v oběhu celou svou peněžní zásobu , jiné nikoliv. Dve největěí kryptoměny, Ethereum a Bitcoin, zvětšují objem oběživa každným dnem prostřednictvím procesu známého jako minování, o kterém velká část lidí nikdy neslyšela. Tento proces a jeho interakce s cenou je hlavním tématem této práce. Cena a hash rate, který je dobrým a flexibilním ukazatelem obtížnosti minování, Bitcoinu a Etherea jsou zkoumány a je ukázáno, že existuje interakce mezi oběma kryptoměnami, ale zároveň mezi obÄ›ma proměnnými uvnitř obou kryptoměn

Klíčová slova	Bitcoin, Ethereum, Kryptoměny, kointegrace, Minování, Cena, Obtížnost, Hash Rate
Název práce	Souhra mezi cenou Bitcoinu a náročností jeho těžby
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Bachelor's Thesis Proposal

Author	Daniel Ondruška
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Proposed topic	Interplay between Bitcoin price and its mining difficulty

Motivation At the very beggining, the development of the price and of the mining difficulty of cryptocurrencies was the same- both price and difficulty were rapidly rising. If we compare graphs of both variables, they are almost identical until a certain point, where the price has stopped growing, but the increase in difficulty has remained untouched. I will try to find any correlation or influence of either of variables on the other. At the end of the work, I will look at the situation, where the mining would become lossy and inefficient because of increase in mining difficulty without any response of price increase.

Methodology I will use data on bitcoin price and mining difficulty and mainly through linear regression with help of other common analysis I will try find any possible correlation. Mining difficulty changes approximately every two weeks. I will compare these changes with specific changes in price. Afterwards, I will take a look at factors, that affect profitability of mining and what could bring the future.

Contribution Thesis will try to find any correlation between mining difficulty and price. results could be used as a prediction of future development of price and difficulty of bitcoin and other currencies. Result should be helpful in deciding whether is it profitable to start mining or when it is a good opportunity to buy a cryptocurrency.

Outline

1. Introduction
2. Basic data and their explanation
3. Calculations based on obtained

4. Shown possible dependencies and possible applications of them
5. Conclusion

Core bibliography

Joseph Bonneau, Andrew Miller, Jeremy Clark, Arvind Narayanan, Joshua A. Kroll, Edward W. Felten. Research Perspectives and Challenges for Bitcoinand Cryptocurrencies.

Joshua A. Kroll, Ian C. Davey, and Edward W. Felten, Princeton University. The economics of Bitcoin mining, or Bitcoin in the presence of adversaries.

Kristoufek L. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis.

Adam S. Hayes, CFA. Bitcoin price and its marginal cost of production: support for a fundamental value.

Satoshi Nakamoto. Bitcoin: A Peer-to-Peer Electronic Cash System

Ayelet Sapirshtein, Yonatan Sompolinsky, and Aviv Zohar. Optimal Selfish Mining Strategies in Bitcoin.

Karl J. O'Dwyer, David Malone. Bitcoin Mining and its Energy Footprint.

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Chapter 1

Introduction

Ten years ago, the whole Bitcoin network was created. On 3.January 2009, first block of bitcoin was mined by its creator Satoshi Nakamoto. That time it was worth *nothing* in the terms of money or value. Now, at the time of writing of this work, total market capitalization equals to approximately 69 000 000 000 USD. Person (or group of people) calling himself Satoshi Nakamoto invented currency by his vision of decentralized and transparent but safe-to-use currency that is not controlled by anyone else but the market and its participants and there is no need for a trusted third party. Other huge feature and innovation was its anonymity. Nobody really needs to know identity of a user to verify his authority to make a transaction. All you need to make a transaction is access to virtual wallet with available currency. However, no control and absolute anonymity led at first to an abuse of it for illegal activities. Since nobody could really tell who owns the currency or makes the transaction, it was a perfect instrument to buy drugs, weapons and other illegal things and services that were and still are available on so called deep web. It is a hidden part of the internet, not visible for every day users of the internet, accessible only through special browser — Tor. If we put this together, almost anyone could use these tools to order absolutely anything, without his identity being revealed, if he knew how and where to search for it. Bitcoin started to grow, and the price changed from $0.30 in 2011 to more than $1000 at the end of 2013 which was its first huge peak. More cryptocurrencies — altcoins, were created as well as more possibilities and places to spend them. Altcoins were created as alternatives of bitcoin, aiming to be a better substitute to Bitcoin. Success of bitcoin made it easier for others to follow in his steps. Even though they tried to be innovative and come with upgrade or an advantage over bitcoin, no altcoin has ever beaten

Bitcoin on its number one in cryptocurrency world.

After this success the price started to slowly decline and in period of one year it dropped back to $200. For two years, the price was unpredictably fluctuating up and down, sometimes even by a hundred of dollars a day, while overall it was slowly rising. The final step for bitcoin to step out of the shadows and be world-renowned currency was when its price shot up over a half a year from $1000 to almost $20 000 per one bitcoin. It followed almost exponential growth for weeks and it seemed like it is not going to stop any soon. There were predictions such that it might reach $100 000 but the opposite was true. Just before reaching magical $20 000, price began a steep descent and after two months it dropped to $8000 and in the following year it dropped to current $3500.

In this thesis, we will look behind the scenes, specifically to the area of *printing* of a new bitcoin — mining, and its influence on the price. Most of centralized currencies are emitted and backed by central banks. Money supply in this case is almost unlimited. However, if a country would keep on expanding its supply, it would end up in a currency with no value, therefore unlimited has to be taken with caution. In the case of bitcoin, there are no physical banknotes or coins, that could be printed. Everything is digital and online just like all the movement of the currency. All the Bitcoins are stored in digital wallets called addresses with a public key that is accessible only by a private key. Transactions between those accounts are recorded on a public ledger called blockchain. Because those transactions are digital, problem called double spending, spending of a certain amount more than once, might occur. In the case of physical currency, one cannot simply spend one coin more than once but that does not apply to a virtual currency, where one could possibly try to spend same *coin* many times. Here comes one of the uniqueness of bitcoin, because it was a first big digital currency to solve this problem by implementing verification unit — miners, who make sure that not a single coin is spend twice and when there is an attempt for such a behavior, only one transaction is confirmed, and the others are rejected. They control every single transaction and encrypt them into block. This block contains, apart from all the transactions also a cryptographic hash of previous one. This way all the blocks are connected back to the original block (genesis block) and together they form blockchain, system that stores whole history of transactions, in which

every block verifies the previous one. This system is public and everybody can look into it and see any historical transaction. Apart from verification of all the transactions, miners are trying to solve cryptographical cipher — they are searching for a long hexadecimal number that is supposed to be lower than current mining difficulty which is called block header. Whoever solves this problem first and creates new block is awarded with specified number of bitcoins additional to fees paid by users for their transactions. In order, to keep stable supply of bitcoins, mining difficulty adapts to the number of miners and their *power*. So far, it might seem, that miners are kind of accountants, going through all the payments and controlling if the accounts and sums are correct, but the actual job is made by the computers and mining machines they own. More powerful computers and mining devices are constantly being developed resulting in bigger mining power and therefore potential faster block creation. For this reason, every 2016 mined blocks the difficulty adjusts to the level of mining power, so that previous blocks would be mined for two weeks at the current mining power, meaning that new block is created every 10 minutes. On the top of that, every 210 000 blocks the reward is halved. Currently the reward for one block is 25 bitcoins and there are almost 18 000 000 bitcoins in circulation. Unlike most of other physical currencies, number of bitcoins in circulation is limited to 21 000 000 meaning that under mentioned difficult adjustment and block reward halving, last bitcoin is predicted to be mined in 2140.

Mining difficulty is the main topic of this thesis. There are thousands of cryptocurrencies all of them trying to bring something new or different than the others have. Nowadays there are so many cryptocurrencies that they vary in almost every aspect. Some of them have unlimited supply, others were created with all coins already pre-mined. There are big differences in block time creations and therefore in the speed of transactions as well. Some cryptocurrencies don't even have blocks and blockchain system at all and for example Ripple, one of the biggest cryptocurrencies, is not even decentralized. It is owned by a private company that controls majority of its coins. Decentralization is one of the reasons, why Ripple is criticized, because it was the innovation and uniqueness of Bitcoin that made it so popular. On the other hand, unlike most of the cryptocurrencies being not so popular in banking system, Ripple is because of its centralization respected by banks and companies that use it as an exchange medium for their transactions.

Some cryptocurrencies might be result of different opinion on the future of certain cryptocurrency. Best example of this is Bitcoin itself. Part of miners and developers were sceptic about the future of the bitcoin in its current form, mainly about its slow speed of transaction processing which is approximately 7 transactions per second. This group of people initiated hard fork — split of the blockchain into two new blockchains, where one follows old rules and protocols and the other follows new rules and protocols. This way Bitcoin cash was created with bigger block size than regular Bitcoin has.

I chose Ethereum for second studied cryptocurrency as it is the second most significant and largest altcoin with respect to market capitalization but also for being different in the way of mining. There are a lot of differences in scripts and functionality between Ethereum and Bitcoin, but for this work the most important is that supply of Ethereum is infinite and unlike for Bitcoin it takes 10 minutes to create a new block, Ethereum takes 10 to 15 seconds to process a new block and reward can be considered stable while Bitcoin's reward is halved approximately every four years. Based on parameters obtained by procedure explained in methodology I will build separate models for both currencies at first based on their lifetime data and afterwards based on data collected after the crash at the end of 2017. Last model will include data after the crash of both Ethereum and Bitcoin to show interactions across these two currencies.

