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FACULTY OF SOCIAL SCIENCES

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Bachelor thesis

2019 **Michael Heller**

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Examining the relationships among cryptocurrencies using Google Trends

Bachelor thesis

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Abstract

The topic of our thesis is the examination of the relationships among cryptocurrencies using Google Trends. In our thesis, we concentrated on four cryptocurrencies, namely: Bitcoin, Litecoin, Ethereum Classic and Ethereum. We obtained the data of daily opening prices, daily trading volumes and daily Google Trends queries in order to examine the relationships among the four cryptocurrencies. Applying the Vector autoregression model and Vector error correction model, we constructed four models. The first model contains only four time series of daily prices of cryptocurrencies. The second model is the first model enriched by the respective four time series of Google Trends queries. The third model contains the four time series of daily trading volumes of the four cryptocurrencies. The fourth model is the third model enriched by the four time series of Google Trends queries of respective cryptocurrencies. Then we applied the Impulse response analysis and the Forecast error variance decomposition in order to find some relationships among the variables. We found that there is some correlation among prices, volumes and Google Trends queries containing the names of the four cryptocurrencies. According to our results acquired by the Forecast error variance decomposition, in all our models, Bitcoin has the strongest explaining power of the variation of the variables.

Keywords

Google Trends, cryptocurrency, Vector autoregression, Vector Error Correction model, Bitcoin, Litecoin, Ethereum Classic, Ethereum

Abstrakt

Tématem naší práce je zkoumání vztahů mezi kryptoměnami pomocí nástroje Google Trends. V naší práci se soustředíme na 4 kryptoměny: Bitcoin, Litecoin, Ethereum Classic a Ethereum. V naší práci jsme získali denní data pro otevírací ceny, denní obchodované objemy a denní data Google Trends dotazů, zachycujících relativní popularitu vybraných kryptoměn. Pro hledání vztahů mezi čtyřmi vybranými kryptoměnami jsme použili Vektorovou autoregresi a Vektorový Error Correction model. Celkem jsme sestavili 4 různé modely. První model obsahuje 4 časové řady denních cen jednotlivých kryptoměn. Druhý model vychází z prvního modelu a je rozšířen o další 4 časové řady Google Trends dotazů souvisejících s danými kryptoměnami. Třetí model obsahuje 4 časové řady denních obchodovaných objemů jednotlivých 4 kryptoměn. Čtvrtý model vychází ze třetího modelu a je obohacen o další čtyři časové řady Google Trends dotazů souvisejících s danými kryptoměnami. Následně jsme použili odezvu na impuls a rozklad rozptylu pro zkoumání vztahů mezi jednotlivými kryptoměnami. V naší práci jsme našli určité korelace mezi proměnnými, v rámci každé ze tří skupin proměnných, tj. ceny, obchodované objemy a Google Trends dotazy. Podle našich výsledků získaných analýzou rozptylu, ve všech našich modelech, má Bitcoin největší podíl na vysvětlování chování proměnných v našich modelech.

Klíčová slova

Google Trends, kryptoměny, Vektorová autoregrese, Vektorový Error Correction model, Bitcoin, Litecoin, Ethereum Classic, Ethereum

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, 8 May 2019

Signature

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Bachelor thesis proposal

Author	Michael Heller
Supervisor	doc. PhDr. Ladislav Krištoufek Ph.D.
Topic	Examining the relationships among cryptocurrencies using Google Trends

Research question and motivation

In recent years, there have emerged two interesting phenomena - cryptocurrencies and Google Trends (Kristoufek, 2013). Cryptocurrencies has no fundamental value, what can lead to interesting dynamics at financial market with cryptocurrencies (Kristoufek, 2013). On the other side, there is a google search analysis tool Google Trends, which is based on Google Search. The Google Trends shows how often a particular query is searched relatively to the total search-volume across various regions of the world, and in various languages (Insights into what the world is searching for – the new Google Trends, Yossi Matias, Insights Search, The official Google Search blog, September 28, 2012). It would be interesting to find out if there are some relationships among cryptocurrencies as Bitcoin, Litecoin, Ethereum and Ethereum Classic. The time series data of queries regarding each cryptocurrency can be collected from Google Trends. Then the time series data of prices and volumes of all these cryptocurrencies can be obtained.

Contribution

According to my best knowledge, there are some theses examining relationships between Bitcoin and Google Trends data but there is no thesis using Google Trends to examine the relationships between Litecoin and the other cryptocurrencies.

The results of this thesis will form plausible evidence for building an investment portfolio through trading with cryptocurrencies. This thesis could broaden the awareness about the behaving of cryptocurrencies at financial markets.

Methodology

The vector autoregression methodology will be applied in order to examine the relationships among cryptocurrencies with the aim to answer two specific questions. First question is the variation of volume of the Litecoin traded at some financial market in the volume searched by Google Trends and prices of each other cryptocurrencies traded at some financial market. The second one is the variation of price of the Litecoin in volume searched by Google Trends and price of each other cryptocurrencies traded at some financial market. The time series for Google Trends queries will be obtained from http://www.google.com/trends and the time series for prices and volumes of the cryptocurrencies from http://www.bitcoincharts.com or from https://www.bfxdata.com/datadownload/. After obtaining the data, the Augmented Dickey-Fuller test and the KPSS test for testing the stationarity will be used. If the unit root in both analyzed series would be found, the time series for the cointegration would have to be tested. If there would be the stationarity present in the time series, then the vector autoregression will be applied.

Outline

1. Introduction
2. Introduction to vector autoregression analysis
3. Data analysis and testing stationarity of the data
4. Applying the vector autoregression analysis for the data
5. Discussion of results and comparison with other conclusions from previous research
6. Conclusions and suggestions for further research

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Contents

Notation

Δy_t	first differences of time series y_t
$\mathbb{E}$	expected value
ϵ_t or u_t	residual error term
$\{y_t\}$	time series
$\mathbb{I}$	identity matrix
μ	population mean
$I(d)$	integrated of order d
BTC	Bitcoin
ETC	Ethereum Classic
ETH	Ethereum
h($\mathbf{\Pi}$)	rank of the matrix $\mathbf{\Pi}$
LTC	Litecoin
m	number of equations in a model
p	number of lags in an autoregressive process
r	number of cointegration relationships
T	length of a time series

1 Introduction

In December 2017, one Bitcoin was traded for USD 20,000 per unit and the market capitalization has reached over USD 300 billion. On the contrary, since May 2017 until today - February 2019, the price of Bitcoin has not exceeded USD 10,000. Therefore, we believe that this huge market bubble was one of the main motivation for many economist to conduct a research regarding the behavior of Bitcoin [21].

In 2018, Sovbetov [58] wrote that in 2017, the popularity, attention and use of cryptocurrencies has increased dramatically. He speculates that a lot of people are "investing" huge amounts of money into such assets that have no history of producing revenue or profit. According to Sovbetov [58], the prices of those assets are rising only as a consequence of many people buying them. He also wrote that there are two major views on cryptocurrency market. On one hand there are people who argue that it is a bubble with no real assets that will inevitably end with a burst. On the other hand, there are people who believe that the cryptocurrency markets will become more and more important part of the financial world. These people believe that cryptocurrencies will give an opportunity to millions of people to participate in a global financial network, which is worth tens of trillion of dollars. These facts encourage us to deal with the topic concerning cryptocurrencies.

Utilization of Google Trends in economics and finance is another relatively new phenomena [15]. According to Google Trends [34], Google Trends is a searching tool giving the relative frequency of lookups for a searched query by Google search, with respect to geographical area and time range. According to Google Trends, the resulting data are obtained through a transformation of the real searches. Results of the transformation are proportionate to the time and location of a query carried out by the process described below.[1]

- Each data point is divided by the total searches counts of the geography, i.e. each data point is representative of specific geographic area and

[1] The following process description is taken from Google Trends support [34].

time range. It compares the relative popularity and scores the most trending one highest. Otherwise, places and time periods with the most search volumes are always ranked highest.

- The resulting numbers are then scaled to a range between 0 and 100, based on a topic's proportion to all searches on all topics.

- Different regions that show the same search interest for a term do not always have the same total search volumes.

Google Trends data is an unbiased sample of Google search data. Only a percentage of searches are used to compute Google Trends data. There are 2 types of Trends data:

- Realtime data is a random sample of searches obtained from the last 7 days.

- Non-realtime data is a random sample of Google search data that can be pulled from as far back as 2004 and up to 36 hours before your search.

After search data are collected, they categorize it, match it to a topic, and remove any personal information from it.

Data that are excluded:

- Searches made by very few people: Trends only shows data for popular terms, so search terms with low volumes appear as "0".

- Duplicate searches: Trends eliminate repeated searches from the same person over a short period of time.

- Special characters: Trends filter out queries with apostrophes and other special characters.

Recently there has been an extensive amount of scientific work done examining the behavior of Bitcoin using Google Trends. These include: BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era - L Kristoufek - Scientific reports, 2013 - nature.com [39], Characteristics of Bitcoin users: an analysis of Google search data - A Yelowitz, M Wilson - Applied Economics Letters, 2015 - Taylor & Francis [60], or Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin - ET Cheah, J Fry - Economics Letters, 2015 – Elsevier [14].

There are three main reasons which have brought us to the topic of our bachelor thesis. The first reason is the raising attention and increase in trading with cryptocurrencies during the last 10 years [21].

The second and third reasons are connected. On one hand, there is unpredictability of behaviour of cryptocurrencies, because their prices are not directly dependent on their intrinsic value or development of an economy or company. Therefore, it is very difficult to predict them or to estimate the future behaviour of cryptocurrency markets [50].

On the other hand, nowadays, we have relatively new feature Google Trends, which can be able to partially explain the behaviour of investors trading with cryptocurrencies, who are probably the key movers of these prices.

In 2013, Preis et al. [54] have shown that Google searches for financial terms can be employed in trading strategies, which can be profitable.

In 2013, Kristoufek [40] used the Google search queries for examining the Dow Jones stock popularity and then he used the information for portfolio diversification.

In further scientific research, Kristoufek [39] uncovered a strong relationship between Google searches, Wikipedia page views and dynamics of the Bitcoin cryptocurrency.

In our thesis we try to examine the relationships between the prices and trading volumes of a cryptocurrencies as we believe that there may exist a strong correlation between them. We expect that Google trends could potentially serve as a good auxiliary tool for examining the relationships among several cryptocurrencies.

Nowadays, there are only 20 cryptocurrencies out of more than 2000, which have market capitalization over USD 500 million [21]. For our thesis we have decided to concentrate on four cryptocurrencies, namely: Bitcoin (BTC), Litecoin (LTC), Ethereum Classic (ETC) and Ethereum (ETH). The reasons for choosing these for our thesis are the following. All of the above have the market capitalization over USD 500 million [21]. According to Coin Market Cap [21], Bitcoin and Ethereum have the largest market capitalization among all cryptocurrencies in the world. Then, Ethereum Classic had a common history with Ethereum until July 2016. Finally, according to the official website of Litecoin, it is verified medium of commerce complementary to Bitcoin [44].

According to the official website of Bitcoin [10], Bitcoin is a decentralized network that enables a new payment system through a completely digital money. It is the first decentralized peer-to-peer payment network that has no central authority or middlemen that would check the transactions among its users. Bitcoin is very suitable for trading or making a transaction over the Internet. Bitcoin is powered by its users and it can also be considered as the most interesting triple entry bookkeeping system in existence [10].

According to the official website of Bitcoin, users are obliged to have a mobile application or computer program in order to use Bitcoin as a payment system. They use the application as an electronic wallet and send their bitcoins using it. The Bitcoin network is based on a public ledger called the "blockchain" [50]. This ledger contains all transactions in the history of Bitcoin. Each transaction is verified by blockchain and signed and protected by digital signatures corresponding to the sending addresses of the users. Therefore, all users have full control to send bitcoins using their own Bitcoin addresses. Anyone, who has the application, can buy bitcoins at cryptocurrecy market. In another way, he or she can be paid by someone, who already owns bitcoins, for some good or service, and or he or she can "mine" bitcoins. The "mining" is a process, where people provide the computing power of his or her computer to verify all the new transactions in the Bitcoin blockchain. These Bitcoin “miners” are then rewarded for their “work” with new bitcoins [11].

In February 2019, BTC had market capitalization almost USD 70 billion and the price of one BTC was around USD 4000 [21].

The second cryptocurrency that we decided to concentrate on is Litecoin. According to the official website of Litecoin [44], it is open source, decentralized and peer-to-peer network that enables a new type of a payment system. Among the advantages of Litecoin, we consider almost zero cost and the fact that there is no central authority, who would influence the system [44].

Litecoin compared to Bitcoin, is using a software which is able to generate the block in its blockchain more frequently. Due to this advantage, Litecoin blockchain is able to handle more transactions in a time period, than Bitcoin blockchain and the software will be up to date in the future without any modification [44].