Chapter 2

LITERATURE REVIEW

Cryptocurrencies are a hot topic since the day, they were presented to the world as an alternative payment system. They brought something new to a market. Decentralized and anonymous, but transparent and safe opportunity to make global payments without any exchange rates, restrictions or taxes almost instantly without any middleman or banks. When we add huge and quite unpredictable price deviations, we get an interesting opportunity for investment and possible *easy* revenue. Kristoufek (2015) in his work says, that people are interested in investing into bitcoins, when they see its fast growth and a profit opportunity and "this interest drives prices further up" but also reverse down. This statement was proven at the end of 2017, when the price has risen drastically high which attracted great attention of many more buyers, resulting in a huge bubble followed by a tremendous fall of price. Even after years of existence of Bitcoin and thousands other altcoins, they are so hard to read and many factors influencing their behavior are not even uncovered yet. However, many tried to uncover at least a part of their market mechanism and some of them successfully found the determinant factors of the Bitcoin price. "Four categories of factors are discussed, including 1) economic factors (e.g., the supply and demand of Bitcoin), 2) technical factors (e.g., hash rate and difficulty), 3) interest factors (through proxy variable such as Google trends) and 4) other financial assets (e.g., gold, stock)" Wu *et al.* (2019)

Supply and demand of Bitcoin is certainly one of the factors influencing its price. Mainly the demand has a strong impact on a bitcoin price. 'Given that BitCoin supply is exogenous, likely, the development of the demand-side drivers will be among the key determinants of BitCoin price also in the future' Ciaian *et al.* (2015). Also, cross-currency correlation is a big factor. Especially from the side of bitcoin, the biggest cryptocurrency, there is huge pressure on the prices of other altcoins. This interdependency can be seen mainly in the short run but in some cases even in a long run Ciaian *et al.* (2017). Second category — technical factors, will be studied in this work. Both hash rate and difficulty will be observed in order to find their place in a system of factors influencing bitcoin price. Difficulty will be represented mainly by hash rate, because it is more flexible and gives us more accurate data since it changes every day but difficulty changes only every two weeks, which would be hard to incorporate into our work. Interesting research by Alaoui *et al.* (2018), similar to ours, was published at the end of 2018. This research uses different approach and methods but results should be similar. In this work it is found that there is interplay between Bicoin volume and its price.

The penultimate category is summarized by comparing the change of bitcoin price with amount of google searches. One of the first papers on this topic was by Kristoufek (2013), who analyzed very strong connection between bitcoin price and public interest in it in the term of google and Wikipedia searches. This relationship is both-sided, meaning that not only price boosts searches but also *vice versa*. Similar research on the same subject was published 5 years later studying behavior of bitcoin from 2013 to 2017 and observing that "there is a bi-directional causal relationship between Bitcoin attention and Bitcoin returns with the exception of some central distributions from 40% to 80%. The bidirectional relationship mainly exists in the left tail (1%, 5%, and 10%) and the right tail (90%, 95%, and 99%) of the distribution "Dastgir *et al.* (2018). Nowadays this impact is not as strong as it used to be since it became more established on financial market and there is much higher trust in the existence and functionality of bitcoin than few years ago. Glaser *et al.* (2014) investigates whether the bitcoin should be considered a currency or an asset providing an indication that "new Bitcoin users rather use It as an asset than as a currency". These new users have intention in using it as a currency and they prefer to keep it as an investment. In 2015, third of bitcoin is found to be held by investors who only receive them but never actually send them Baur *et al.* (2015).

Dyhrberg (2016) comes with deeper research showing that for bitcoin there are big similarities to both dollar and gold. It is undoubtedly close to the medium of exchange but with its specific characteristics like decentralization a and no regulation it can never behave like other currencies. On the other hand it has a lot in common with gold as it "reacts to similar variables in the GARCH model, possess similar hedging capabilities and react symmetrically to good and bad news". The author also suggests that bitcoin can combine good features of both commodities and currencies and so it can be useful tool for portfolio management. As already mentioned, bitcoin is quite similar to gold and therefore it is hard to distinguish how much does the price of gold influence the price of bitcoin from how much they are both influenced from third party. Zhu (2017) proves that in the long run there is no influence on bitcoin price.

There are other interesting papers trying to uncover the drivers of the price, but most of them are very similar to these mentioned above. Other approach to how to make money on this cryptocurrency trend is from the already mentioned mining side. This part of cryptocurrency is very important for this work because it helps us understand how the miner's strategies work but also explains why there is such a huge deviation of hash rate volume as well as price deviation which is key for this research. Process of mining was explained in the introduction, but it is very important to mention that mining is not simply plugging a computer or mining device into the network under any circumstances and watching bank account growing. Electricity is not free and once somebody wants to make decent profit he is going to use a lot of it for his devices. If we skip the possibility of choosing in which country to mine and therefore influence the price of the electricity, which is for all the big mining companies crucial and so they choose countries like Islan or even Venezuela, where the electricity is ultra-cheap, we get that well managed mining devices is key to success. Mining difficulty adapts to the total amount of mining power to assure that every block is created roughly every 10 minutes. With increase of global mining power, the difficulty gets harder and every miner has to increase his personal mining power in order to obtain same amount of reward or has to sacrifice part of this reward. In both cases his revenues will decrease. He might get to the point where he losses more than he earns which is the reason to stop mining or transfer his computation power to different currency which is still profitable for him. This simple rule has to be followed by anyone who wants to profit out of the cryptocurrency mining and it is cause of hash rate

volume being so volatile.

This allocation of mining power because of price change or other factor that causes mining of different currency more profitable is very important for us, because it moves with one of our two main variables — hash rate. It would be nice to mention that most of the miners would be so insignificant in the whole process so they join mining pools, because otherwise it would be almost impossible for them to generate the block and claim the reward for themselves. Mining pool gathers processing power of all its participants to generate the block, claim the reward and spread it according to contributed power. Miner's choice of allocation remains quite mysterious. They either leave the choice up to the pool, who chooses currently most profitable cryptocurrency based on difficult algorithms, or choose their own favorite based on the short or long run profitability or personal preference. Bissias *et al.* (2018) tries to explain behavior of pools and how they allocate their resources and on top of that builds a model capable of predicting future allocation of these resources. This model also analyzes theoretical scenarios and predicts that big deviation in Bitcoin price might cause huge delay in processing speed of Bitcoin cash blocks for more than a day which is similar model we will try to build in this work, just between Bitcoin and Ethereum.

So far we have mentioned only main cryptocurrency - Bitcoin, but as already mentioned, there are thousands of altcoins and I would say that today not only a Bitcoin should be considered undoubtable number one. We already know that all these cryptocurrencies are different and vary in many ways and principles and therefore somebody might consider even Ripple or mentioned Ethereum to be actualy the strongest cryptocurrency out there which means that days when somebody would mention cryptocurrency and everyone would come up with only Bitcoin are gone, these altcoins are no longer just a creation and matter of small group people and therefore should be taken with similar respect as Bitcoin. Talking about altcoin and especially Ethereum, Ozisik *et al.* (2018) builds model predicting these two cryptocurrencies in order to show vulnerability of them for speculative attack or possible double spending. These two cryptocurrencies will be main topic of this thesis and it should analyze any relationship between them. As mentioned above, there are many studied factors to drive the price of Bitcoin and main contribution of this thesis should be to add a piece to this puzzle and prove that there is cointegration

between our two cryptocurrencies and results might prove our statement that Bitcoin might not be considered the strongest cryptocurrency and driver of prices of other altcoins. For this purpose we are going to use two time periods which is something new and which might be proven to be a good way how to approach cryptocurrencies in general. First period will be lifetime of Bitcoin and Ethereum and for second period we are going to use data collected after the so far biggest bubble in the history of cryptocurrencies at the end of 2017. In my opinion these using data collected around this bubble are damaged and would deflect our results because mainly the prices were driven by speculant investors and were generally deviated. It is hard to estimate the beggining and the end of it, so even though I used data starting 3 months after the drop of price of Bitcoin from almost 20 000$, these data might still be damaged. On the other this way we have only one year of data usefull for our second period so it is second factor we have to be catious about and if we replicate same steps in few months or even years it might bring clearer results.

Chapter 3

Methodology

For both cryptocurrencies I will use their lifelong price and hash rate data which should be available online and in the best .csv format. If any data were missing it should not be a big problem and I should be able to fill them up from another website. For the practical part I will follow procedure of Filip *et al.* (2017). At first, we must test both these datasets for a unit root. We will use augmented dickey-fuller test with the maximum lag of 12. If the null hypothesis is rejected, series are stationary, and we must add time trend into the model. If the null hypothesis is not rejected, series are unit roots and we can proceed. Second step is to find optimal number of lags based on Akaike Information Criterion which finds the model with the most suitable number of lags. Based on the optimal lag length and stationarity of our data, we will run Johansen test to test whether there is a cointegration between our variables. When all the parameters are clear we can build final vector error-correction model. Our last step will be running of variance decomposition of forecast errors and impulse response function which both will be based on our vector error correction model made in previous step.

3.1 Data

Data for both cryptocurrencies, Bitcoin and Ethereum, are quite easy to obtain since most of it are publicly available and downloadable. Bigger cryptocurrencies data are often available to download already in .csv format which is great for our work and makes it a lot easier to proceed. For the main data used in a model, only two websites specializing in cryptocurrencies were needed.

3.1.1 Bitcoin

Bitcoin data are obtained from the server data.bitcoinity.org where all required data can be found and downloaded in .csv format. In our case we need daily hash rate and price in USD from to 17.7.2010 to 22.3.2019. The reason for starting more than one year after the introduction is that for this time bitcoin had almost no value and even after first bitcoin exchange site — Bitcoinmarket.com started operating it was not significant for almost half a year. This half a year is however included in our dataset as it should have no negative influence on the results, on the contrary it could stabilize them. These data are quite raw and must be edited for future study. In the end total of 3171 daily observations of price and hash rate are used for future study. We have summarized historical development of bitcoin and its price in the introduction, so for better image we can see price development in figure **??** and hash rate development in figure 3.2

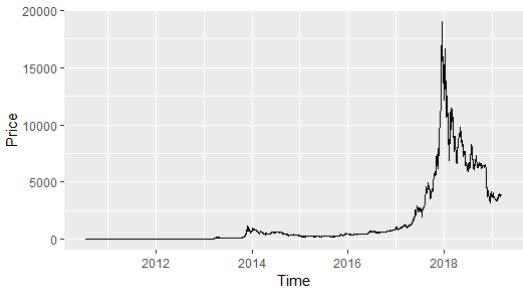


Figure 3.1: Bitcoin price

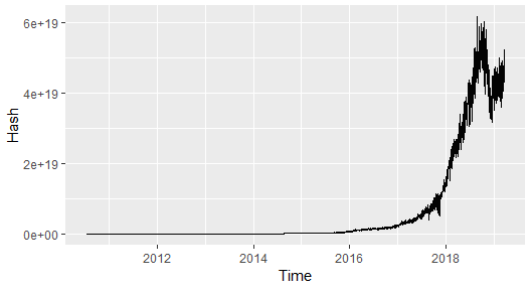
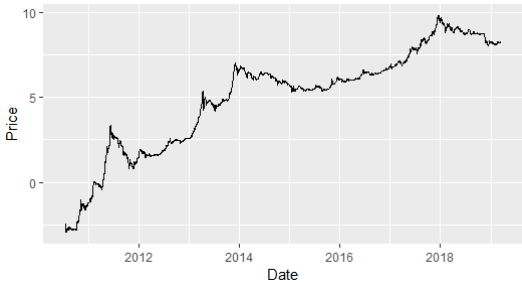


Figure 3.2: Bitcoin hash rate



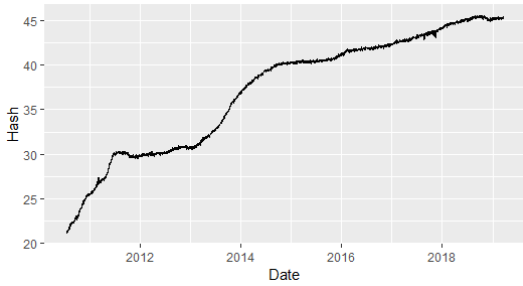


Figure 3.3: Bitcoin logarithmic price Figure 3.4: Bitcoin logarithmic hash rate

Because Bitcoin and cryptocurrencies in general are very volatile a can move by ten percent's a day, I will be using both price hash rate in logarithmic form shown in the figure 3.3 and figure 3.4. We can see that compared to figures **??** and 3.2, the results are much smoother. In both linear and logarithmic scale, it is very clear that the hash rate transitions are cleaner than in the case of price. In the end, both variables in both cases seem to reach certain point, where they match each other so at the first sight it looks like there might be certain connection.