According to the official website of Litecoin, Litecoin is the second most popular cryptocurrency after Bitcoin. They also claim that due to the significant industry support, huge trading volume and high liquidity of Litecoin, it can be a good complement to Bitcoin in commerce. In comparison of Litecoin and Bitcoin, Litecoin overcomes Bitcoin with faster transaction confirmation times (2.5 minutes) and better storage efficiency [43, 48, 50].

In February, 2019, LTC had market capitalization almost USD 3 billion and the price of one LTC was around USD 50 [21].

According to the official website of Ethereum Classic [27], Ethereum Classic is a network, community and a smart blockchain. It is also cryptocurrency or digital asset. Ethereum Classic enables the people to use it as payment system or send some “value” to someone else in general. Using Ethereum Classic, people can operate complex contract. The advantage of Ethereum Classic is that it can not be censored or modified [27].

Ethereum Classic has evolved from Ethereum after a hack attack on the DAO, venture capital fund [49]. The Decentralized Anonymous Organization (DAO) is a organization investing in projects using smart contracts via

Ethereum currency. In May 2016, the fund has reached around USD 168 million of its value. In June 2016, hackers have stolen about 3.6 million Ether, what was approximately USD 50 million, from the fund. Members of DAO and the Ethereum community led discussion about what attitude should they stand for. In July 2016, they decided to implement a hard fork to the Ethereum blockchain code, and the stolen Ethers were given back to the original owners through a new smart contract. Part of the Ethereum community has decided to reject the hard fork, because of "immutability principle" the blockchain cannot be changed once it is written. On July 20$^{\text{th}}$, 2016, the first Ethereum Classic block was not included in the forked Ethereum chain, the block number 1,920,000 and the Ethereum Classic was born [5, 42, 49, 53].

In February 2019, the market capitalization of ETC was over USD 460 million and the price of one ETC was around USD 5 [21].

The fourth cryptocurrency is Ethereum. In February 2019, ETH had market capitalization almost USD 15 billion and the price of one ETH was around USD 150. It is the second most market capitalized cryptocurrency after BTC [21].

Ethereum is a new system of payment. All the transaction of the clients using Ethereum platform are executed by machines [28].

Below, we would like to summarize the main research questions of our thesis.

1. Does any relationships among prices of cryptocurrencies, namely Bitcoin, Litecoin, Ethereum Classic and Ethereum exist, and what are they?

2. Do Google Trends queries regarding relevant cryptocurrencies improve the examination of the relationships among prices of cryptocurrencies?

3. Does any relationships among trading volumes of cryptocurrencies, namely Bitcoin, Litecoin, Ethereum Classic and Ethereum exist, and what are they?

4. Do Google Trends queries regarding relevant cryptocurrencies improve the examination of the relationships among trading volumes of cryptocurrencies?

The thesis is structured as follows: in the subsequent section we will review the literature and past results from our field of interest. In chapter Methodology, we will introduce the Vector autoregression and Vector Error Correction models. We will also describe the issues regarding non-stationary time series. In chapter named Data, we will present how we have obtained data, the descriptive statistics of the obtained time series and finally test the time series for stationarity. In chapter Applying the Vector autoregression model, we will estimate the models for our data and we will present the diagnostics of our model. In chapter Results, we will present the results from our models. In chapter Discussion of the results, we will discuss the results from our models and compare them with previous research. Finally, in the last chapter we will present the main findings and conclude the thesis.

2 Literature review

In 2005, Ettredge, Gerdes and Karuga [29] conducted their study through the 77-week period and found that Web-based search data is associated with future unemployment data [29]. Due to their results, they suggest that search-term data might be useful in predicting other important macroeconomic statistics.

Around the same time, Cooper et al. [22] conducted their research concerning the search activity and cancer incidence. They found that The Yahoo! search activity associated with specific cancers is correlated with estimated incidence of specific cancers (Spearman rank correlation, $\rho = 0.50, P = .015$), estimated mortality of specific cancers ($\rho = 0.66, P = .001$), and volume of related news coverage ($\rho = 0.88, P < .001$) [22].

According Choi et al. [15], these two papers were among the first ones to use web search data for forecasting economic statistics. In the field of epidemiology, for instance, Polgreen et al. [52] have conducted a research using internet searches for influenza surveillance. Their models, based on search frequencies, have predicted positive increase in cultures of influenza from 1 to 3 weeks in advance before their occurrence with p-value: ($P < .001$). Moreover, similar models have predicted increase in mortality attributable to pneumonia and influenza up to 5 weeks in advance ($P < .001$) [52].

Another research in the field of epidemiology, using Google search queries, conducted by Jeremy Ginsberg et al. [32] was concentrated on the detection of influenza epidemics using search engine query data. Their resulting estimates of ILI (Illnesses like influenza) were consistently estimated from 1 to 2 weeks ahead of CDC (the U.S. Centers for Disease Control and Prevention) ILI surveillance reports.

In the field of economics, Choi et al. [15] have found that fixed effects models and simple seasonal autoregressive model with some relevant Google Trends variables tend to outperform models without these Google Trends variables. Their models were applied on data about unemployment, automobile demand, and vacation destinations. They have shown that the relevant Google Trends variables improve the predictions of their models up to 20%, when measuring the Mean Absolute Error of their models.

Guzman [36] has used the metadata, i.e. data about data, constructed from search queries performed on Google search engine to anticipate inflation.

In 2013, Kristoufek [40] has shown that Google queries can be used as a useful tool for portfolio diversification at DJIA (Dow Jones Industrial Average) index. He has utilized Google queries of stock ticker (e.g. GE for General Electric Company or XOM for Exxon Mobil Corporation) for assigning the weights to each stock in a portfolio. Then he has shown that his portfolio diversification strategy performs 163% of cumulative profit during 8.5 years in comparison with 38% of cumulative profit of DJIA index.

In 2013, Preis et al. [54] have shown that their investment strategy based on Google Trends queries has significantly higher overall returns than random strategies. They also found that strategies based on U.S. queries only outperform the strategies based on global queries across the whole world. Their results are consistent with the part hypothesis. First part says that the price of DJIA has significantly increased after decrease in search volume for certain financially related term. The second part says that the price of DJIA has significantly decreased after increase in search volume for certain financially related term. Their results show that performance of the Google Trends strategy differs with the search term chosen.

Matta, Lunesu and Marchesi [47] used Google Trends to analyze Bitcoin's popularity evolving in time. They have used a time series of the volume of queries made by users in Google Search, and found interesting correlation between Bitcoin's price spread and changes in query volumes for the "Bitcoin" search term. They had also analyzed a collection of tweets, mentioning Bitcoin, posted on Twitter from time period January 2015 until March 2015 (60 days). They have collected 1,924,891 tweets during this period, and had used SentiStrength automated sentiment analysis to extract the information about social mood regarding Bitcoin. They have found correlation between price of bitcoins and tweets regarding Bitcoin as well.

In 2011, Bollen et al. [12] tried to examine how a collective mood of a society expressed by tweets is correlated with the values of DJIA. They have utilized OpinionFinder which is a publicly available software package for sentiment analysis that can be applied to determine if the expression of its author is positive or negative. To capture more dimensions of mood in the society they have created a second mood analysis tools, labeled GPOMS, that can differentiate among 6 different mood states in terms of 6 different mood dimensions. These include: Calm, Alert, Sure, Vital, Kind and Happy. GPOMS has been derived from an existing and well-vetted psychometric instrument, called the Profile of Mood States. They have shown that rather calm mood in the society, measured by GPOMS, can predict the evolution of DJIA than positive mood in general, measured by the OpinionFinder.

In 2018, Burnie [13] has examined the correlations among 14 different cryptocurrencies. He has shown that cryptocurrency returns were positively correlated with each other and this association was statistically significant, except for one cryptocurrency, USD Tether. "The pairs Ethereum and Ethereum Classic, and Ripple and Stellar, and Bitcoin and Litecoin had the highest Spearman's ρ correlation values when considering the longer dataset (Table 3)[2]. The positive associations between Bitcoin and Litecoin, and Ethereum and Ethereum Classic were particularly robust." [13]. Therefore, we would expect that we could find some significant relationships among Bitcoin, Litecoin, Ethereum Classic and Ethereum applying the VAR model.

Burnie [13] has shown evidence to support his hypothesis that similar cryptocurrencies in the way of their functionality supplying mechanism or the mechanism of its emergence, are positively associated but he could not specify which characteristics were the important one.

He suggests a hypothesis that when a cryptocurrency is forked from another, the investors can perceive them as similar and they can expect close development of their prices. He also admits that this hypothesis is limited by

[2]This refers to the table in author's publication.

his results regarding correlation between Bitcoin and Bitcoin Cash. According to his dataset, these two cryptocurrencies are not particularly correlated despite the fact, that they share similar name and Bitcoin Cash is a fork from Bitcoin's codebase [9].

In 2018, Sovbetov [58] chose the most common five digital currencies namely: Bitcoin, Ethereum, Litecoin, Dash, and Monero. He examined the interaction of these cryptocurrencies with stock market utilizing SP500 index, with prices of gold, and with macroeconomic indicators such as interest rate. Then he applied the autoregressive distributed lag model to examine both, short-run and long-run dynamics of cryptocurrecy prices. His results indicate that Bitcoin and Ethereum have higher responsiveness to the market in the long-run. In case of the short-run, a unit increase in cryptocurrency market return causes Bitcoin, Ethereum, Dash, Litecoin, and Monero to increase by 0.85, 0.39, 0.04, 0.12, and 0.09 units respectively. He concludes that Bitcoin and Ethereum response more sensitively in the short-run.

Regarding the trading volume, his results show significant long-run impact on Bitcoin at 1% significance level. A unit increase in weekly trading volume for Bitcoin causes 0.14 rise in trading volume of Bitcoin. For Ethereum, Litecoin and Monero, it is just at 10% significance level. A unit increase in weekly trading volume for Ethereum, Litecoin and Monero causes 0.13, 0.06, and 0.03 raises in trading volumes of Ethereum, Litecoin, and Monero cryptocurrencies in the long-run.

In our thesis we would like to focus on the relationships among prices and trading volumes of cryptocurrencies, namely: Bitcoin, Litecoin, Ethereum and Ethereum Classic. We suppose that the relationships among the prices could be connected to the price formation of cryptocurrencies.

According to Sovbetov [58], there are a few cryptocurrency price drivers. Supply and demand of cryptocurrencies are key internal factors that influence the market price of a cryptocurrency. Key external drivers include attractiveness or popularity, legalization or adoption by some institution and few macro-finance factors such as interest rates, stock markets and gold prices.

The previous research has shown that the price of Bitcoin can be affected by the global financial development which can be captured for example by stock exchange indices, exchange rates and oil prices [59].

In 2013, Van Vijk [59] has found that the price of Bitcoin positively depends on the value of DJIA in the long-run. He has also found that in the long-run, the euro-dollar exchange rate and the price of barrel of Crude Oil negatively influence the price of Bitcoin. In the short-run, he has found that the price of Bitcoin in the previous period has negative effect on the change of the price of Bitcoin in current period. The change in value of DJIA has positive effect on the price of Bitcoin.

According to another previous research the price of Bitcoin is determined by three main factors. These three factors are: the interaction of supply and demand of Bitcoin, Bitcoin attractiveness for investors and global macroeconomic and financial developments [8, 40, 59].

On the other side, Ciaian et al. [16] do not support previous findings that macroeconomic and financial developments are one of the key factors which influence the price of Bitcoin. Bartos [8] has found that the price of Bitcoin in the short-run depends on the change in total number of minded bitcoins. In his research, Bartos [8] has also tested the impact of positive and negative announcements concerning Bitcoin. He has found that the Bitcoin price increased by 8% in days with positive announcements and the Bitcoin price has decreased by 14.21% in days with negative announcements, in comparison with another days. He has shown that cryptocurrency markets significantly react to announcements. He suggests that the interesting fact that the negative announcements have higher impact can be caused by risk aversion of the investors. He also adds that the market of cryptocurrencies does not contain any anomaly that we can observe on "classical" financial markets. According to Bartos [8], there can not emerge weekend effect, because Bitcoin is traded 24 hours, 7 days in a week. Also, there can not be January effect, because cryptocurrencies are usually not used for tax optimization. He concludes that his empirical analysis supports the efficient market hypothesis for cryptocurrency market. Thus, prices of cryptocurrencies should reflect all known information and there should not be a possibility to outperform the market unless by through luck or by obtaining some insider information.

Furthermore, his analysis supports the claim that supply and demand of bitcoins are the key factors for the Bitcoin price formation. He adds that results of his analysis contradict findings of previous research claiming that some important macroeconomic indicators have impact on the Bitcoin price formation.

3 Introduction to vector autoregression analysis

3.1 Definition and description of the VAR(p) model

We will apply Vector Autoregression model to our dataset and examine the relationships among given cryptocurrencies. In this chapter, we utilized several sections, regarding the methodology, from textbook Finanční ekonometrie written by Tomáš Cipra [17, 18].