3.1.2 Ethereum

Daily Ethereum data of hash rate and price in USD between 8.7.2015 and 22.3.2019 are obtained from etherscan.io. It is not possible to make the same dataset as for Bitcoin, since Ethereum is newer than Bitcoin. They are complete and apart from removing first few days when the price was 0 and labeling these data sets together there is no need for addition edit. In figures 3.5 and 3.6 we can see this time linear Ethereum price and hash rate development (Figure 3.7 and 3.8 logarithmic). As with the previous cryptocurrency, we used logarithmic scale for future research, which mainly in the case of price gives better results.

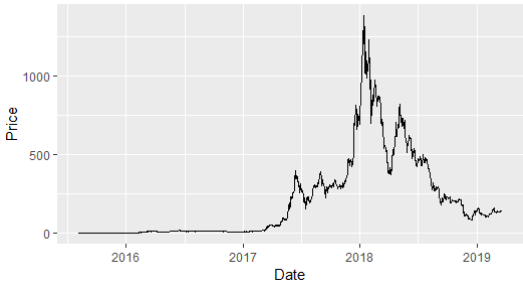


Figure 3.5: Ethereum price

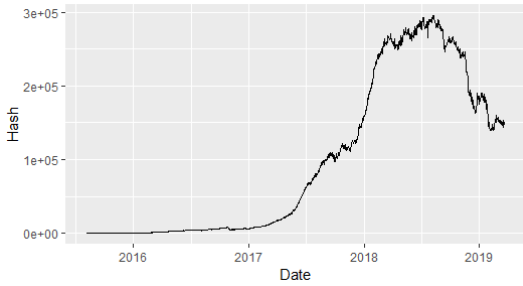


Figure 3.6: Ethereum hash rate

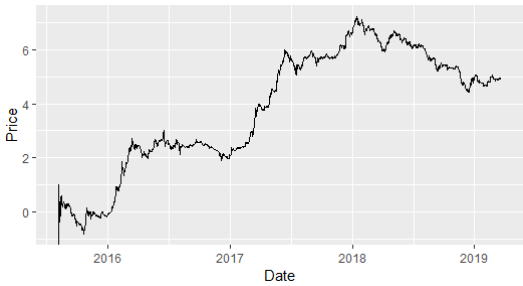


Figure 3.7: Ethereum logarithmic price

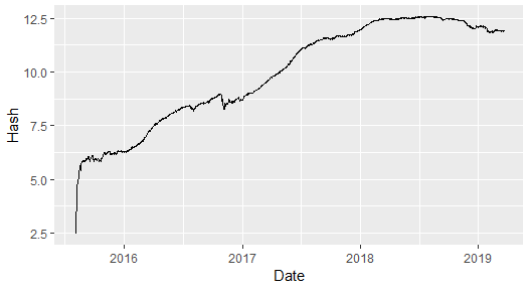


Figure 3.8: Ethereum logarithmic hash rate

In general, cryptocurrency prices have very similar development. Most of them react to bitcoin price changes within a short period of time which can be seen very well in the Figure 3.9. Same development does not mean same prices, since mainly supply of particular currency but many other factors as well are different, causing the price to be on the different level (In our case the price of Bitcoin is approximately ten times the price of Ethereum). However, hash rate development is not similar at all so at the end of this research one of these two cryptocurrencies will end up with weaker relationship between its price and hash rate than the other which could help to determine which specific factors influence this relationship and also give a direction for future study .

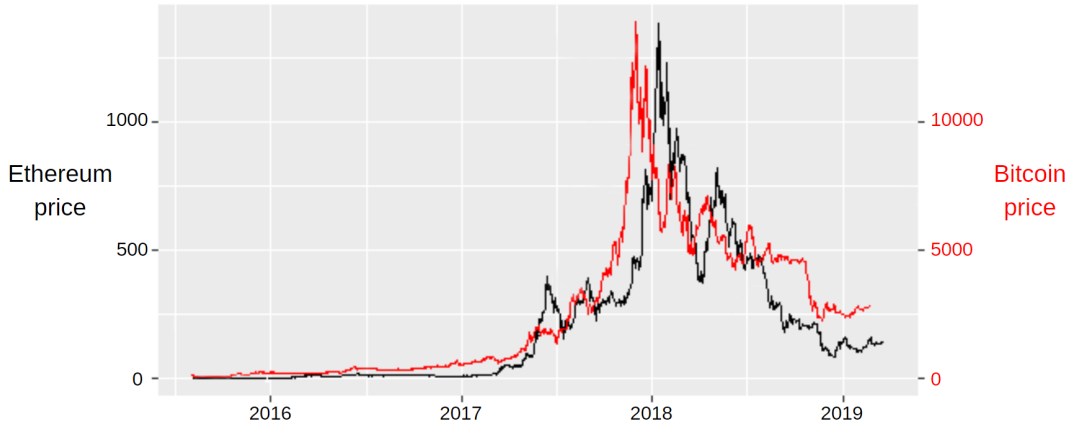


Figure 3.9: Comparison of Bitcoin and Ethereum price

3.2 Augmented Dickey-Fuller test

As a first step we need to test both variables in both our datasets for stationarity. This can be achieved by running augmented Dickey-Fuller test with a lag selection based on the Akaike information criterion. This is an advanced version of basic Dickey-Fuller test and tests the null hypothesis that there is a unit root in our time series. If the null hypothesis is rejected, the time series is stationary, and we can proceed. If it is not rejected and the unit root is present, we need to use first differencing to achieve a stationarity. The ADF statistic result is a negative number. Critical values of this test are shown in Figure 10. The more negative this number is, the stronger the rejection of the null hypothesis is.

3.3 Akaike Information Criterion

In order to find optimal number of lags we are going to use Akaike information criterion (AIC) introduced by H.Akaike (1947). It is an estimator that studies quality of each possible model, compared to the other possible ones and chooses the most fitting model for given dataset. In other words, it goes through all the models in our case including up to 12 lags of our variables, compares amount

of information lost in every of them and selects the one with least information lost. It is very similar to Bayesian information criterium and there are many comparisons of which one is better. The biggest difference is a penalty for number of parameters. Comparison given by Vrieze (2012) suggests that BIC is consistent in selecting the true model when it is a candidate. However, if the true model is not present and the sample is complex and finite, AIC might be preferred over BIC, sometimes even when the true model is candidate but is very complex.Yang (2005) tried to combine both AIC and BIC but shows that it is not possible and always it is necessary to sacrifice advantage of one for an advantage of the other model. One must go either for BIC and its consistency or AIC with its minimax.

3.4 Cointegration test

We have two options how to test cointegration. We can go either for Engel-granger cointegration test or Johansen test. There is no clear answer which one is better of more efficient and it mostly depends on the situation and each of them will perform better in certain context. Bilgili (1998) says, that Johansen test dominates Engle-Granger in the way of Engle-Granger methodology being defective. It relies on two-step estimator where first step generates the residuals and second step uses them to estimate regression of first-differenced residuals on lagged residuals. The problem is that when there is any error in first step, it moves on to the second step. If we had more than two variables, Johansen test would be chosen, because it permits more than one cointegrating relationship between variables. In our paper we study only relationship within one currency at a time not both combined (Bitcoin price and hash rate separately from Ethereum price and hash rate) so both variants are viable, and the choice between them should not be crucial, since both should bring us correct results when they are correctly formulated. This means, that the important part is choosing correct parameters of either of these two tests rather than deciding which one to choose. We are going to use both of the test, assuming that results from both will be the same, either there will be a cointegration or not. In the scenario that these results do not match we know that there is already kind of bad approach in previous steps.

3.5 Vector error correction model and Vector autoregression

Once we know all the necessary parameters we can build a final model. In the case of series being cointegrated we are going to use to be vector error correction model (VECM). It is very useful in estimating both short- and long-term effect of one variable on the other and how fast it can return to its long run equilibrium after the other variable changes in the short run. If there is no cointegration between our time series, we are going to use vector autoregression model (VAR) because our time series do not exhibit long run relationship.

3.6 Variance decomposition of forecast error and Impulse response function

Forecast error variance decomposition (FEVD) is used to explain the amount of the information transferred from one variable in another in the fitted VAR or VECM. Impulse response function shows a response of one variable to an exogenous impulse or change called shocks. In our topic of cryptocurrencies this is very important part of the study because there are so many impulses that can influence either of our variables.

Chapter 4

Results

This chapter will have two parts where first part will have two sections, lifetime data and data after the biggest speculative bubble that popped at the end of 2017. Each of these sections will have its own two subsections, each focusing on one of our cryptocurrencies. Steps listed above in the methodology section will be applied to both original and shortened datasets in both sections and all the results will be compared in the conclusion. It is hard to say when the effect of this shock ended because from the fluctuation of the price it is obvious that the price was finding its optimal level of price, so for the after-bubble section we are going to use data starting on 22.3.2018 which is exactly one year of data but also more than a month after the huge drop followed by little increase of price.

Second part will contain data after the bubble of both Bitcoin and Ethereum. After running all the steps of methodology and having all the neccesary parameters, we are going to build model including both of our cryptocurrencies to see any relationship between their price and hash rate.

4.1 Lifetime Data

4.1.1 Bitcoin

First step is to find optimal number of lags of our time series. Based on the Akaike information criterion, optimal model is detected to be the one with number of 11 lags included in the model for both hash rate and price.

Table 4.1: Augmented Dickey-Fuller test for bitcoin

	ADF	*p-Value*
Log		
Price	−2.48	0.3751
Hash	−2.6953	0.2839
Log-differences		
Price	−12.169	<0.01
Hash	−12.837	<0.01

Second step is to test for a unit root. Using logarithmic transformation, augmented dickey-fuller test refuses the null hypothesis for both hash rate and price series, meaning they are detected as unit roots and therefore there is no need to include time trend in the model to avoid stationarity. When testing differences of both variables, ADF test rejects non-stationarity at 1% level for both. Johansen test suggests that there is a cointegration between our two variables. To check these results, I go for Granger-Engel cointegration test. It confirms this statement with the results of price having significant influence on the development of hash rate.

Because our time series are cointegrated, we will use vector error-correction model since we know that there is no need to include and check significance of time trend. Optimal number of lags was found to be 11 based on the Akaike information criterion and there is significant cointegration between our two variables. The main question here is how much one variable is influenced by the other and if it can help in predicting future development. From table 4.2 it is clear, that hash rate is significantly influenced the most by its 6 most recent lags, while the other 5 are not significant at all except for its ninth

lag. All these 7 significant lags are negatively influencing the current value of hash rate. This negative effect is diminishing with every day, so that the effect of previous day is 100 times higher than the effect of the seventh lag. It means that if during the previous week the hash rate was going up it is most likely going to go down. If we think about it, this statement is quite logical, because if it kept going up without other factors like energy prices going down on, or rise of bitcoin price, mining would not be profitable anymore, because there would be still the same reward for more and more people or hash rate in general which would cost still more in total up to the point where the cost would exceed revenue. That is why there is this kind of stabilizing process when these miners for whom it is not profitable, either because their electricity is for some reason more expensive than for the others (very important factor in mining), or for example because they have only few graphic cards or mining devices and they cannot compete with huge companies owning factories or warehouses full of mining devices which gives them better conditions. Currency is very volatile and either its price can go down again causing other miners to turn off their devices or switch to mine different cryptocurrency or it can go up, allowing those who stopped mining to enter again. This is one of the key specifics of cryptocurrency. In the highly competitive market system, subjects enter and leave until the equilibrium point is reached, where only those who can make profit at the current situation will stay and others will not, and if nothing significant happens, market participants will not change. In the cryptocurrency environment, it is hard to achieve such an equilibrium, because at the current situation all the factors like price and total mining power are way too variable.

Influence of price on hash rate is less significant. From the first price lags there is only the third one significant for the hash rate. Other significant lagged values of price for hash rate are last two lags of our model. Overall, according to our model, there is not a significant influence of price on hash rate in a short term. Price is according to our results not driven by any of hash rate lagged values at all so in the short-term there is no push on hash rate from the price which was already proposed by the results of Granger-Engel cointegration test. On the other hand, in the long-term, hash rate volume is driven by the price of Bitcoin and by itself while price is once more not influenced at all.

Table 4.2: Bitcoin vector error-correction model

	Hash	Price
ECT	−0.055 325***	−0.0005
Intercept	0.1786***	0.0168
Hash -1	−0.6500***	−0.0020
Price -1	0.0281	0.1789***
Hash -2	−0.4526***	0.0196
Price -2	0.0315	−0.0667***
Hash -3	−0.3462***	0.0038
Price -3	0.1458***	−0.0329·
Hash -4	−0.1950***	0.0141
Price -4	−0.0183	0.0568**
Hash -5	−0.1465***	0.0114
Price -5	0.0411	0.0379*
Hash -6	−0.0868***	−0.0023
Price -6	0.0558	0.0509**
Hash -7	−0.0095	0.0120
Price -7	0.0441	−0.0116
Hash -8	0.0230	0.0059
Price -8	0.0051	−0.0299
Hash -9	0.0444*	0.0072
Price -9	−0.0312	0.0050
Hash -10	0.0231	0.0076
Price -10	0.0963**	0.0471**
Hash -11	0.0068	−0.0024
Price -11	0.1016**	0.0098

Results of the last step, study of the effect of one variable on the variance of the other, the forecast error-variance decomposition is shown in table 3 4.3. Only 1% of the variance of the hash rate is explained by the price after one week. After two weeks it is more than 3% and after one month approximately 6.5% of the variance of the hash rate which can be considered quite insignificant. Price predicts its own future development even more. After one week only 0.36% of its variance is explained by the hash rate. After two week this number slightly grows to 0.43% but declining back to 0.41% after one month, so we can say that the hash rate does not play any role in predicting of the future of the price.

Response to a shock to hash rate on price as well as to hash rate is positive but practically zero in the case of price. Effect of hash rate on itself declines over the first three period until it hits its steady state value. Shock to a price has positive impact on both hash rate and price itself in both short and long run. This effect is considerably greater on price than on hash rate.

Period	Hash	Price
1	0.00115	0.99885
2	0.00104	0.99896
3	0.00231	0.99769
4	0.00262	0.99738
5	0.00324	0.99676
6	0.00369	0.99631
7	0.00364	0.99636
14	0.00433	0.99567
30	0.00419	0.99581

Variance decomposition of price

Period	Hash	Price
1	1.00000	0.00000
2	0.99959	0.00041
3	0.99895	0.00105
4	0.99306	0.00694
5	0.99219	0.00781
6	0.98995	0.01005
7	0.98610	0.01390
14	0.96654	0.03346
30	0.93579	0.06421

Variance decomposition of hash rate

Table 4.3: Variance decomposition of Bitcoin

4.1.2 Ethereum

By replicating steps described in methodology and already used on Bitcoin data, we find out, that based on the AIC the optimal number of lags is 4 which is considerably less than in the case of Bitcoin. Results in table 4.3 show that

both logarithmic series are unit roots and after first-differencing unit roots are rejected and we can proceed to cointegration test.

Table 4.4: Augmented Dickey-Fuller test for Ethereum

	ADF	*p-Value*
Log		
Price	−0.3728	0.9876
Hash	0.3027	0.99
Log-differences		
Price	−10.047	<0.01
Hash	−12.837	<0.01

Johansen test suggests that there is a significant cointegration between arourariables which is proven by Granger-Engel test with very significant level of influence of price on hash rate. With previous parameters, we can proceed to a building of a the vector error correction model. Results in table 4.5 suggests, that in the short-term, there is significant positive influence of price on hash rate because all the lags up to the fourth one is very significant. There is a negative push on hash rate by itself, but it is much shorter and is significant only up to its second lagged value. Price is in the case of Ethereum not driven by neither hash rate or price unlike in the case of Bitcoin. Only notable effect of price on price is from its second and fourth lagged value. In the long-term, the hash rate is driven by the price of the Ethereum and by itself.

Table 4.5: Ethereum vector error-correction model

	Hash	Price
ECT	−0.0092***	−0.0034
Intercept	0.0649***	0.0255
Hash -1	−0.1024***	−0.0526
Price -1	0.0826***	0.0113
Hash -2	−0.0476·	−0.0258
Price -2	0.0353**	0.0560*
Hash -3	−0.0111	0.0548
Price -3	0.0461***	0.0394
Hash -4	0.0482·	0.0596
Price -4	0.0174	−0.0497*

As with the Bitcoin, last step will be variance decomposition of forecast errors and impulse response function. In the table 4.6 we can see that after one week, almost 13% of the variance of the hash rate is explained by a price. After two weeks it is already by 21% and after one month it is 35%. However, not even 0,5% of the variance of the price is explained by hash rate after one week and this influence is even lower after one month. Results also suggest that impact of shocks to hash rate from itself slowly decline with each following period but in general it will have positive impact both in short and long run. Effect of a shock of hash rate on price is at first almost unnoticeable, it goes negative between first and third period, but keeps on being positive after fourth period. Overall, shocks to hash rate it will have asymmetric impact on price. Shocks to price will have almost no impact on hash rate in first period but will gradually increase so in both short and long run it will have positive impact on hash rate.

Period	Hash	Price
1	0.00013	0.99987
2	0.00016	0.99984
3	0.00029	0.99971
4	0.00021	0.99979
5	0.00026	0.99974
6	0.00027	0.99973
7	0.00028	0.99972
14	0.00022	0.99978
30	0.00012	0.99988

Variance decomposition of price

Period	Hash	Price
1	1.00000	0.00000
2	0.97861	0.02139
3	0.95637	0.04363
4	0.92412	0.07588
5	0.89779	0.10221
6	0.87815	0.12185
7	0.86179	0.13821
14	0.78356	0.21644
30	0.64672	0.35328

Variance decomposition of hash rate

Table 4.6: Variance decomposition of Ethereum

4.2 After-Bubble Data

4.2.1 Bitcoin

The procedure will be the same as in the lifetime data. First step is to test for unit roots. Using augmented dickey-fuller we get that both our series are stationary after their first difference so there is no need for adding of a time trend. We can proceed to cointegration test. According to granger-causality test, there is no significant influence of either hash rate or the price on the other. We run Johansen test only to confirm this statement, because we cannot reject the null hypothesis that there is no cointegration.