Definition [3]**.** *We say that sequence ϵ_t, for $t = 1, \ldots, T$, is a white noise if the sequence fulfill the following conditions:*

1. $\mathbb{E}\ (\epsilon_t) = 0$ *for all* t
2. $Var(\epsilon_t) = \sigma^2 < \infty$
3. $Corr(\epsilon_t, \epsilon_s) = 0$ *for all* $t \neq s$.

Definition [4]**.** *A $p-th$ order VAR, denoted VAR(p) is a stochastic process model described by the following equation:*

$$\mathbf{y}_t = \mathbf{\Phi}_0 + \mathbf{\Phi}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{\Phi}_p \mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t, \qquad t = 1, \ldots, T,$$

where the observation $\mathbf{y}_{t-i}$ (i periods into the past) is called the $i-th$ lag of a random variable $\mathbf{y}_k$, $\mathbf{\Phi}_0$ is a $(m \times 1)$ vector of intercepts, $\mathbf{\Phi}_1, \ldots, \mathbf{\Phi}_p$ are time-invariant $(m \times m)$ matrices of parameters and $\boldsymbol{\epsilon}_t$ is a $(m \times 1)$ vector of error terms satisfying the following three conditions:

- $\mathbb{E}(\epsilon_t) = \mathbf{0}$, *i.e. every error term has zero mean*
- $\mathbb{E}(\epsilon_t \epsilon_t`) = \mathbf{\Omega}$, *i.e. the contemporaneous covariance matrix of error terms is $\mathbf{\Omega}$ (a $(m \times m)$ positive-semidefinite matrix)*
- $\mathbb{E}(\epsilon_t \epsilon_{t-k}`) = \mathbf{0}$, *i.e. for any non-zero k - there is no correlation across time; in particular, no serial correlation in individual error terms.*

[3]This definition is taken from Cipra [19].
[4]This definition is taken from Cipra [17].

The VAR(p) is a m-dimensional generalization of one-dimensional autoregressive process AR(p). VAR(p) is very useful econometric tool somewhere in between Simultaneous Equations Models (SEM) and one-dimensional time series models [17].

Advantages and disadvantages of VAR model

The advantages of VAR include its richer structure, than is the structure of one-dimensional AR models. The VAR models include not only lagged variables but even the lagged terms of the other variables [17].

Another advantage of VAR model is that all the random variables are endogenous. Therefore, we do not have to specify, which random variables are endogenous, and which are exogenous. Moreover, the practical econometric experience show that using a VAR model, we are able to obtain better predictions than using a SEM model [17].

There are also some disadvantages of VAR. Sometimes, an application of VAR is too technical and there can be problem of a good interpretation and reasoning. Another disadvantage is that we have to find the correct p, the number of lags. Choosing incorrect number of lags, the results will be most likely biased. Moreover, even with low p, for example 1, we get at least $(m \times m)$ of parameters which can be hard to interpret [17].

Another disadvantage of using VAR is that we assume that each one-dimensional autoregressive process is stationary. If they are not, we can lose some information about the relationships among individual processes during the differencing [17].

Interpretation of coefficients in VAR(1) model

Let us consider that we have the lag $p = 1$ and 2 dimensions, i.e. $m = 2$. Then we can describe our model in two equations in the following manner:

$$y_{1t} = \phi_{10} + \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + \epsilon_{1t} \tag{1}$$

$$y_{2t} = \phi_{20} + \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + \epsilon_{2t} \tag{2}$$

Let us also assume that covariance matrix Σ of white noise is diagonal, i.e. all the components of the white noise are uncorrelated, then we can state that:[5]

- If $\phi_{12} = \phi_{21} = 0$, then y_{1t} and y_{2t} are contemporaneously uncorrelated.
- If $\phi_{12} = 0$ and $\phi_{21} \neq 0$, then there exists one directional dependency of y_{2t} on y_{1t}.
- If $\phi_{12} \neq 0$ and $\phi_{21} \neq 0$, then there exists feedback between y_{1t} and y_{2t}

.

Estimation and diagnostics of VAR model

It is possible to estimate VAR model by two ways. Either, we can estimate VAR model by the Maximum likelihood Estimation (MLE) method or by the Ordinary Least Squares (OLS) method. In that case, if we use MLE method, we have to assume some distribution of white noise [17].

After the estimation of VAR model, we should primarily check the stationary condition for the VAR model, which is described in the next Section 3.2. Then, we will apply diagnostic procedures for testing if the estimated error terms are uncorrelated in time.

Using Jarque-Bera test [38], we can test the normality of estimated error terms [17].

3.2 Problem of stationarity

In general, the stationarity of a time series means that the dynamics of the time series is stochastically stable. For one-dimensional time series we distinguish strong (or strict) and weak stationarity.

Strict stationarity means that probabilistic behavior of a stochastic process is invariant in time, i.e. the joint distribution of vector $(y_{t1}, \ldots, y_{tk})$ is the same as the joint distribution of vector $(y_{t1+h}, \ldots, y_{tk+h})$ for any positive integer h. Weak stationarity is less restrictive than the strict stationarity, because it is sufficient if the stochastic process is time invariant just for the moments of the second order, i.e. for every t and s it holds:

[5]This interpretation is taken from Cipra [17].

1. $\mathbb{E}(y_t) = \mu = constant$

2. $Cov(y_t, y_s) = \mathbb{E}(y_t - \mu)(y_s - \mu) = Cov(y_{t+h}, y_{s+h})$ for any h,

   i.e. specially also $Var(y_t) = \sigma_y^2 = constant$

In other words, the level and the variance of a stationary time series is constant in time. Therefore, any time trend, seasonality or changing variance in time automatically violate the stationarity assumption [17].

Generalization of stationarity for multivariate time series

The generalized definition of (weak) stationarity can be formulated in the following manner: [6]

The weak stationarity of multidimensional time series $\{\mathbf{y}_t\}$ means that the generating stochastic process of this time series is invariant in time for the second order moments, i.e.:

1. $\mathbb{E}(\mathbf{y}_t) = \boldsymbol{\mu} = constant$

2. $Cov(\mathbf{y}_t, \mathbf{y}_s) = \mathbb{E}(\mathbf{y}_t - \boldsymbol{\mu})(\mathbf{y}_s - \boldsymbol{\mu})^\top = Cov(\mathbf{y}_{t+h}, \mathbf{y}_{s+h})$ for any h,

   i.e. specially also

   $Var(\mathbf{y}_t) = \boldsymbol{\Sigma}_{\mathbf{yy}} = constant$, where $\boldsymbol{\Sigma}_{\mathbf{yy}}$ is the covariance matrix of time series $\{y_{1t}\}, \ldots, \{y_{mt}\}$.

Sufficiency condition for (weak) stationarity of VAR model

The sufficiency condition for (weak) stationarity of VAR(1) is that all m eigenvalues of matrix $\boldsymbol{\Phi}$ lie inside unit circle in the complex plane, i.e. they are in absolute value strictly lower than 1. Eigenvalues of matrix $\boldsymbol{\Phi}$ are the roots of polynomial equation $det(\boldsymbol{\lambda}\mathbb{I} - \boldsymbol{\Phi}) = 0$ or equivalently inverse roots of polynomial equation $\boldsymbol{\Phi}(z) = \mathbb{I} - \boldsymbol{\Phi}z$. In the second case, the sufficiency condition is formulated inversely, i.e. all m roots of the polynomial equation $\boldsymbol{\Phi}(z) = \mathbb{I} - \boldsymbol{\Phi}z$ lie outside unit circle in the complex plane.

[6] This definition is taken from Cipra [17].

Then, the generalization of the sufficiency condition for stationarity and linearity is that all roots of the polynomial equation

$$\mathbf{\Phi}(z) = \mathbb{I} - \mathbf{\Phi}_1 z - \cdots - \mathbf{\Phi}_p z^p \tag{3}$$

lie outside of unit circle in the complex plane [17].

3.3 Testing the stationarity

DF test

Dickey-Fuller test or DF-test [23, 24, 30] is pioneering test for unit roots in a time series process. There are three versions of DF-test, called τ - tests.

1. τ–*test* : $H_0 : y_t = y_{t-1} + \epsilon_t$ against $H_1 : y_t = \phi_1 y_{t-1} + \epsilon_t$, where $\phi_1 < 1$.

   It is a one-sided test for random walk against stationary AR(1) process. Cases of non-stationary time series with $\phi_1 \leq -1$ are not important for usual practice.

2. τ_μ–*test* : $H_0 : y_t = y_{t-1} + \epsilon_t$ against $H_1 : y_t = \alpha + \phi_1 y_{t-1} + \epsilon_t$, where $\phi_1 < 1$.

   It is a one-sided test for random walk against stationary AR(1) process with intercept.

3. τ_τ–*test* : $H_0 : y_t = y_{t-1} + \epsilon_t$ against $H_1 : y_t = \alpha + \beta t + \phi_1 y_{t-1} + \epsilon_t$, where $\phi_1 < 1$.

   It is a one-sided test for random walk against stationary AR(1) process with intercept and a linear trend captured by parameter β.

For all these versions of DF-tests we can rewrite the hypotheses:

$$H_0 : \Delta y_t = \psi y_{t-1} + \epsilon_t \qquad \text{for} \quad \psi = 0 \tag{4}$$

against

$$H_1 : \Delta y_t = \alpha + \beta t + \psi y_{t-1} + \epsilon_t \qquad \text{for} \quad \psi < 0, \tag{5}$$

where $\psi = \phi_1 – 1$, 1. $\alpha = \beta = 0$, 2. $\beta = 0$

Test statistics for all three versions of DF-test use t-test:

$$DF = \frac{\hat{\psi}}{\hat{\sigma}(\hat{\psi})} \tag{6}$$

with critical region:

$$DF \leq t_{\alpha}(n). \tag{7}$$

If H_0 holds, then the DF-test statistics does not follow t-distribution, even asymptotically. The critical values have to be calculated by simulation. Generally, the distribution has heavier tails than t-distribution [18].

Augmented DF-test

We can use DF-test only if the errors ϵ_t are the white noise, i.e. $\mathbb{E}(\epsilon_t) = 0$, $Var(\epsilon_t) = \sigma^2 < \infty$ and $Corr(\epsilon_t, \epsilon_s) = 0$ for $t \neq s$. If the dependent variable Δy_t suffer from autocorrelation, which is not captured in the model, then the type 1 error, i.e. incorrectly rejecting the H_0, is greater than the tabulated values. In such cases, we should use the Augmented Dickey-Fuller test (ADF). The null hypothesis of ADF is:

$$H_0 : \Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \epsilon_t \qquad \text{for} \qquad \psi = 0. \tag{8}$$

The test statistics and the critical values are the same for all versions of the DF-test. There are autoregression terms added into the model, which should capture the dynamic structure of the variable Δy_t. We should use the information criteria, which will be discussed in Section 3.4 to choose the correct number of lags p [18].

KPSS-test

KPSS-test named after its authors Kwaitkovski, Phillips, Schmidt, Shin [41] is a suitable complement to ADF-test. Let us consider a theoretical model described by following equation:

$$y_t = 0.95 y_{t-1} + \epsilon_t, \tag{9}$$

where ϵ_t is the white noise. We can see that the null hypothesis of unit root presence should be rejected but it may happen that ADF – test can not be rejected at some significance level. It can be caused by too small dataset. Therefore, there is KPSS test. KPSS test is the same as ADF test but the null hypothesis and the alternative hypothesis are reversed. It is recommended to use both tests together and to rely on two outputs only:

1. H_0 of ADF is rejected and at the same time H_1 of KPSS cannot be rejected, what implies stationarity of tested time series.

2. H_0 of ADF cannot be rejected and at the same time H_1 of KPSS is rejected, what implies non-stationarity of tested time series.

The two remaining cases are considered as inconclusive [18].

3.4 Overview of information criteria model

The crucial issue of VAR model is to find out the correct p, the number of lags, which should be included in the model. According to Cipra [17], we can use statistical test and information criteria.

Mostly used statistical test is Likelihood ratio test - LR-test. The critical region of LR-test is defined as follows:

$$LR = n(\ln\det(\hat{\mathbf{\Sigma}}_R) - \ln\det(\hat{\mathbf{\Sigma}}_U)) > \chi^2_{1-\alpha}(qm^2), \tag{10}$$

where $\hat{\mathbf{\Sigma}}_R$ is the estimated covariance matrix of residuals of the restricted model and $\hat{\mathbf{\Sigma}}_U$ is the estimated covariance matrix of residuals of the unrestricted model [17].

Akaike Information Criterion

Akaike Information Criterion (AIC) is other way how to find out the correct number of lags. We can use m-dimensional version of AIC:

$$AIC(p) = \ln\det(\hat{\Sigma}_u(p)) + \frac{2}{T}pm^2 \quad , \tag{11}$$

where $\hat{\Sigma}_u(p)$ is estimate of covariance matrix of estimated errors in VAR(p) and pm^2 is the number of parameters in the m-dimensional VAR(p) model without intercept. The AIC is minimized in order to find out the correct value of p [1, 2, 3, 4, 17].