Table 4.7: Augmented Dickey-Fuller test for Bitcoin

	ADF	*p-Value*
Log		
Price	−3.0455	0.1357
Hash	−1.7429	0.6855
Log-differences		
Price	−7.156	<0.01
Hash	−10.174	<0.01

There is no cointegration between hash rate and price, so we are going to use vector autoregression including 11 lags of both variables. From the results in table 4.8 we can see that in the short run hash rate is very significantly driven by all its first 11 lags which is huge difference from the lifetime data. All these 11 lags have negative impact on current volume of hash rate. There is also response to a price, even though it is with certain delay. It is positively driven by price's 5.-7. lag only which suggests that increase in price could boost in volume of hash rate after approximately one week. Price is most significantly driven by first lag of itself and by first two lags of hash rate which is also huge different from lifetime data

Table 4.8: Bitcoin vector error-correction model

	Hash	Price
ECT	−0.0583*	−0.0025
Intercept	2.6191*	0.1090
Hash -1	−0.7460***	0.0278·
Price -1	0.0011	0.1964***
Hash -2	−0.6395***	0.0516*
Price -2	0.1076	0.0602
Hash -3	−0.5005***	0.0203
Price -3	0.0484	−0.0245
Hash -4	−0.377***	0.0399·
Price -4	−0.0263	−0.0343
Hash -5	−0.3274***	0.0515*
Price -5	0.2973·	0.1359**
Hash -6	−0.297***	0.0490*
Price -6	0.3205·	0.0423
Hash -7	−0.2842***	0.0302
Price -7	0.0741	−0.0449
Hash -8	−0.3021***	0.0070
Price -8	−0.3270*	−0.1043*
Hash -9	−0.2347**	0.0020
Price -9	0.1358	−0.0163
Hash -10	−0.2364***	−0.0129
Price -10	0.1277	0.125**
Hash -11	−0.1411**	−0.0159
Price -11	−0.0880	−0.0260

Variance of the hash rate is explained mostly by itself as the share of the price influencing it is barely 2% one week, 3% two weeks and 4% one month. The same applies to the variance of the price with little more than 2.5% hash rate being included in it after first and second week. This number declines up to over 1.5% one month so the variance is again explained by itself. Final step, impulse response function with results below shows that shocks to price have positive impact on price itself in short and long run and on hash rate in long run as well. Its impact on hash rate in short run is almost zero. Impulse from hash rate to both our variables is positive in both short and long run while effect on itself is quite bigger than on price.

Period	Hash	Price
1	0.00130	0.99870
2	0.00203	0.99797
3	0.00722	0.99278
4	0.00719	0.99281
5	0.01063	0.98937
6	0.01691	0.98309
7	0.02281	0.97719
14	0.02342	0.97658
30	0.01322	0.98678

Variance decomposition of price

Period	Hash	Price
1	1.00000	0.00000
2	0.99904	0.00096
3	0.99821	0.00179
4	0.99829	0.00171
5	0.99831	0.00169
6	0.99320	0.00680
7	0.98478	0.01522
14	0.98245	0.01755
30	0.98542	0.01458

Variance decomposition of hash rate

Table 4.9: Variance decomposition of Bitcoin

4.2.2 Ethereum

Optimal number of lags for our model is according to AIC is going to be 2 in the case. Our time series is stationary after first differencing, so we can proceed to cointegration test. Johansen test suggests that there is a significant cointegration and granger-causality test proves significant influence of price on hash rate, so we proceed to build our VEC model with 2 lags included.

Table 4.10: Augmented Dickey-Fuller test for Ethereum

	ADF	*p-Value*
Log		
Price	−1.9285	0.6071
Hash	−1.6345	0.7312
Log-differences		
Price	−6.4796	<0.01
Hash	−5.9587	<0.01

In table 4.11 we can see that the hash rate is in the short run very significantly influenced by both included lags of price and first lag of itself. This effect is positive from price and negative from itself. Price is significantly and positively influenced by its second lag but by nothing else. In the long run there is also strong causality from price to hash rate.

Table 4.11: Ethereum vector error-correction model

	Hash	Price
ECT	−0.0148***	−0.0021
Intercept	0.1299***	0.0153
Hash -1	−0.2827***	−0.1356
Price -1	0.0574**	−0.0737
Hash -2	−0.0554	0.1347
Price -2	0.0781***	0.1242*

As a last step we obtain result of FEVD that are shown in table 4.12 and from which we can see that the variance of price is explained by hardly 0,1% even after 30 days so price is mostly self-explanatory. Hash rate is absolute opposite. After one week its variance is explained by more than 15% by price, after two weeks this number rises to 22% and after one month is it almost 40%

which is a lot. Results of impulse response function in Table 12 suggest that impulse response from price to both hash rate and itself are positive and rather stable, only response to hash rate is increasing during first three periods while still being very low, almost zero. When there is a shock to hash rate, there is positive stable response after the first day, when the tendency is decreasing. Response of price is at first negative, staying stable but almost zero after it increases and becomes positive.

Period	Hash	Price
1	0.00069	0.99931
2	0.00078	0.99922
3	0.00117	0.99883
4	0.00093	0.99907
5	0.00088	0.99912
6	0.00080	0.99919
7	0.00077	0.99923
14	0.00059	0.99941
30	0.00039	0.99961

Variance decomposition of price

Period	Hash	Price
1	1.00000	0.00000
2	0.97964	0.02036
3	0.93148	0.06852
4	0.91220	0.08780
5	0.89233	0.10767
6	0.87643	0.12357
7	0.86194	0.13806
14	0.78036	0.21964
30	0.61870	0.38130

Variance decomposition of hash rate

Table 4.12: Variance decomposition of Ethereum

4.2.3 Bitcoin and Ethereum

We apply the same methodology used untill now to data after the bubble for both Ethereum and Bitcoin to build one final model. According to AIC optimal number of lags of this model is going to be 4. Based on our previous models we know that all our data are stationary after first differencing so we can proceed to cointegration test. Results of Johansen test suggest that there are 3 cointegrating vectors meaning that we will build VEC model.

Table 4.13: Bitcoin and Ethereum vector error-correction model

	BTC Hash	*BTC Price*	*ETH Hash*	*ETH Price*
ECT	−0.0536·	0.0193*	0.0226***	−0.0167
Intercept	2.2125·	−0.7981*	−0.9309***	0.6848
BTC Hash -1	−0.6862***	−0.0072	−0.0116	0.0950**
BTC Price -1	0.2866	−0.1764**	−0.1120*	0.0714
ETH Hash -1	0.2965	−0.1310·	−0.3178***	−0.1605
ETH Price -1	−0.0966	0.3427***	0.0834***	−0.0902
BTC Hash -2	−0.5398***	−0.0069	−0.0190	0.0569
BTC Price -2	−0.1763	−0.0557	0.0120	0.0053
ETH Hash -2	0.5163*	−0.0935	−0.1243*	0.0832
ETH Price -2	−0.0221	0.0861*	0.1304***	0.1321·
BTC Hash -3	−0.3416***	−0.0349*	−0.0250·	−0.0034
BTC Price -3	0.2168	−0.1814**	−0.0575	−0.0882
ETH Hash -3	0.3036	0.0181	−0.0767	−0.1057
ETH Price -3	−0.0553	0.0854*	0.0657*	0.0833
BTC Hash -4	−0.1344*	−0.0193	−0.0095	−0.0018
BTC Price -4	0.1105	−0.0120	0.0209	0.0814
ETH Hash -4	0.0124	−0.1312*	−0.0006	−0.2414·
ETH Price -4	−0.3195*	0.0619·	0.0358	−0.0128

Results in table 4.13 brought very interesting and unexpected results. First of them is that price of Bitcoin is significantly and positively driven by all the lags of Ethereum price which is quite unexpected and one would say that it would be other way arround since Bitcoin still is the biggest cryptocurrency and one would expect it to drive others. Apart from Ethereum price it is driven by its own lags as already said in the previous section. Bitcoin hash rate is significantly influenced only by itself. Ethereum price is significantly influenced by Bitcoin hash rate which is also little strange and unexpected result. Last variable, hash rate of Ethereum brings nothing new, as it is significantly driven

mainly by Ethereum's price and hash rate which was already proven by its own model.

Table 4.14: Variance decomposition of Bitcoin

Period	*BTC Hash*	*BTC Price*	*ETH Hash*	*ETH Price*
Hash rate				
1	1.000 00	0.000 00	0.000 00	0.000 00
2	0.990 14	0.002 31	0.003 70	0.003 89
3	0.979 55	0.002 90	0.012 93	0.004 61
4	0.975 56	0.003 77	0.014 80	0.005 88
5	0.969 93	0.003 70	0.013 92	0.012 45
6	0.971 26	0.003 71	0.013 70	0.011 34
7	0.969 67	0.003 48	0.014 97	0.011 88
14	0.964 28	0.002 51	0.018 48	0.014 74
30	0.953 01	0.001 66	0.021 68	0.023 65
Price				
1	0.000 29	0.999 71	0.000 00	0.000 00
2	0.001 57	0.841 64	0.002 74	0.154 05
3	0.006 60	0.808 63	0.006 72	0.178 06
4	0.004 99	0.762 95	0.005 18	0.226 88
5	0.004 22	0.734 06	0.008 43	0.253 29
6	0.004 60	0.724 60	0.010 36	0.260 44
7	0.004 70	0.717 63	0.011 87	0.265 79
14	0.004 62	0.702 57	0.015 40	0.277 42
30	0.004 90	0.693 70	0.017 04	0.284 28

From the results of FEVD of Bitcoin in table 4.14 we obtain once more quite interesting results. Variance of hash rate is even after 30 days influenced mostly by itself. Only 2% is explained by Ethereum hash rate and other 2% by Ethereum price but when we look at the price of Bitcoin, we can see that after 7 days 25% of its variance is explained by Ethereum price and this number increases to almost 30% after 30 days. Other variables have almost no impact on it so it explains its own variance from almost 70%.

FEVD of Ethereum offers quite different results to the one of Bitcoin. In table 4.15 we can see that 1% of variance of hash rate is explained by hash rate of Bitcoin after one week, after two weeks its 5% and after 30 days its already 10%. Participation of Ethereum price on its variance is similar to tab:12 and after 30 days its more than 30%. Only 50% of the variance is explained by itself. Other interesting result comes from the variance of the Ethereum price. After

Table 4.15: Variance decomposition of Ethereum

Period	*BTC Hash*	*BTC Price*	*ETH Hash*	*ETH Price*
Hash rate				
1	0.005 75	0.000 03	0.994 21	0.000 00
2	0.010 97	0.001 00	0.954 09	0.033 93
3	0.012 44	0.008 32	0.893 35	0.085 88
4	0.012 51	0.010 24	0.828 94	0.148 30
5	0.018 84	0.017 74	0.781 92	0.181 50
6	0.023 92	0.012 76	0.745 98	0.208 82
7	0.027 23	0.024 84	0.717 59	0.230 33
14	0.050 85	0.033 16	0.620 61	0.295 38
30	0.103 41	0.034 76	0.528 75	0.333 07
Price				
1	0.000 32	0.226 09	0.000 62	0.772 97
2	0.012 32	0.237 66	0.001 05	0.748 97
3	0.011 78	0.247 23	0.000 93	0.740 06
4	0.008 83	0.240 83	0.000 80	0.749 56
5	0.007 23	0.247 99	0.002 16	0.742 62
6	0.006 05	0.251 35	0.002 60	0.739 99
7	0.005 31	0.254 97	0.003 39	0.736 33
14	0.003 64	0.267 97	0.005 28	0.723 11
30	0.015 99	0.281 70	0.007 56	0.694 75

one week, 25% of Bitcoin information is contained in the variance of Ethereum price and this value goes up to almost 30% after one month.
In general it is obvious that variances of both prices are explained a lot by the other price in the long term but interesting results come from explanation of variance of Ethereum's hash rate to which Bitcoin contributes quite a lot of information in long run.
Responses to shocks of our variables offer nothing interesting. Almost all responses can be considered zero except for a response of Ethereum price from a shock to Bitcoin price, which is positive, than negative response to Bitcoin price from shock to Ethereum hash rate and lastly positive response from a shock to Ethereum price to Bitcoin price. All these responses are very small.