Hannan-Quinn criterion

Another information criterion is Hannan-Quinn criterion (HQ). It is defined as follows:

$$HQ(p) = \ln \det(\hat{\Sigma}_u(p)) + \frac{2\ln(\ln(T))}{T} pm^2 \quad , \tag{12}$$

The HQ is minimized in order to find out the correct value of p [37, 55].

Bayes-Schwarz information criteria

The Bayesian information criterion (BIC) or Schwarz information criterion (SC) is defined as follows:

$$SC(p) = \ln \det(\hat{\Sigma}_u(p)) + \frac{\ln(T)}{T} pm^2 \quad , \tag{13}$$

The BIC is minimized in order to find out the correct value of p [56].

From these formulas, we can see that all these information criteria give us low values if the determinant of the covariance matrix of residuals from model with p lags is low and vice versa. If we have a long time series enough, i.e. T goes to infinity, then the information criterion tends to give us lower values as well. On the other hand, there is a penalization for the increasing number of lags. Therefore, the unrestricted model with higher value of p has to explain the dynamics of the data better enough than the restricted model with the lower value of p that the penalization pays off.

3.5 Testing the causality

According to Granger [35] and Sims [57], if one time series influences the second one, then the first time series should give us better information about the behavior of the second one. We can use here Granger-causality [17] for testing the causality in our model. In VAR model, Granger–causality shows the correlation between contemporaneous value of a one random variable and the lagged values of another random variables.

- If lagged values of variable y_j in VAR model are jointly statistically significant, then variable y_i Granger-causes variable y_j.

- If a variable y_i Granger-causes a variables y_j but y_i does not Granger-causes a variables y_i, then there exists unidirectional relationship from y_i to y_j and we say that y_i is strongly exogenous.
- If a variable y_i Granger-causes y_j and vice versa, then we say that there exists a feedback between y_i and y_j.
- If a variable y_i does not Granger-causes y_j and y_j does not Granger-causes y_i, then we say that y_i and y_j are Granger-independent.

Example

Let us show an example of Granger-causality for one-dimensional VAR(1) model, i.e.:

$$y_{1t} = \phi_{10} + \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + \epsilon_{1t} \tag{14}$$

$$y_{2t} = \phi_{20} + \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + \epsilon_{2t} \tag{15}$$

According to Cipra [17] it holds:

- for $\phi_{12} \neq 0$: y_2 Granger-causes y_1
- for $\phi_{21} \neq 0$: y_1 Granger-causes y_2
- for $\phi_{12} \neq 0$ and $\phi_{21} = 0$: there exists unidirectional relationship from y_2 to y_1
- for $\phi_{12} = 0$ and $\phi_{21} \neq 0$: there exists unidirectional relationship from y_1 to y_2
- for $\phi_{12} \neq 0$ and $\phi_{21} \neq 0$: there exists a feedback between y_1 to y_2
- for $\phi_{12} = 0$ and $\phi_{21} = 0$: y_1 to y_2 are Granger-independent

3.6 Impulse response analysis and variance decomposition

From the Granger-causality, we cannot see the sign of causal relationship among different variables or how long some shock persists in the relationship. This information can be obtained from impulse response analysis and forecast error variance decomposition [17].

Impulse response analysis

Impulse response analysis shows the reaction of one variable of VAR model after some impulse (innovation shock) in some selected equation of VAR model. It tracks the impact of one variable to some other variables in the system of equations. In m-dimensional VAR model, we can observe m^2 responses for some impulse. Assuming the stationarity of VAR model, all shocks gradually disappear but it is important how fast [17].

Let us consider an m-dimensional VAR model in the linear form:

$$y_t = \epsilon_t + \psi_1 \epsilon_{t-1} + \psi_2 \epsilon_{t-2} + \dots, \tag{16}$$

then the values of the $i-th$ column of matrix ψ_i represents the impulses of dependent variables for some unit innovation shock, which has occurred in the $i-th$ equation before time t. In some cases, it is desirable to investigate the response for a shock, which has occurred repeatedly. In such a case, assuming the stationarity of VAR model, the response does not disappear, but it converges to some (non-zero)-level. Mostly, the impulse is standardized to one or multiple times of estimated standard deviation of the white noise.

The individual components of white noise are correlated. Therefore, it is desirable to orthogonalize the white noise applying the Cholesky decomposition, in such way that we get:

$$\boldsymbol{y}_t = \boldsymbol{L}\boldsymbol{L}^{-1}\boldsymbol{\varepsilon}_t + \boldsymbol{\Psi}_1\boldsymbol{L}\boldsymbol{L}^{-1}\boldsymbol{\varepsilon}_{t-1} + \dots = \boldsymbol{L}\boldsymbol{u}_t + \boldsymbol{\Psi}_1\boldsymbol{L}\boldsymbol{u}_{t-1} + \dots, \tag{17}$$

where $\{\boldsymbol{u}_t\} = \left\{\boldsymbol{L}^{-1}\boldsymbol{\varepsilon}_t\right\}$ is orthogonalized white noise with contemporaneously uncorrelated components and matrix of parameters $\boldsymbol{L}$ is lower triangular matrix [17].

Forecast error variance decomposition

Variance decomposition gives us the information about relative influence of shocks from individual equations to selected variable. This method shows us how much of variance of predicted errors for a selected variable, h steps ahead, is explained by shock in individual equations. In practice, the highest explained variance of a dependent variable in some equation has the impulse in the same equation [17].

3.7 Cointegration of time series and EC model

In most cases, if we combine two and more (one-dimensional) non-stationary time series together, we will get again (one-dimensional) non-stationary time series. Mostly, for:

$$y_{it} \sim I(d_i), i = 1, \ldots, m \tag{18}$$

(i.e. for m one-dimensional time series, which can get stationary by differencing) it holds that:

$$\sum_{i=1}^{m} \alpha_i y_{it} \sim I(\max_{i=1,\ldots,m}(d_i)), i = 1, \ldots, m \tag{19}$$

Especially, linear combinations of time series with (stochastic) linear trend contain a linear (stochastic) trend as well.

For economic and financial time series, very often we can construct such a linear combination of non-stationary times series that the resulting combination is stationary time series. It is called cointegration of time series, which can be interpreted as some long-run equilibrium among economic variables. For example, we can have cointegration between two time series of ration of prices of goods in two countries and the exchange rate between two currencies of those countries. Another example of cointegration can emerge between prices of stocks and their dividends [17].

Definition [7]**.** *Let $\{y_{1t}\}$, ..., $\{y_{mt}\}$ be non-stationary time series and for each time series, the non-stationarity is caused by just one unit root which is contained in respective autoregression polynomial. Then we say that time series $\{y_{1t}\}$, ..., $\{y_{mt}\}$ are cointegrated if:*

1. *There exists non-trivial linear combination of time series $\{y_{1t}\}$, ..., $\{y_{mt}\}$ such that it is stationary time series or equivalently*

[7] This definition is taken from Cipra [17].

2. *M-dimensional VAR model for* $(y_{1t}, \ldots, y_{mt})^\top$ *has* $m - r$ *unit roots, where it holds:* $0 < r < m$ *and* r *represents the number of cointegration relationships.*

Example of cointegrated time series

Let us consider two time series described by this model:

$$y_{1t} = 0.5y_{1,t-1} - 0.25y_{2,t-2} + \epsilon_{1t} \sim I(1) \tag{20}$$

$$y_{2t} = -1y_{1,t-1} + 0.5y_{2,t-2} + \epsilon_{2t} \sim I(1) \tag{21}$$

Now, let us sum the first equation with the half times of the second one and we get:

$$y_{1t} + 0.5y_{2t} = \epsilon_{1t} + 0.5\epsilon_{2t} \tag{22}$$

We can see that on the right side of the equation both time series $\{y_{1t}\}$ and $\{y_{2t}\}$ have canceled out and only the error terms have remained. If we denote $z_t = y_{1t} + 0.5y_{2t}$ and $u_t = \epsilon_{1t} + 0.5\epsilon_{2t}$, we get:

$$z_t = u_t \sim I(0), \tag{23}$$

where u_t is the white noise compounded of the two white noises ϵ_{1t} and ϵ_{2t}, and therefore the new time series z_t is trivially stationary [17].

EC model

EC model or ECM states for Error correction model. If we have one-dimensional non-stationary time series which is integrated of order d, it is recommended to make $d-th$ differencing of this time series to get a new time series integrated of order 0, i.e. stationary time series. If we have m-dimensional non-stationary time series (assuming $m > 1$), we can lose some information about relationships among these time series by differencing [17]. Let us consider two time series, both integrated of order 1, and a model:

$$\Delta y_t = \gamma \Delta x_t + \epsilon_t \tag{24}$$

We are interested in relationship between variables x and y in the long-run equilibrium, where the changes of x and y between time t and time $t+1$

is almost zero. From this point of view the relationship described by the equation has a low explanation value.

Let us assume that $\{y_t\}$ and $\{x_t\}$ are cointegrated time series. Let us consider a following model:

$$\Delta y_t = \Delta x_t + \alpha(y_{t-1} - \beta x_{t-1}) + \epsilon_t \tag{25}$$

where $y_{t-1} - \beta x_{t-1}$ is the error correction term, which is created by level values of variables x and y (and not by changes of values of variables x and y) at time $t-1$. The coefficient α represents the speed of getting the system of variables to long-run equilibrium [17].

VEC model

VEC or VEC model states for Vector Error correction model. Let us consider a 2-dimensional VAR(1) model:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \mathbf{\Phi} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \tag{26}$$

which can be written in the following way:

$$\begin{pmatrix} \Delta y_{1t} \\ \Delta y_{2t} \end{pmatrix} = \mathbf{\Pi} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \tag{27}$$

where $\mathbf{\Pi} = \mathbf{\Phi} - \mathbb{I}$

For the decision if we should consider the VAR model as VEC model, we have to find the rank of matrix $\mathbf{\Pi}$, which is connected with the form of eigenvalues of matrix $\mathbf{\Phi}$ or equivalently with roots of autoregression polynomial $\mathbf{\Phi}(z) = \mathbb{I}–\mathbf{\Phi} z$ [17].

Let us consider the cases, which can occur:

- $r = h(\mathbf{\Pi}) = 0$: In such a case, $\mathbf{\Pi}$ is zero matrix and therefore according to the equation 27, both time series $\{y_{1t}\}$ and $\{x_{2t}\}$ are non-stationary, integrated of order 1 and there is no cointegration relationship between them.

- $r = h(\mathbf{\Pi}) = 2$: In such a case, matrix $\mathbf{\Pi}$ has full rank and therefore both its eigenvalues are non-zero and none of the roots of polynomial $\mathbf{\Phi}(z)$ is a unit-one.

  Moreover, if we assume that both roots of polynomial $\mathbf{\Phi}(z)$ lie outside of the unit circle, then the VAR model described by the equation 26 is stationary and there is no reason to convert the VAR model to a VEC model.

- $r = h(\mathbf{\Pi}) = 1$: In such a case, just one of both eigenvalues of matrix $\mathbf{\Pi}$ is non-zero, i.e. just one root of both roots of polynomial $\mathbf{\Phi}(z)$ is a unit root.

  Moreover, if we again assume that the remaining root of polynomial $\mathbf{\Phi}(z)$ lies outside of the unit circle, it is possible to show that both time series $\{\Delta y_{1t}\}$ and $\{\Delta y_{2t}\}$ are stationary.

  Moreover, we can write the equation 27 as:

$$\begin{aligned} \begin{pmatrix} \Delta y_{1t} \\ \Delta y_{2t} \end{pmatrix} &= \boldsymbol{\alpha}\boldsymbol{\beta}^\top \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \\ &= \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \Big(\beta_1 y_{1,t-1} + \beta_2 y_{2,t-1} \Big) + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \end{aligned} \tag{28}$$

Time series $\{\Delta y_{1t}\}$ and $\{\Delta y_{2t}\}$ are stationary and therefore time series $\{\beta_1 y_{1,t-1} + \beta_2 y_{2,t-1}\}$ is also stationary and it represents the cointegration relationship between $\{y_{1t}\}$ and $\{y_{2t}\}$.

The construction of the model described by the equation 28 can be reached by applying the Granger‘s representation theorem [6]. In general, it holds that the rank r of matrix $\mathbf{\Pi}$ represents the number of cointegration relationships in respective EC model, while $m-r$ is the number of unit roots in the system of m time series equations [17].

Testing the cointegration

Before we can apply the VAR model for our data, we have to test the data for cointegration among time series due to possibility of VEC model construction. If $r > 0$, then the cointegration is confirmed. Engle and Granger [25] have suggested simple test for cointegration among variables y_t, x_{1t}, $\ldots$, x_{kt}. The crucial idea is that the estimated OLS residuals ϵ_t calculated from the model:

$$y_t = \beta_0 + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \epsilon_t, \tag{29}$$

where ϵ_t is the white noise. Thus, we can apply modified DF-test (i.e. test for unit root) and test the null hypothesis:

$$H_0 : \Delta\hat{\epsilon}_t = \psi\hat{\epsilon}_{t-1} + u_t \qquad \text{for} \quad \psi = 0 \tag{30}$$

We cannot use tabulated critical values for DF-test, because we work here with estimated values of residuals. Therefore, Engle and Granger [25, 26] have tabulated another critical values by simulation. If the time series are not stationary, the OLS estimates are not very reliable [17].

Another way of testing for cointegration are Johansen tests [17]. These tests are based on Maximum Likelihood Estimation (MLE) of so called canonical vectors, which measure the practical dependency among m-dimensional vectors $\Delta\boldsymbol{y}_t$ and $\Delta\boldsymbol{y}_{t-1}$ with fixed values of vectors $\Delta\boldsymbol{y}_{t-1}$, $\ldots$, $\Delta\boldsymbol{y}_{t-p+1}$.

Specially, the number of non-zero (positive) values λ_1, $\ldots$, λ_n ($\lambda_{r+1} = \ldots = \lambda_m = 0$) is equal to the rank of the matrix $\mathbf{\Pi}$, i.e. it is equal to the number of cointegration relationships among m-dimensional equation system.

Johansen tests are designed to test if the values of λ_1, $\ldots$, λ_m are zeroes.

There are two types of Johansen tests:

$$\lambda_{trace}(r) = -n \sum_{i=r+1}^{m} \ln(1 - \hat{\lambda}_i) \tag{31}$$

It is a joint test of null hypothesis that the there is at most r cointegration relationships against the alternative that the number of cointegration relationships is greater than r. The null hypothesis is rejected if $\lambda_{trace}(r)$ is greater than the relevant critical value. The test is performed gradually for

$r = 0, 1, \ldots, m-1$.

$$\lambda_{max}(r) = -n \ln(1 - \hat{\lambda}_{r+1}) \tag{32}$$

The second type of Johansen test has the null hypothesis that the number of cointegration relationships is r, against the alternative that it is $r+1$. The test rejects the null hypothesis if $\lambda_{max}(r)$ is greater than the relevant critical value. The test is performed also gradually for $r = 0, 1, \ldots, m-1$ [17].

The construction of VEC model

Let us assume that we have time series $\boldsymbol{y}_{1t}, \ldots, \boldsymbol{y}_{mt}$, which are stationary or integrated of order 1. Let us proceed through following steps: [8]

1. We have to test all m time series for a unit root applying ADF, KPSS tests each time series $\{y_{1t}\}, \ldots, \{y_{mt}\}$ individually. If the null hypotheses of unit root are rejected, then these time series are stationary or at least trend-stationary and we can apply the VAR model for these time series. Otherwise, these time series contain a unit root and we have to go to step number 2.

2. We employ Johansen tests or some other test for cointegration. If we reject the cointegration (i.e. $r = 0$), then we go to the step number 3. Otherwise, if the r cointegration relationships are present (i.e. $0 < r < m$), then we go to step number 4 (The case, where $r = m$, is contained in the first step.).

3. Due to the rejection of cointegration, we can apply VAR model for stationary time series $\Delta\boldsymbol{y}_1, \ldots, \Delta\boldsymbol{y}_n$.

4. There exist r cointegration relationships ($0 < r < m$) and therefore we can estimate the relevant EC model for time series $\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n$.

[8]This procedure is taken from Cipra [17].

4 Data analysis and testing stationarity of the data

4.1 Obtaining data

We used the RStudio software for the whole work with the data. Firstly, we have obtained the data of Google Trend queries from [33]. We used the RStudio function *gtrends()* from R package "gtrendsR". On the Google Trends website, there are available 90 days periods for daily data only. Therefore, we retrieved 11 times 90 days periods of daily data for each examined cryptocurrency for a purpose to get 990 daily hits for each cryptocurrency. There are 3 arguments, which have to be specified. The first is the "query", where we have used gradually: "bitcoin", "litecoin", "ethereum classic" and "ethereum". The second one is the "geo" - geographical location, e.g. France, Germany etc., which we set to its default value - "all", because cryptocurrencies can be traded and searched from everywhere, where is an internet access. The third is "cat" as category, e.g. cars, games, home, traveling, finance, which we set to its default value, 0, not specifying any category. The fourth is "gprop", which states for Google product, e.g.: "news", "images", "froogle" and "youtube". We set it to "web". The fifth argument is "time", which we set to the time periods from the 24^{th} of July 2016 until the 9^{th} of April 2019 [46].

We could not merge these 90 days datasets, because they are standardized between 0 and 100 values with respect to other searched queries in the time period and geographic location. Thus, a value of 100 "hits", as the maximum value in one time period, does not respond to the same amount of popularity as a value 100 in another time period.

Therefore, we have to transform the data of Google Trends queries in the following way. We utilized the RStudio function *gtrends()* in order to retrieve weekly data for the same four queries as for the daily data for the the whole time period. Then, we multiplied each datapoint of the daily data by the relevant datapoint of the weekly data and we divided all the results by 100 with the intention to preserve the daily data in the 0 - 100 range. In this way we got the dataset of 990 daily Google Trends hits for 4 cryptocurrencies.

We have obtained the open prices by downloading csv files from [20]. There are freely available historical data of opening prices, market capitalization and of the trading volumes for more than 4000 cryptocurrencies. We obtained 990 period daily data for opening prices and for daily trading volumes for all examined cryptocurrencies, namely: Bitcoin, Litecoin, Ethereum Classic and Ethereum. All the prices are in USD for one unit of the respective cryptocurrency and all the volumes are in USD.

4.2 Descriptive statistics of the data

In this section, we will present the descriptive statistics of the data.

Table 1: Daily opening prices in USD

Statistic	N	Mean	St. Dev.	Min	Q1	Q3	Max
BTC_price	990	4,796.86	3,814.12	517.14	1,196.94	6,763.65	19,665.40
LTC_price	990	63.21	65.70	3.55	7.34	80.10	360.66
ETC_price	990	11.15	9.44	0.75	2.62	16.41	44.34
ETH_price	990	276.50	277.38	6.82	45.74	398.69	1,448.18

As we can see from the Table 1, the time series of prices of cryptocurrencies are quite different. The prices of Bitcoin ranges between USD 500 and USD 20,000. It gains the greatest values with sample mean around USD 4,800. On contrary, the prices of Ethereum Classic ranges between USD 0.746 and USD 44.344, and it gains around USD 11 in average. All prices range in positive value only as it is natural for prices of financial instruments.

We divided the boxplot into three sections, because the prices of Bitcoin are mostly in thousands of USD and the prices of Ethereum Classic are in units of USD.

From the Figure 1 we can see that the price of Bitcoin varies the most from our examined cryptocurrencies. There are many outliers in Bitcoin

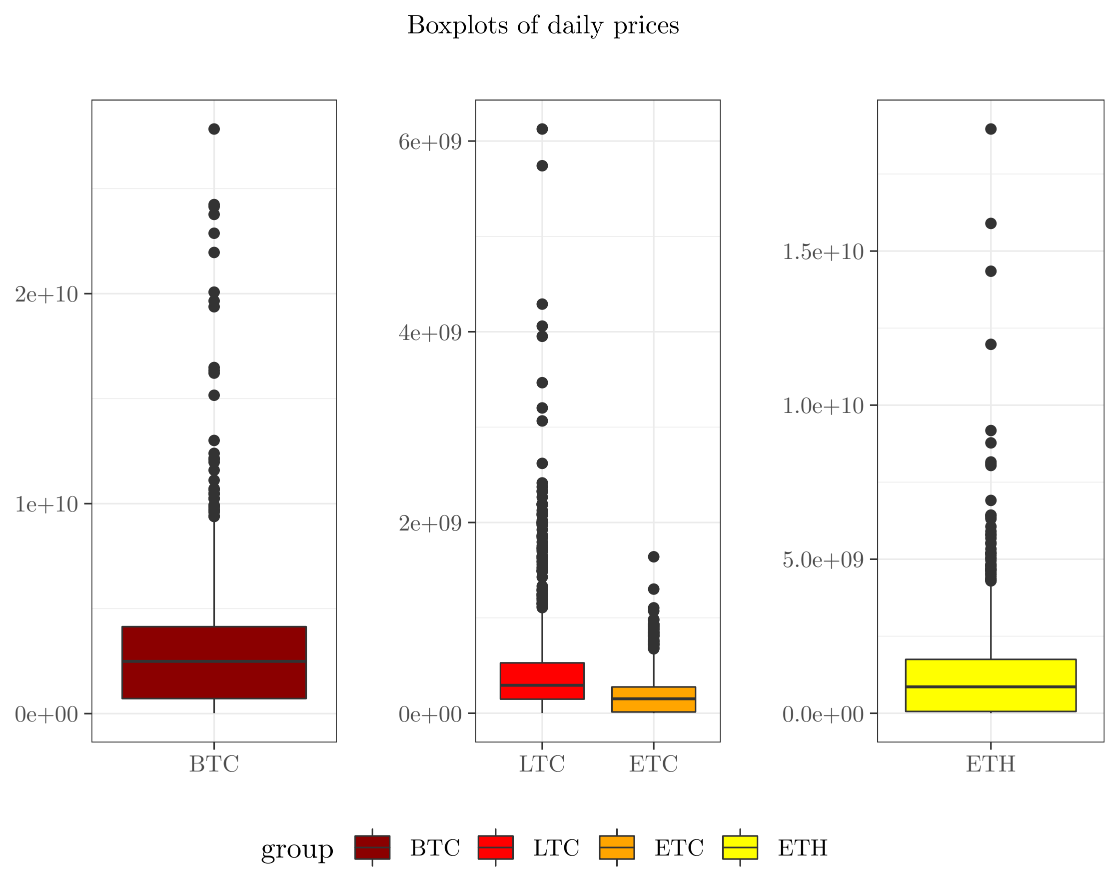

Figure 1: Boxplots of daily opening prices of cryptocurrencies

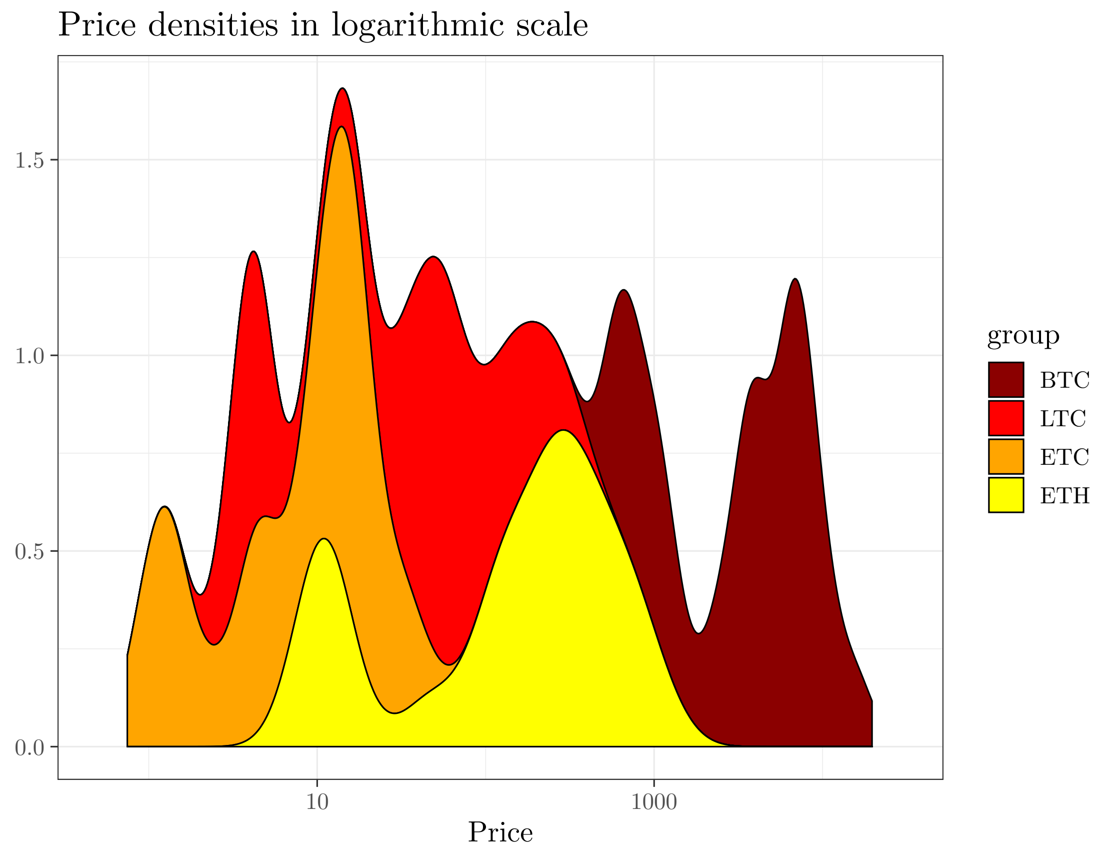

Figure 2: Densities of daily opening prices of cryptocurrencies

price and the average price for one coin is much greater than for the others. In comparison with the price of Bitcoin, other prices change only slightly around their median value.