Chapter 5

Conclusion

Results of this thesis reveal, that there is an interplay between our two studied variables, price and hash rate of both studied cryptocurrencies but not only within themselves but also among each other and there results could be useful for future study of cryptocurrency price. This study could be very useful for miners to predict future development, mainly of the hash rate, and adapt their strategies. We use Johansen test to test the cointegration and build corresponding model (VAR or VECM) to find the most significant lagged values of our two variables and apply FEVD and IRF to these models to better interpret actual effects. We observed two cryptocurrencies, Ethereum and Bitcoin, in order to see, whether we can apply our results to the whole subject of cryptocurrencies or only to Bitcoin in particular, and we obtained little different results for both. It was mentioned at the beginning of this work why we compared exactly these two cryptocurrencies which might make the difference in results. Other reason could be simply Bitcoin being the biggest one and in general leader in cryptocurrencies and therefore being impacted by different factors, so it must be taken with caution. On the other hand, these results have in general almost the same effect on each of these cryptocurrencies, so I would say that it applies to most of them.

We studied two periods, lifetime and after bubble and the biggest difference between these two datasets is that in the case of bitcoin there was no significant influence of the volume of hash rate on price when using the lifetime data, but if we use the data collected after the so called Bitcoin crash, we find out that the price is influenced by hash rate's most recent lags. Other difference is that

when using data collected this last year, hash rate is driven much more by itself and is influenced by its earlier lags and these coefficients are bigger as well. Ethereum was different from Bitcoin already in the number of optimal number of lags. Most suitable models for Ethereum included three times less lags in the lifetime data and five time less after the bubble. Ethereum's hash rate seems to be driven a lot by the lags of its price, in both observed periods there were more of the significant price lags than these of hash rate itself, pointing to a possibility of hash rate being driven by the price in general. On the other hand, price of Ethereum is driven mostly by itself, but this effect seems to be very weak, especially after the bubble.

In general, hash rate of both cryptocurrencies in both time periods is influenced negatively by itself. This is probably caused by the fact that with growing total volume of the hash rate, it is impossible to keep mining profitable with other variables fixed, since it would result in harder mining difficulty, leading to more of the mining power needed, which results in miners turning off their mining devices to avoid losses.

Apart from Ethereum having much lower optimal number of lags included in its model, there is also difference in the amount of contributed information of price to hash rate. Bitcoin's variance is in both periods explained mainly by itself, even after longer period like 30 days. Ethereum's variance can be explained by roughly 40% after 30 days.

Most interesting results were obtained from the model including both cryptocurrencies. One would say that price of Ethereum would be driven by the price of Bitcoin as it might be the main driver of prices, but it is exactly the opposite. In this cross section model, price of Bitcoin is influenced by two lags of Ethereum apart from its own lags. Other interesting fininding is that Ethereum price is driven by first lag of Bitcoin, which is driven mainly by itself, so in the end it looks like the hash rate of Bitcoin could play role in Ethereum price and therefore in Bitcoin price.

It would be wise to mention, that after the bubble data are still not comprehensive and the future development of cryptocurrencies in general will show its true potential. However, even though there was a little of data after the bubble (I consider these data very important), the results are straightforward. This might be caused by bitcoin slowly stabilizing after its price explosion followed by a huge fall. This process of stabilization might still be not over, and there is a chance that cryptocurrencies are still trying to find its optimal level but also full trust from the market participants. I believe that once this happens,

data could be used to give clear results about this interplay.
For now, with the current data it is clear, that there exists an interplay between hash rate and price, but also between Bitcoin and Ethereum, however it is hard to tell how big it is and how far it reaches. Results proposed by me could be useful for future study and might bring a new vision of how to approach this topic, mainly those result concerning Bitcoin price being influenced by Ethereum price and Ethereum hash rate being influenced by Bitcoin price. This might be a strong statement but maybe the time when Bitcoin will no longer be number one is coming and altcoins which are trying to be better in than Bitcoin in certain aspects might detrhone their king simply because of their easier, faster and overally more efficient utilization. For now Bitcoin is still and for some probably will be a number one and it might take some time for this status to change, but if our results are correct and if its price is already driven by Ethereum at least a little bit, change might come very soon.
For future research it might be usefull and I would highly recommend to include other big altcoins or even assets like gold to a single model in order to either prove that Bitcoin is losing its dominant position or that it strenghtens it.

Bibliography

Alaoui, M. E., E. Bouri, & D. Roubaudc (2018): "Bitcoin priceâ€"volume: A multifractal cross-correlation approach." https://doi.org/10.1016/j.frl.2018.12.011.

Baur, D. G., K. J. Hong, & A. D. Lee (2015): "Bitcoin â€" Currency or Asset? ." https://ssrn.com/abstract=2736020.

Bilgili, F. (1998): "Stationarity and cointegration tests: Comparison of Engle - Granger and Johansen methodologies." https://mpra.ub.uni-muenchen.de/id/eprint/75967.

Bissias, G., B. N. Levine, & D. Thibodeau (2018): "Using Economic Risk to Model Miner Hash Rate Allocation in Cryptocurrencies ." arXiv:1806.07189[cs.CR].

Ciaian, P., M. Rajcaniova, & d. Kancs (2015): "The economics of BitCoin price formation." https://doi.org/10.1080/00036846.2015.1109038.

Ciaian, P., M. Rajcaniova, & d. Kancs (2017): "Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets." https://doi.org/10.1016/j.intfin.2017.11.001.

Dastgir, S., E. Demir, G. Downing, G. Gozgor, & C. K. Marco-Lau (2018): "The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test ." https://doi.org/10.1016/j.frl.2018.04.019.

Dyhrberg, A. H. (2016): "Bitcoin, gold and the dollar â€" A GARCH volatility analysis ." https://doi.org/10.1016/j.frl.2015.10.008.

Filip, O., K. Janda, L. Kristoufek, & D. Zilberman (2017): "Food versus fuel: An updated and expanded evidence." https://doi.org/10.1016/j.eneco.2017.10.033.

Glaser, F., K. Zimmermann, M. Haferkorn, M. C. Weber, & M. Siering (2014): "Bitcoin â€" asset or currency? revealing usersâ€™ hidden intentions." https://ssrn.com/abstract=2425247.

H.Akaike (1947): "A new look at the statistical model identification ." *IEEE* **19**.

Kristoufek, L. (2013): "BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era." https://www.nature.com/articles/srep03415?WT.ec_id=SREP-20131210.

Kristoufek, L. (2015): "What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis." https://doi.org/10.1371/journal.pone.0123923.

Ozisik, A. P., G. Bissias, & B. Levine (2018): "Estimation of Miner Hash Rates and Consensus on Blockchains (draft)." arXiv:1707.00082[cs.CR].

Vrieze, S. I. (2012): "Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC)." http://dx.doi.org/10.1037/a0027127.

Wu, J., W. Chen, Z. Zheng, C. Chen, & Y. Zhou (2019): "Market Manipulation of Bitcoin: Evidence from Mining the Mt. Gox Transaction Network." arXiv:1902.01941q-fin.GN.

Yang, Y. (2005): "Can the strengths of AIC and BIC be shared? A conflict between model indentification and regression estimation ." *Biometrika* **92**: p. 937â€"950. https://doi.org/10.1093/biomet/92.4.937].

Zhu, Y. (2017): "Analysis on the influence factors of Bitcoinâ€™s price based on VEC model." https://doi.org/10.1186/s40854-017-0054-0.