Now, let us inspect the densities of prices of cryptocurrencies. According to the Figure 2, we have a strong believe that they are not normally distributed, even in the logarithmic transformation. Without the logarithmic transformation, they would be all very skewed right.

From the plots of time series of prices of the cryptocurrencies, which are captured in Figure 7, Figure 8, Figure 9 and Figure 10, included in the Appendix, we can see, that all have a very steady development from the July 2016 until the May 2017. Then, all the prices started rise and they all have a significant peak between December 2017 and January 2018. After that big bubble burst, all the prices got slightly over the level on which they were at the beginning of the observed time period.

Table 2: Daily trading volumes in million USD

Statistic	N	Mean	St. Dev.	Min	Q1	Q3	Max
BTC_vol	990	3,053.1	3,275.7	20.3	731.0	4,210.6	27,840.3
LTC_vol	990	451.9	577.3	1.3	149.4	530.0	6,126.1
ETC_vol	990	190.7	206.3	0.3	13.0	275.3	1,640.4
ETH_vol	990	1,256.1	1,694.4	1.9	60.1	1,755.5	18,960.6

According to the daily trading volume captured in Table 2, Bitcoin is again the most dominant cryptocurrency among these four with over USD 3 billion in average. The second most traded cryptocurrency among these four is Ethereum with USD 1.256 billion in average. The daily average trading volume for the Litecoin and the Ethereum is much lower with almost USD 452 million and USD 190 million respectively. Considering the minimum and maximum values of trading volumes for all the cryptocurencies, we can see that the trading volume fluctuates in a similar manner as the prices of these four cryptocurrencies.

Looking at the boxplot of daily trading volumes in Figure 3, which is included in the Appendix, we can see that there are many outliers for all cryptocurrencies. The interquartile range is the greatest for the Bitcoin, then Ethereum, Litecoin and Ethereum Classic but the differences are not so large as for the prices.

All the plots of densities of daily trading volumes are in logarithmic scale. These boxplots are presented in Figure 4, which is included in the Appendix. According to the density plot, we believe that they are not normally distributed. Without the logarithmic scaling, they would be very skewed right.

According to time series plot of daily trading volumes in Figure 11, Figure 12, Figure 13 and Figure 14, which are included in the Appendix, we can see that the volume is very volatile. We can see similar peaks during December 2017 and January 2018 as for the prices but there are some other peaks as well.

Table 3: Daily hits of Google Trends queries

Statistic	N	Mean	St. Dev.	Min	Q1	Q3	Max
BTC_query	990	6.557	8.869	0.740	2.643	7.100	100.000
LTC_query	990	1.703	4.640	0.040	0.340	1.550	100.000
ETC_query	990	6.803	11.592	0.000	0.960	6.697	100.000
ETH_query	990	9.158	13.701	0.120	1.380	9.445	100.000

Examining the Table 3 with descriptive statistics of Google Trends queries all the queries range between 0 and 100. The sample means of queries vary between approximately 1.7 and 9.2 Google Trends hits. It is interesting that 75% of data, for all four cryptocurrencies, lie under the 10 points of Google Trends hits.

A visual inspection of boxplot for Google Trends hits of cryptocurrencies in Figure 5, which is included in the Appendix, shows that indeed the most of the data lie between 0 and 20 Google Trends hits. On the other hand, there are many outliers between 20 and 100 hits.

The densities of Google Trends hits for all four cryptocurrencies are also plotted in the logarithmic transformation and captured in Figure 6, which is included in the Appendix. Inspecting the densities of Google Trends data, we believe that they are not normally distributed. Without the logarithmic transformation, they would be very skewed right.

The time series plots of Google Trends queries, captured in Figure 15, Figure 16, Figure 17 and Figure 18 are included in the Appendix. They show us the evolution of the Google Trends hits through the period of our interest. For Bitcoin, Litecoin, and Ethereum, we can see suspicious peaks somewhere between December 2017 and January 2018, which might be related to the peaks in time series of prices of the cryptocurrencies. For Ethereum Classic, we can observe some peak as well but it is not so significant among the other turbulences in the time series.

4.3 Testing the stationarity of the data

Testing the stationarity of the prices

Table 4: Results of testing stationarity of time series of prices

	BTC			LTC			ETC			ETH		
	test	lag	p	test	lag	p	test	lag	p	test	lag	p
level												
ADF	-1.74	9	0.69	-2.29	9	0.46	-1.73	9	0.69	-1.40	9	0.83
KPSS	4.94	7	0.01	3.51	7	0.01	3.16	7	0.01	3.50	7	0.01
PP	-1.59	7	0.75	-2.10	7	0.54	-1.96	7	0.59	-1.53	7	0.78
diff												
ADF	-7.59	9	0.01	-9.77	9	0.01	-11.00	9	0.01	-10.53	9	0.01
KPSS	0.12	7	0.10	0.06	7	0.10	0.10	7	0.10	0.14	7	0.10
PP	-30.39	7	0.01	-30.65	7	0.01	-34.64	7	0.01	-29.69	7	0.01
log												
ADF	-0.86	9	0.96	-1.06	9	0.93	-0.83	9	0.96	-0.66	9	0.97
KPSS	8.40	7	0.01	7.65	7	0.01	5.36	7	0.01	6.96	7	0.01
PP	-0.74	7	0.97	-1.00	7	0.94	-0.89	7	0.95	-0.52	7	0.98
log-diff												
ADF	-8.78	9	0.01	-9.56	9	0.01	-9.58	9	0.01	-9.03	9	0.01
KPSS	0.41	7	0.07	0.29	7	0.10	0.32	7	0.10	0.58	7	0.02
PP	-31.55	7	0.01	-31.00	7	0.01	-33.15	7	0.01	-31.90	7	0.01

Firstly, we utilized the *adf.test()* function in RStudio in order to compute ADF test. According to the ADF test, we cannot reject the null hypothesis of presence of a unit root in all time series of log prices for Bitcoin, Litecoin, Ethereum Classic and Ethereum. The respective p-values are attached in the Table 4. Then we utilized the *kpss.test()* function in RStudio in order to confirm the non-stationarity of log prices by KPSS test. Here, we reject the null hypothesis of stationarity of time series for log prices of all four cryptocurencies at 1% significance level. Therefore, we conclude that log prices of all cryptocurrencies are non-stationary time series.

Due to the non-stationarity of the prices we transformed the data to the log-differences utilizing the RStudio function *diff()*. Then we performed the ADF and KPSS tests again. According to the ADF test, we reject the null hypothesis that the time series contains a unit root at the 1% significance level for all four cryptocurrencies. Performing the KPSS test, we reject the null hypothesis of stationarity at 5% significance level only for the time series of Ethereum prices. Thus, we got to the contradictory results. Therefore, we used the RStudio function *PP.test()* which employs the PP test (Phillips and Perron test) [7, 51]. PP test is similar to ADF test but the PP test estimates the standard errors by Newey-West estimator [18, 31]. According to the PP test, we reject the null hypothesis that a unit root is present in the time series at 1% significance level. Despite the fact the KPSS test rejects the stationarity for three out of four time series of prices we rely on large number of observations, 990 for each cryptocurrency, and we will consider the log-difference transformation of the time series as stationary.

Testing the stationarity of the volumes

In this section, we tested the stationarity of time series of daily trading volumes of the four examined cryptocurrencies. All the results of testing the stationarity of trading volumes, are presented in Table 9, which is included in the Appendix. We applied RStudio function *adf.test()*, which performs the ADF test, in order to test the four time series of volumes for unit roots. According to the ADF test, we cannot reject the null hypothesis of presence of a unit root for BTC, LTC and ETH at 5% significance level with p-values: 0.77, 0.98, and 0.11. We can reject the null hypothesis at the 5% significance level only for ETC with p-value: 0.01. Then, we applied the

RStudio function *kpss.test*, which performs KPSS test, in order to test the stationarity of the four time series of volumes. According to the KPSS test, we reject the null hypothesis of stationarity for all four time series at the 5% significance level, with p-values lower than 0.01 for all four time series. Therefore, we performed the ADF and KPSS tests for log-differences of the data. According to the ADF test, we reject the null hypothesis of presence of a unit root for all four time series at the 5% significance level with p-value lower than 0.1 for all four time series. According to the KPSS test, we cannot reject the null hypothesis of stationarity for all four time series at the 5% significance level with p-value greater than 0.1. Thus, log-differences of time series of volumes are stationary.

Testing the stationarity of the Google Trends queries

Now, let us test the stationarity of Google Trends queries in logarithmic transformation. We performed the ADF and KPSS test for all four time series of Google Trends queries. All the results of testing the stationarity of Google Trends queries are presented in Table 10, which is included in the Appendix. According to the ADF test, we reject the null hypothesis of presence a unit root at the 5% significance level for all time series of Google Trends queries. Then, we applied the KPSS test for all four time series. According to the KPSS test we reject the null hypothesis of stationarity at the 5% significance level for all four time series. In order to get some better information about these time series, we applied the PP test. According to the PP test, we can reject the null hypothesis of presence of a unit root at the 5% significance level for all four time series. Performing the ADF test for log-differenced Google Trends queries, we can reject the null hypothesis of the presence of a unit root in all four time series at the 5% significance level with p-values lower than 0.01. Applying the KPSS test, we cannot reject the null hypothesis of stationarity for all queries at the 5% significance level with p-value greater than 0.1. Therefore, we consider the log-difference transformation of Google Trends queries as stationary time series.

5 Applying the vector autoregression model for the data

In this section, we will consider four different models in order to examine the relationships among cryptocurrency prices and volumes, and Google Trends queries. The first and the third model will consider only the four time series of cryptocurrency prices and the four time series of cryptocurrency trading volume, respectively. Into the second and the fourth model, we will add the four time series of Google Trends queries. We will apply VAR or VEC models for all the models according to the cointegration relationships among the respective time series. Then we would like to compare the first and the second model in order to show if the Google Trends queries improve the explaining power of the model. Similarly, we would like to compare the third and the fourth model.

5.1 Model with prices

Estimation of the model with prices

We used the RStudio function *VARSelect()*, which employs information criteria enabling us to decide how many lags we should choose for our VAR model. The results are captured in Table 5. According to the AIC criterion, we should choose 2 lags.

Table 5: Results of information criteria for model with prices

AIC(n)	HQ(n)	SC(n)
2	1	1

Then, we performed the Johansen test employing the RStudio function *ca.jo()*. According to the results of the Johansen test we cannot reject the null hypothesis that there is 0 cointegration relationships at the 5% significance level. Thus, there is no sufficient evidence for the cointegration relationship among the time series of log prices. Consequently, we will apply the VAR(2) model in log-differences.

Diagnostics of the model with prices

Using the RStudio function *normality.test()*, we performed the Jarque-Bera test [38] to test if the residuals of the estimated VAR(1) model are normally distributed. We rejected the null hypothesis that the estimated residuals are normally distributed at the 1% significance level. Then we used the RStudio function *serial.test()*, which employs Portmanteau test [45] for serial correlation in the estimated residual errors. We rejected the null hypothesis that there is no serial correlation at the 1% significance level. Utilizing the RStudio function *roots()*, we estimated the eigenvalues of the companion matrix of the VAR(1) model. They are all inside the unit circle in a complex plain.

Therefore, the VAR(1) model for prices is stable. We applied the ADF and KPSS test for the estimated residual error terms. According to the ADF test, we reject the null hypothesis of the presence of a unit root in estimated residuals. According to the KPSS test, we reject the null hypothesis of stationarity of estimated residuals. Again, we got contradictory results.

5.2 Model with prices and Google Trends queries

Estimation of the model with prices and Google Trends

In this section, we will add Google Trends queries to the previous model. We used the RStudio function *VARSelect*, which computes the information criteria, in order to select the right number of lags. We can see the results of function *VARSelect()* in the Table 6. According to the Hannan-Quin and Schwarz criterion, we should choose 1 lag. According to the AIC we should choose 5 lags.

We chose 5 lags for our model with prices and Google Trends queries of cryptocurrencies. Then, we applied the Johansen test in order to test cointegration among all 8 time series. According to RStudio function *ca.jo()*,

Table 6: Results of information criteria for model with prices and Google Trends queries

AIC(n)	HQ(n)	SC(n)
5	1	1

we reject the null hypothesis of 2 cointegrating relationships among the 8 time series. Therefore, we considered the VEC model with 3 cointegration relationships.

Diagnostics of the model with prices and Google Trends

We had to use the RStudio function *vec2var.test()* in order to convert the results of VEC to VAR model. Applying the RStudio function *normality.test()*, we got results of Jarque-Bera test. We rejected the null hypothesis that residuals from our model are normally distributed even at the 1% significance level. For testing the serial correlation in residuals, we applied the RStudio function *serial.test()*, which gave us the results of Portmanteau test. According to the Portmanteau test, we rejected the null hypothesis of no serial correlation in our model even at the 1% significance level. We tested the residuals from our model for stationarity. According to the ADF, we rejected the null hypothesis of presence of a unit root even at the 1% significance level for all 8 time series of residuals. According to the KPSS test, we rejected the null hypothesis of stationarity for all 8 time series of residuals. Thus, we got contradictory results for stationarity or non-stationarity of residuals from our model.

5.3 Model with volumes

Estimation of the model with volumes

We used the RStudio function *VARSelect()* in order to find the correct number of lags in the model with cryptocurrency volumes. We present the results of information criteria in Table 7.

Table 7: Results of information criteria for model with volumes

AIC(n)	HQ(n)	SC(n)
8	5	4

We chose 8 lags due to the result of AIC. Then, we applied the RStudio function *ca.jo()*, which employs the Johansen test, in order to find the correct number of cointegration relationships. According to the results of Johansen test, we rejected the null hypothesis of 0 cointegrations relationships among the four time series of volumes. Therefore, we estimated VEC model with 8 lags and 1 cointegration relationship. Then, we used the RStudio function *vec2var()* in order to convert the results of VEC model to the results of VAR model.

Diagnostics of the model with volumes

We used the RStudio function *normality.tests()*, which employs the Jarque-Bera test, in order to test the normality of residuals. According to the results of the Jarque-Bera test, we can reject the null hypothesis that estimated residuals are normally distributed at 5% significance level. We used the RStudio function *serial.test()*, which employs the Portmanteau test, in order to test the serial correlation in estimated residuals. According to the result of the Portmanteau test, we rejected the null hypothesis of no serial correlation at the 5% significance level.

5.4 Model with volumes and Google Trends queries

Estimation of the model with volumes and Google Trends queries

We used the RStudio function *VARSelect()*, which employs the information criteria, in order to to choose the correct number of lags in the model with volumes and Google Trends queries.

According to results of the AIC, which are captured in Table 8, we chose

Table 8: Results of information criteria for model with volumes and Google Trends queries

AIC(n)	HQ(n)	SC(n)
8	5	1

8 lags. Then, we used RStudio function *ca.jo()*, which employs the Johansen test, in order to find the correct number of cointegration relationships among the 8 time series of volumes and Google Trends queries. According to the results of Johansen test, we rejected the null hypothesis that there are just 3 cointegration relationships at the 5% significance level. Therefore, we estimated the VEC model with 8 lags and 4 cointegration relationships. Then, we applied the RStudio function *vec2var()* in order to convert the results of the VEC model to the results of the VAR model.

Diagnostics of the model with volumes and Google Trends queries

We used the RStudio function *normality.test()*, which employs the Jarque-Bera test, in order to test normality of estimated residuals. According to the result of the Jarque-Bera test, we rejected the null hypothesis that the estimated residuals are normally distributed at the 5% significance level.

Then, we applied the RStudio function *serial.test()*, which employs the Portmanteau test, in order to test the serial correlation of the estimated residuals. According to the results of the Portmanteau test, we rejected the null hypothesis that there is no serial correlation in the estimated residuals at the 5% significance level.

6 Results

6.1 The results of the model with prices

Granger causality

Firstly, we used the RStudio function *causality()*, which performs the test for Granger causality and Instantaneous causality [17, 35, 57]. The null hypothesis of the Granger causality test for the first equation is that: $\Delta \log(BTC)_t$ do not Granger cause $\Delta \log(LTC)_t$, $\Delta \log(ETC)_t$, and $\Delta \log(ETH)_t$

According to the test, we can reject the null hypothesis only for the Ethereum Classic, i.e. we reject that: $\Delta \log(ETC)_t$ do not Granger cause $\Delta \log(LTC)_t$ $\Delta \log(BTC)_t$, and $\Delta \log(ETH)_t$.

Then, according to the test, we reject the null hypothesis that there is no instantaneous causality among all log-differenced prices of cryptocurrencies.

Impulse response analysis for the model with prices

Overall results of IRF are presented in Table 11, Table 12, Table 13 and Table 14, which are included in the Appendix. Let us inspect the Table 11 with Impulse response analysis for the responses from log-differenced Bitcoin price. We used the RStudio function *irf()*, which computes the impulse response coefficients of a $VAR(p)$ model or transformed VEC model to $VAR(p)$ model n steps ahead. The results of impulse response function shows how the log-differenced price of Bitcoin would react in terms of 1 standard deviation of the estimated error to the 1 standard deviation of the estimated error terms shock in some other currency. From the Table 11, we can see that log-differenced price of all cryptocurrencies jump to the value of 0.04 of its standard deviation immediately after the shock in Bitcoin variables. Then during two steps ahead they all falls to zero value in a very similar way.

There is almost zero response of Bitcoin variable to shock in the Litecoin variable. There are 0.05, 0.02 and 0.015 responses from log-differenced prices of Litecoin, Ethereum Classic and Ethereum, respectively, responding to the shock in Litecoin variables. All the responses fall to zero until 3 steps ahead. There is almost zero response of Bitcoin and Litecoin for a shock in Ethereum Classic, at the zero time. Then it goes slightly under the zero and it gets back until 3 steps ahead. The response from Ethereum Classic and Ethereum is approximately 0.06 and 0.02 for a impulse shock in Ethereum Classic. These responses get to the zero value until the three steps ahead as well. There is a significant response, around 0.05, in Ethereum variable only for the shock from the same variable.

Forecast error variance decomposition for the model with prices

In this part, we will examine the Forecast error variance decomposition for the model with prices. Overall FEVD results for the model with prices are presented in Table 15, Table 16, Table 17 and Table 18, which are included in the Appendix.

From the Table 15, which is included in the Appendix, we can see that the variation of Bitcoin price is explained by itself only, for all 10 steps ahead. According to the Table 16, which is included in the Appendix, for the Litecoin price, there is around 60% explained by itself and the rest is explained by the Bitcoin price. According to the Table 17, which is included in the Appendix, the variable for Ethereum Classic is explained around 65% by the Ethereum price, around 30% is explained by the Bitcoin price and the rest 5% is explained by the Litecoin price. According to the Table 18, which is included in the Appendix, the Ethereum is explained around 52% by Ethereum price, then around 33% is explained by Bitcoin price, around 8% is explained by Ethereum Classic price and around 7% by the Litecoin price. All FEVD results for the model with prices are also presented in Figure 19, which is included in the Appendix.

6.2 The results of the model with prices and Google Trends queries

Impulse response analysis for the model with prices

We used the RStudio function *irf()* in order to compute the Impulse response analysis of the VEC model for prices and Google Trends queries of cryptocurrencies.

The results of impulse response analysis of the model with prices and Google Trends queries are presented in following tables: Table 19, Table 20, Table 21, Table 22, Table 23, Table 24, Table 25 and Table 26 which are included in the Appendix. We can see that there is response in Ethereum query only for the impulse in Bitcoin price. There is a decrease approximately 0.1 of the standard deviation of error residuals at time zero. Then, there is an increase approximately 0.1 of the standard deviation of error residuals at time three steps ahead and then it goes to zero. Considering the impulse from the Litecoin price, we can observe approximately 0.1 increase of Litecoin query, 4 steps ahead, which persist more than 20 steps ahead. There is the response in the Ethereum query, an increase approximately 0.1 of standard deviation of the error residuals, which persist for more than 20 steps ahead as well. For the impulse from the Ethereum Classic, there is response in Ethereum query. It starts around 0.2 standard deviation of the error residuals. Then there is a small decrease followed by a peak around 0.3, 4 steps ahead. Then, there is a persisting response around 0.2. The impulse from Ethereum price causes some response in Ethereum query. It is -0.2 at zero time, then it goes up to 0.1, 4 steps ahead and then it goes to zero.

In the Table 23, we can see that impulse in Bitcoin query causes responses in 4 variables. There are 2 responses, approximately 0.2, in Bitcoin query and Litecoin query, which go slowly to zero. Then, there are almost stable responses in Ethereum Classic query and Ethereum query, approximately 0.1.

Impulse from Litecoin query causes two responses. The first response is in Litecoin query, around 0.2, which slowly goes to zero. The second one is in Ethereum Classic query, which starts around 0, peaks around 0.25, 2 steps ahead, gets back to 0, 3 steps ahead, then it peaks around 0.1, 6 steps ahead and finally goes to 0.

Ethereum Classic query causes the strongest response in the same variable around 4 standard deviations of error residuals. Then it goes to 0, 2 steps ahead, peaks around 0.5, 4 steps ahead and then it goes slowly to 0.

Lastly, Ethereum query causes the responses in Ethereum Classic query and in itself. There are two peaks in Ethereum Classic query variables, around 0.15, at 1 and 3 steps ahead and then it is persisting around 0.1. Then, there is response in Ethereum query, around 0.3 consequently persisting around 0.2.

Forecast error variance decomposition for the model with prices

In this part, we will examine the Forecast error variance decomposition for the prices and Google Trends queries. All the FEVD results for the model with prices and Google Trends queries are presented in Table 27, Table 28, Table 29, Table 30, Table 31, Table 32, Table 33 and Table 34, which are included in the Appendix.

From the Figure 20, which is included in the Appendix, we can see that each variable is most explained by itself. Almost all the variance in the Bitcoin price is explained by itself. Litecoin price is explained around 60% by itself and the rest is explained by the Bitcoin price. Ethereum price is explained by around 50% by itself, 32% by Bitcoin price, 8% by Litecoin price, 6% by Ethereum Classic price, 2% by Litecoin query, 1% by Bitcoin query, 1% by Ethereum Classic price and 0% by Ethereum query. We rounded all the numbers to whole percentage points.

Now, let us inspect the Forecast error variance decomposition from the perspective of the Google Trends queries. This is also presented in Figure 21, which is included in the Appendix. From the results, we can see that around 98% of variance in the Bitcoin query variable is explained by itself and the rest is distributed mostly among the variables of Google Trends queries.

Around 65% of variance of Litecoin query is explained by itself, around 27% by Bitcoin query, around 7% by Litecoin price and the rest is distributed among the other variables with shares less than 1%. The Ethereum Classic query is explained around 96% by itself, around 1% by Ethereum Classic price and the rest is distributed among the other variables with shares less than 1%. The Ethereum query is explained around 69% by itself, around 20% by Bitcoin query, around 6% by Litecoin query, 2% by Ethereum Classic query, 1% by Ethereum price, 1% by Ethereum price and the rest is distributed among the other variables with shares less than 1%.

6.3 The results of the model with volumes

Impulse response analysis for the model with volumes

All the results of IRF for the model with volumes are presented in Table 35, Table 36, Table 37 and Table 38, which are included in the Appendix.

According to the Table 35 with results of IRF for impulse from BTC volume in model with volumes, which is included in the Appendix, we can observe the strongest response from BTC volume around 0.34 of the standard deviation of estimated error residuals. It decreases 5 steps ahead and then it is persisting around 0.17 until 20 steps ahead. LTC volume has also positive response, around 0.2, which decreases to 0.09 until 5 steps ahead and then it is persisting around 0.1. ETC volume has the lowest response, around -0.002, and then it increases to its maximum value around 0.14 and then it stabilizes around 0.065. ETH volume responses around 0.19, then it decreases to 0.041 and then it stabilizes around 0.065. Inspecting the responses for impulse from LTC volume in model with volumes, we observe almost zero responses from BTC volume. The response of LTC volume starts at 0.35 of the standard deviation of estimated error residuals, then it decreases to 0.185, 5 steps ahead. Then, the response of LTC volume is persisting around 0.18. The response of ETH volume starts around 0.088, then it decreases to 0.028, 2 steps ahead, increases to 0.049, in steps 3 and 4, decreases to 0.014 in 7^{th} step and then it stabilizes around 0.02. Looking at the responses for impulse from ETC volume, we observe small oscillation around zero for BTC volume, LTC volume and ETH volume. The ETC volume responses by 0.398 at time zero. Then, it decreases to 0.142, 3 steps ahead, then it oscillates between 0.16 and 0.1 and it stabilizes around 0.08 for the last four steps. Looking at the responses for impulse from ETH volume, we observe almost zero responses from BTC and LTC volumes. Then, we observe small response from ETC volume, 0.026 at the 1^{st} step ahead, which increases to 0.148 at the 4^{th} step ahead and then it stabilizes around 0.125. The response from ETH volume starts at 0.393 at the zero time, then it decreases to 0.127 at the 6^{th} step and then it stabilizes around 0.130.

Forecast error variance decomposition for the model with volumes

Now, let us present the results of FEVD for the model with daily trading volumes. All the FEVD results for the model with volumes are presented in Table 39, Table 40, Table 41 and Table 42, which are included in the Appendix. All these results are also presented in graphical way in Figure 22, which is also included in the Appendix.