Appendix A

Appendix A

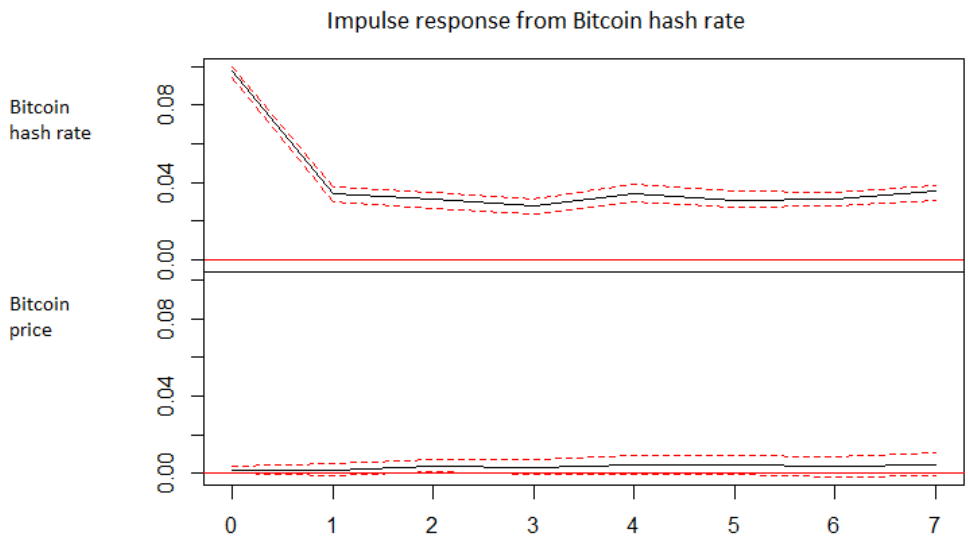


Figure A.1: Impulse response function from Bitcoin hash rate - Lifetime

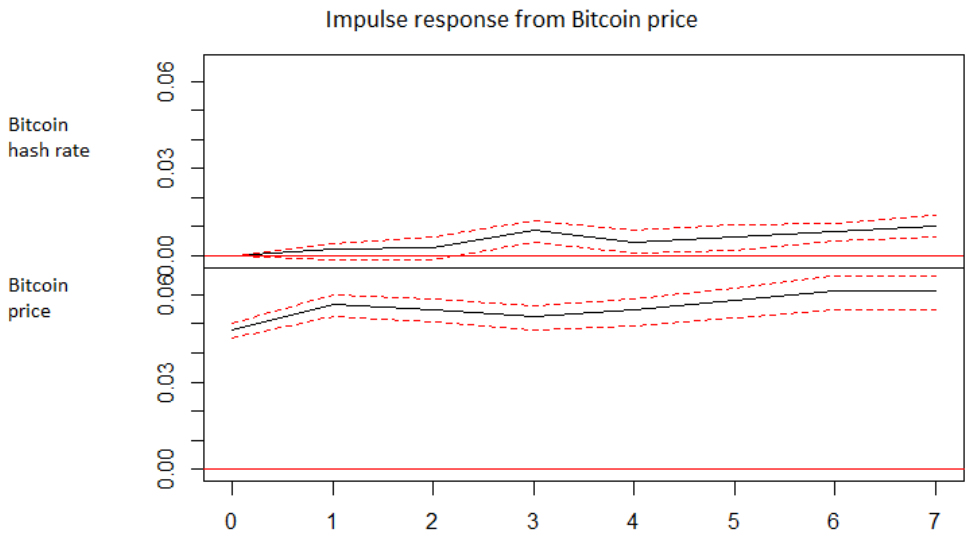


Figure A.2: Impulse response function from Bitcoin price - Lifetime

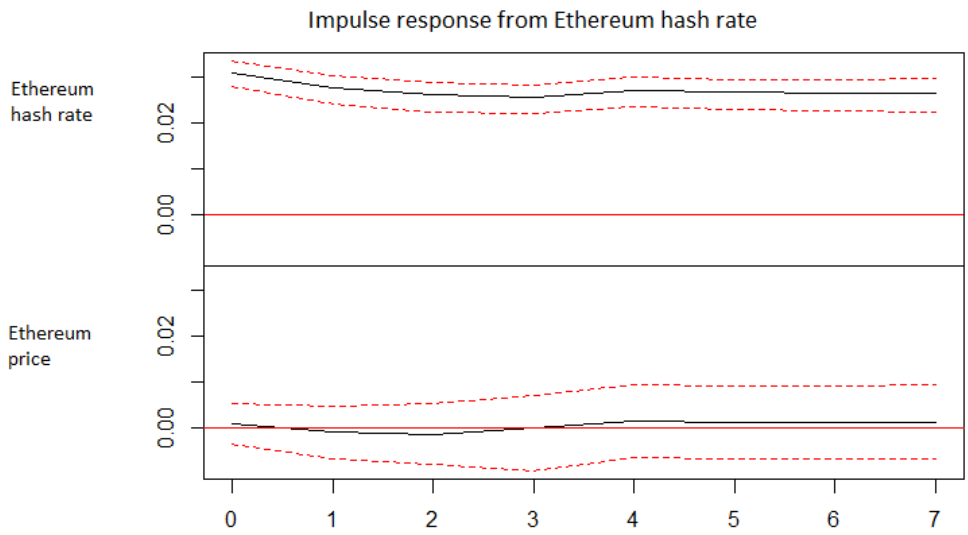


Figure A.3: Impulse response function from Ethereum hash rate - Lifetime

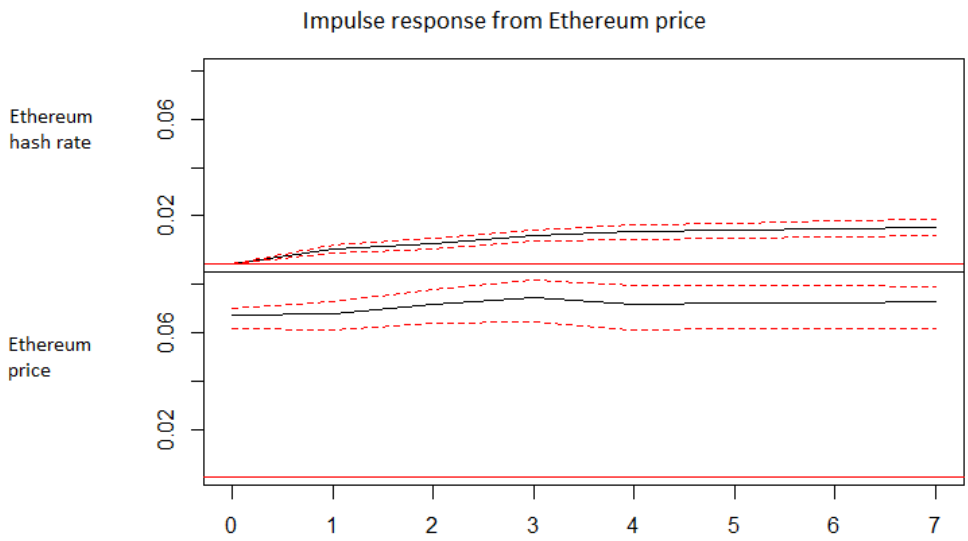


Figure A.4: Impulse response function from Ethereum price - Lifetime

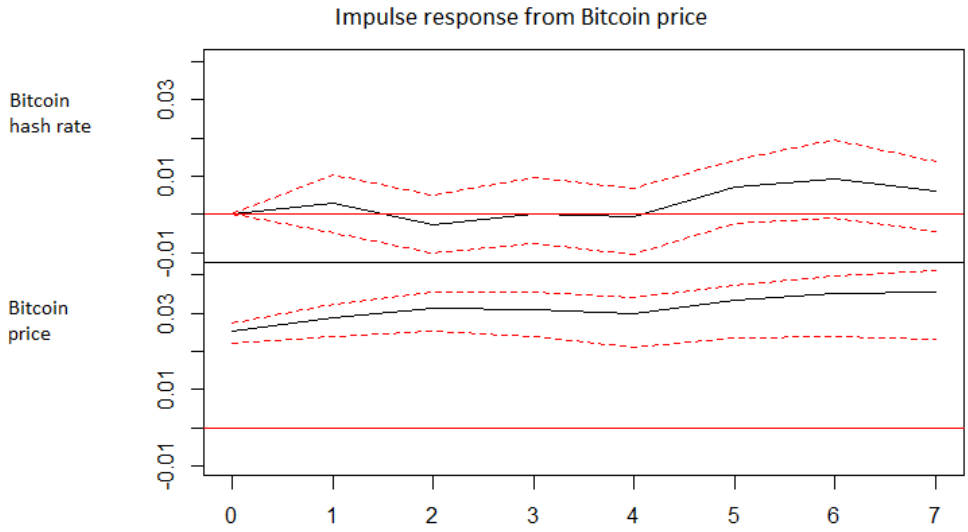


Figure A.5: Impulse response function from Bitcoin price - After bubble

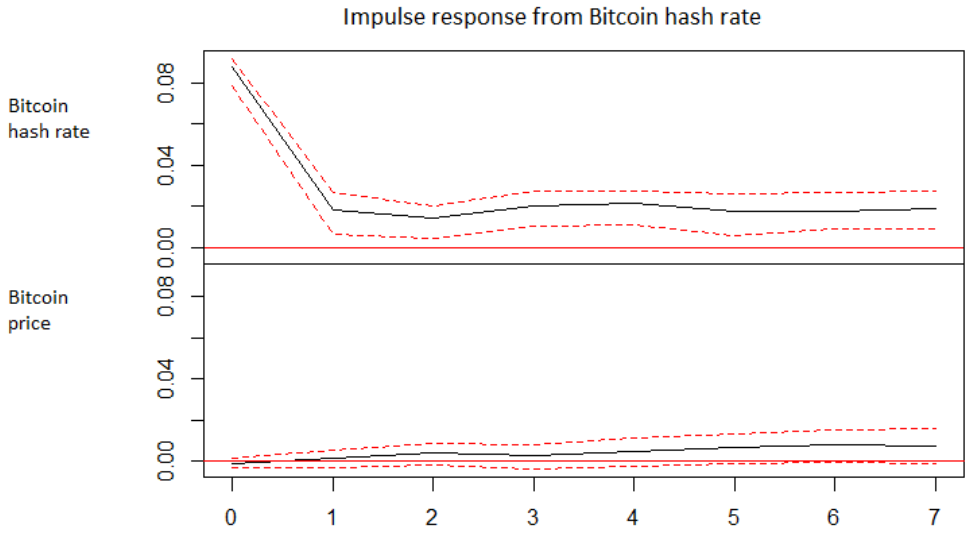


Figure A.6: Impulse response function from Bitcoin hash rate - After bubble

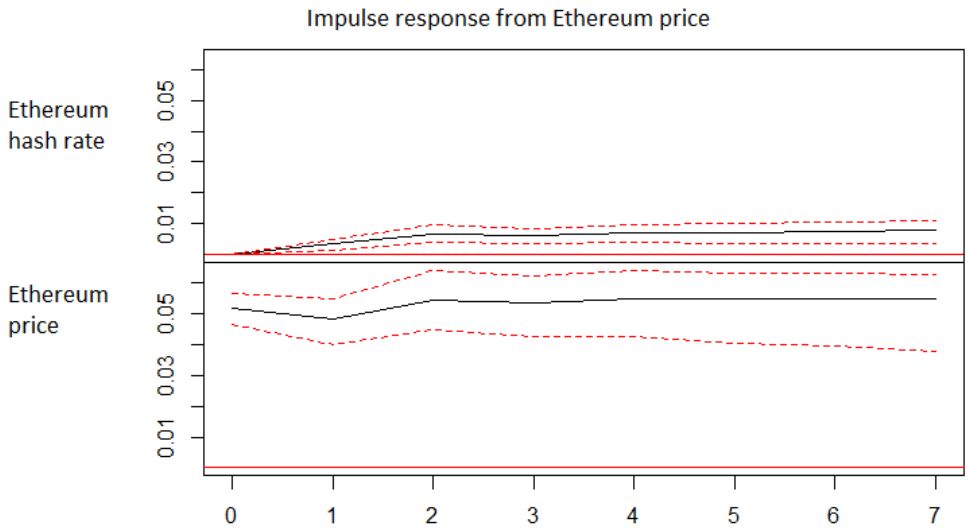


Figure A.7: Impulse response function from Ethereum price - After bubble

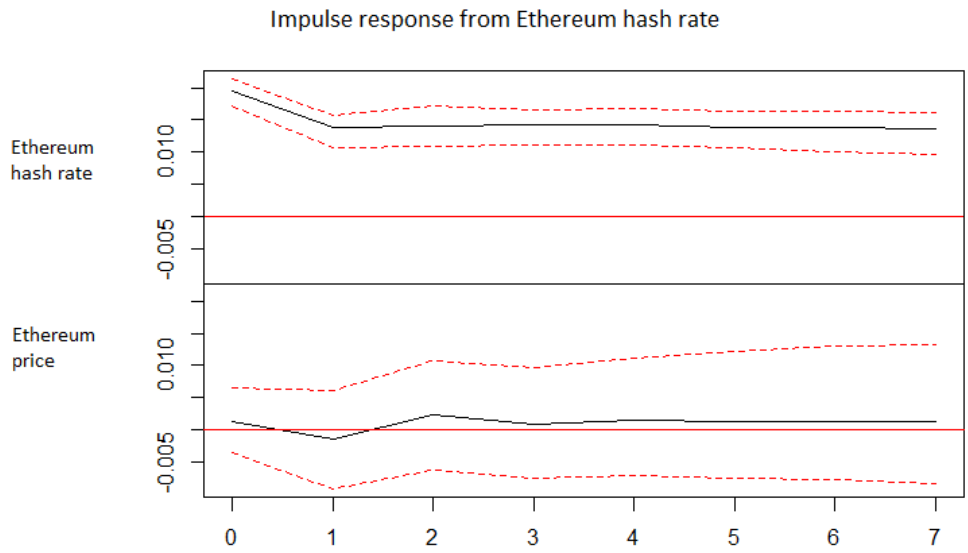


Figure A.8: Impulse response function from Ethereum hash rate - After bubble

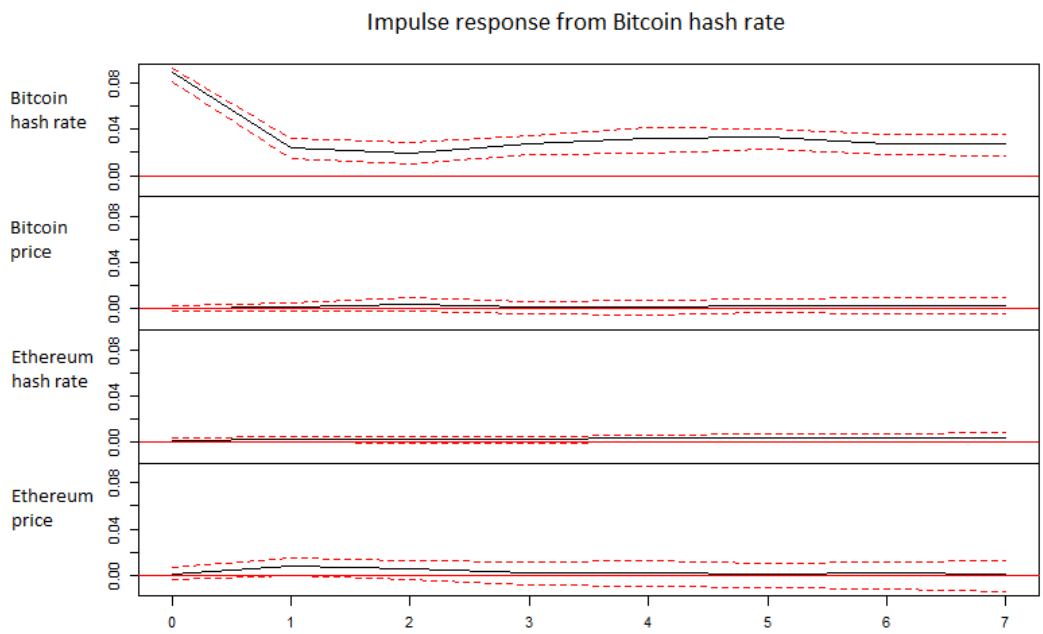


Figure A.9: Impulse response function from Bitcoin hash rate

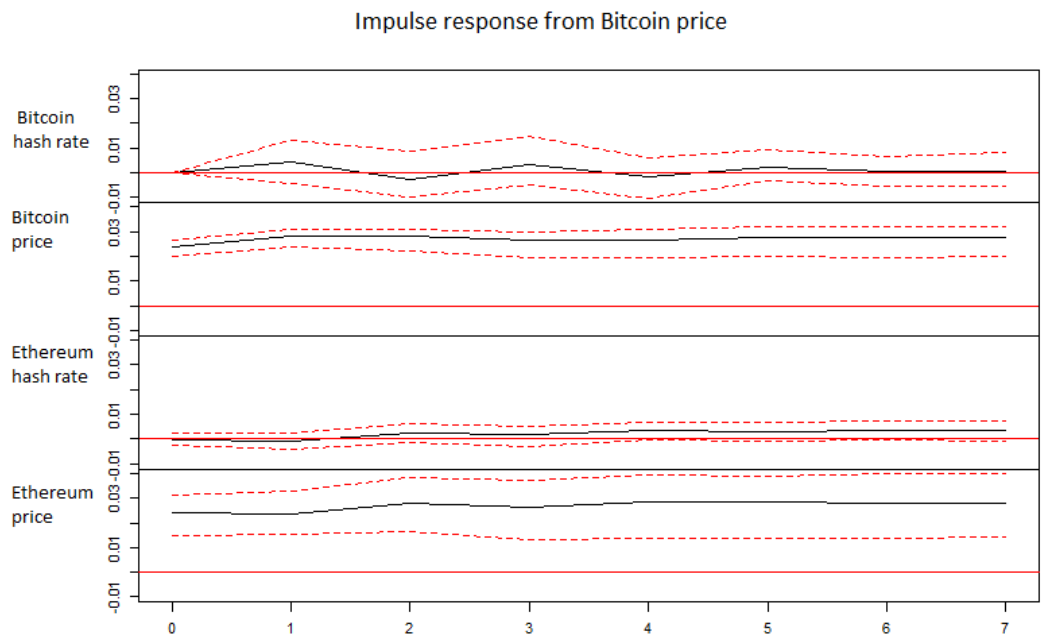


Figure A.10: Impulse response function from Bitcoin Price

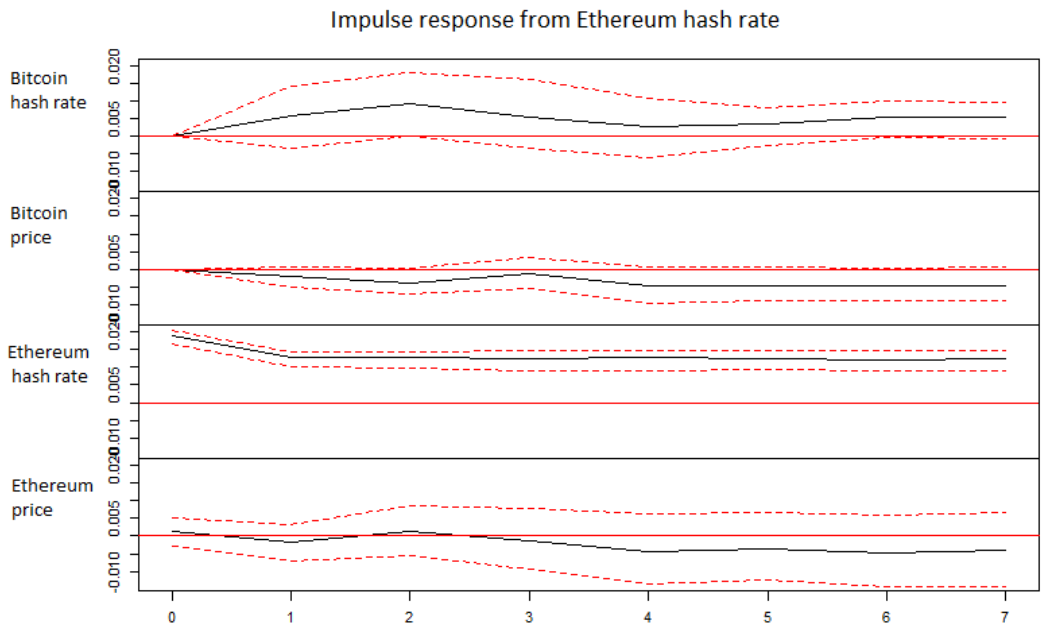


Figure A.11: Impulse response function from Ethereum Price

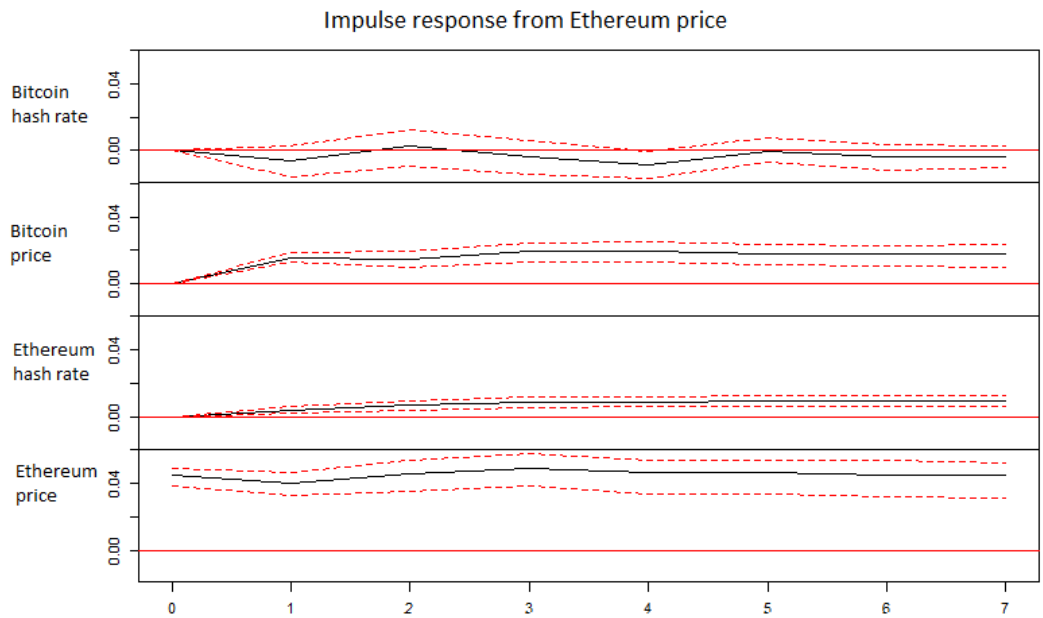


Figure A.12: Impulse response function from Ethereum Price