The results from Table 39 show that around 99% of the variation of BTC volume is explained by the BTC volume. The remaining 1% of the variation is spread out among the LTC, ETC and ETH volume. The results are very similar through all 10 steps ahead.

Inspecting the FEVD results for LTC volume, captured in Table 40, we observe that around 75% of the variation of LTC volume is explained by the LTC volume. Around 24% is explained by BTC volume. The remaining 1% of the variation of LTC volume is divided between ETC volume and ETH volume. The results are very similar through all 10 steps ahead.

The FEVD results for ETC volume, captured in Table 41, show that at the 1^{st} step ahead time zero almost 100% variation of ETC volume is explained by the ETC volume. This value decreases to less than 69% during 10 steps ahead. The rest of the variation of ETC volume is explained by BTC, LTC, and ETH volumes, where the values increase from almost 0% to 8%, 9% and 13%, respectively.

Looking at the results of FEVD for ETH volume in model with volumes, captured in Table 42, we observe that around 76% of the variation of ETH volumes is explained by ETH volume. Around 19% of the variation is explained by BTC volume and around 4% of the variation is explained by LTC volume. Less than 1% of the variation is explained by ETC volume. The results are very similar through all 10 steps ahead. All these FEVD results are also presented in a graphical way in Figure 22.

6.4 The results of the model with volumes and Google Trends queries

Impulse response analysis for the model with volumes and Google Trends queries

All the IRF results for the model with volumes and Google Trends queries are presented in Table 43, Table 44, Table 45, Table 46, Table 47, Table 48, Table 49 and Table 50, which are included in the Appendix.

Now, let us present the results of IRF for the model with daily trading volumes and Google Trends queries. From the table Table 43 that for the impulse from BTC volume, which is included in the Appendix, there is the strongest response by the same variable, around 0.333 at the time zero. The response of BTC volume decreases to 0.129 at the 5th step and then it stabilizes around 0.160. LTC volume responses by 0.193 at the time zero, then it decreases to 0.094 at the 5th step, and then it stabilizes around 0.100. ETC volume responses around -0.003 at the time zero, then it peaks around 0.132 at the 4th step and then it stabilizes around 0.07. ETH volume starts around 0.187 at the time zero, then it decreases to 0.043 at the 5th step and then it stabilizes around 0.07. BTC query responses around 0.002 at the time zero, then it peaks around 0.102 at the 4th step and then it stabilizes around 0.07. LTC query responses around 0.011 at the time zero, then it increases around 0.074 the 4th step and then it stabilizes around 0.06. ETC query responses around 0.019 at the time zero, then it is jumping between -0.345 and 0.276 through the first 8 steps and then it oscillates around 0.09.

ETH query responses around 0.007 at the time zero, then it increases to 0.106 at the 4^{th} step and then it stabilizes around 0.07.

Table 44, which is included in the Appendix, captures the responses for impulse from LTC volume in model with daily trading volumes and Google Trends queries. Here, BTC volume has almost zero responses through all 20 steps. LTC volume responses around 0.347 at the time zero, then it decreases to 0.157 at the 7^{th} step and then it stabilizes around 0.16. ETC volume responses around 0.007 at the time zero, then it peaks around 0.120 at the 4^{th} step and then it stabilizes around 0.08. ETH volume responses around 0.089 at the time zero, then decreases to 0.018 at the 7^{th} step and then it stabilizes around 0.03. BTC query responses around -0.004 at the time zero, then it oscillates around zero and then it stabilizes around 0.02. LTC query responses around 0.009, then it peaks around 0.151 at the 5^{th} step and then it stabilizes around 0.1. ETC query responses around 0.267, then it jumps between -0.017 and 0.314 and then it oscillates around 0.17. ETH query responses around 0.003, then it increases to 0.05 at the 8^{th} step and then it stabilizes around 0.03.

For the impulse from ETC volume, which is captured in Table 45, which is included in the Appendix, BTC volume and LTC volume response around zero at the beginning and then they stabilize around 0.02 and 0.016, respectively. ETC volume responses around 0.387 at the time zero, then slowly decreases and stabilizes around 0.084. BTC query and LTC query response around zero at the beginning and then they stabilize around 0.04 and 0.05, respectively. ETC query responses around 0.308 at the time zero, then it decreases to -0.009 at the 7^{th} step and then it stabilizes around 0.1. ETH query responses around 0.016 at the time zero, then it increases and stabilizes around 0.04.

For the impulse from ETH volume, which is captured in Table 46, which is included in the Appendix, BTC, LTC and ETC volumes have 0 responses at the time zero, then they stabilize around 0.008, 0.02 and 0.1 respectively. ETH volume responses around 0.380 at the time zero, then it decreases and stabilizes around 0.095. BTC query responses around 0.009 at the time zero and then it increases and stabilizes around 0.05. LTC query responses around 0.012 at the time zero, then it increases and stabilizes around 0.05. ETC query responses around -0.506, then it increases to 0.391 at the 8^{th} step and stabilizes around 0.21. ETH query responses around 0.009 at the time zero, then in increases to 0.130 at the 4^{th} step and then it stabilizes around 0.1.

For the impulse from BTC query, which is captured in Table 47, which is included in the Appendix, BTC, LTC, ETC and ETH volumes have zero responses at the beginning. Then, they stabilize around -0.007, -0.045, 0.03 and 0.06, respectively. BTC query responses around 0.167 at the time zero, then it decreases and it stabilizes around 0.08. LTC query responses around 0.13, then it decreases and stabilizes around 0.05. ETC query responses around -0.013, then it oscillates between -0.204 and 0.191, and then it stabilizes around 0.06. ETH query responses around 0.098, then it decreases and stabilizes around 0.08.

For the impulse from LTC query, which is captured in Table 48, which is included in the Appendix, BTC, LTC, ETC and ETH query have zero responses at the beginning. Then they oscillate around 0 and stabilize around -0.025, 0.01, -0.007 and -0.012, respectively. BTC query responses around 0 at the time zero, then it decreases and stabilizes around -0.025. LTC query responses around 0.26, then it decreases and stabilizes around 0.03. ETC query responses around -0.024 at the time zero, then it oscillates between -0.099 and 0.220 and then it stabilizes around -0.02. ETH query responses around 0.039 at the time zero, then it increases to 0.062 at the 2^{nd} and 3^{rd} steps and then it stabilizes around -0.03.

For the impulse from ETC query, which is captured in Table 49, which is included in the Appendix, BTC, LTC, ETC and ETH volumes response around 0 at the beginning, then they all decrease after some oscillation to -0.037, -0.018, -0.003 and -0.016, respectively. BTC and LTC queries response around 0 at the beginning, then oscillate around 0 and consequently they stabilize around -0.016 and -0.006, respectively. ETC query responses around 3.479, then it decreases to -0.061 at the 2^{nd} step, then it increases to 0.487 and then it stabilizes around 0.02. ETH query responses around 0.013 and then it decreases and stabilizes around -0.45.

For the impulse from ETH query, which is captured in Table 50, which is included in the Appendix, BTC, LTC, ETC and ETH volumes response around 0 at the time zero, then they jump to 0.048, 0.036, 0.054 and 0.022, respectively and then they stabilize around 0.023, 0.025, 0.013 and 0.005, respectively. BTC and LTC queries response around 0 at the time zero, then they oscillate around 0 and stabilize around 0.018 and 0.001, respectively. ETC query responses around 0 at the time zero, then increases to 0.167 at the 1^{st} step, oscillates around 0 and then it stabilizes around 0.03. ETH query responses around 0.264 at the time zero, then it decreases to 0.097 at the 2^{nd} step and then it stabilizes around 0.135.

Forecast error variance decomposition for the model with volumes and Google Trends queries

All the FEVD results for the model with volumes and Google Trends queries are presented in Table 51, Table 52, Table 53, Table 54, Table 55, Table 56, Table 57 and Table 58, which are included in the Appendix. All these results are also presented in graphical way in Figure 23 and Figure 24, which are also included in the Appendix.

Now, let us present the results of FEVD in the model with volumes and Google Trends queries, captured in Table 51. We observe that at the 1^{st} step, 100% of variation of BTC volume is explained by BTC volume. These 100% decreases in favor of the other variables through 10 steps, which we observe. In the 10^{th} step, there is around 93% of the variation of BTC volume explained by BTC volume, around 2.5% is explained by ETC query, around 2% is explained by ETH query and around 1% is explained by ETH volume. The remaining 1.5% spread out among the LTC and ETC volumes and BTC and LTC queries.

The variation of LTC volume in our model with volumes and Google

Trends queries, captured in Table 52, is explained in the following way. In the 1^{st} step, around 76% of the variation of LTC volume is explained by LTC volume and the remaining 24% is explained by BTC volume. In the 10^{th} step, around 73% is explained by BTC volume and around 24% is explained by LTC volume. The remaining 3% are spread out among the remaining 6 variables. However, none of these 6 variables explain even 1% of the variation of LTC volume.

At the 1^{st} step, around 100% of variation of ETC volume in model with volumes and Google Trends queries, captured in Table 53, is explained by the same variable. Consequently, the value decreases through the 10 observed steps in favor of the other variables. At the 10^{th} step, around 64% of the variation of ETC volume is explained by the same variable. Around 15% is explained by ETH volume, around 9% is explained by LTC volume, around 7.5% is explained by BTC volume, less than 3% is explained by ETH query, 1% is explained by ETC query and the remaining less than 1% is explained by BTC and LTC queries.

At the 1^{st} step, around 77% of the variation of ETH volume in the model with volumes and Google Trends queries, captured in Table 54, is explained by the same variable. Less than 19% is explained by BTC volume, around 4% is explained by LTC volume and less then 1% is explained by ETC volume. At the 10^{th} step, around 69% of the variation of ETH volume is explained by the same variable. Around 20% is explained by BTC volume, around 6% is explained by LTC volume, more than 1% for each is explained by ETC volume, BTC and LTC queries. The remaining less than 2% is explained by ETC and ETH queries.

Now, let us inspect the FEVD results for Google Trends queries in model with volumes and Google Trends queries, captured in Table 55. At the 1^{st} step, around 99% of the variation of BTC query in the model with volumes and Google Trends queries is explained by the same variable. The remaining 1% is spread out among the other variables for volumes. At the 10^{th} step, around 76% is explained by the BTC query, around 19% is explained by

BTC volume, less than 3% is explained by ETH volume and less than 2% is explained by ETC volume. The remaining part of the variation of BTC query is spread out among LTC volume, LTC, ETC and ETH queries.

The variation of LTC query at the 1^{st} step, in the model with volumes and Google trends queries, captured in Table 56, is explained almost 80% by the same variable, 20% by BTC query and the rest is spread out among the variables of volumes. At the 10^{th} step, around 50% is explained by LTC query, around 22.5% is explained by LTC volume, around 20% is explained by BTC query, around 5% is explained by BTC volume and around 2% is explained by ETH volume. The remaining 0.5% is spread out among ETC volume and ETC and ETH queries.

Now, let us inspect the FEVD results for ETC query in the model with volumes and Google Trends queries, captured in Table 57. At the 1^{st} step, around 97% of the variation of ETC query is explained by the same variable, around 2% is explained by ETH volume and the remaining 1% is spread out among the other variables but ETH query. At the 10^{th} step, around 87% is explained by ETC query, around 4.5% is explained by ETH volume, almost 3% is explained by BTC volume, around 2% for each is explained by LTC volume and ETC volume. The remaining 1.5% is spread out among BTC, LTC and ETH queries.

Lastly, we look at the FEVD results for ETH query in the model with volumes and Google Trends queries, captured in Table 58. At the 1^{st} step, around 85% of the variation of ETH query in the model with volumes and Google Trends queries is explained by the same variable. Around 12% is explained by BTC query, around 2% is explained by LTC query. The remaining 1% of the variation of ETH query is spread out among the other variables.

At the 10^{th} step, around 53% is explained by ETH query, around 18% is explained by ETH volume, around 11% is explained by BTC query, around 8% by BTC volume, around 4% by LTC query, more than 2% by LTC volume, almost 2% by ETC query and rest 1% is explained by ETC volume.

7 Discussion of the results

In the first model with prices of cryptocurrencies, we found that according to Forecast error variance decomposition of the VAR model BTC variable for prices has relatively strong explaining power for all the variables in the model.

In the second model with prices of cryptocurrencies and with Google Trends queries, we found that according to Forecast error variance decomposition of the VEC model, BTC price variable has relatively strong explaining power for the variation in all variables of prices. BTC query variable has relatively strong explaining power for variation of variables for Google Trends queries but ETC query. In the LTC query variable, from the 5^{th} step ahead, part of the variation is explained by LTC price variable.

In the third model with trading volumes of cryptocurrencies, we found that BTC volume variable has relatively strong explaining power for the variation of the volume variables but ETC volume variable.

In the fourth model with trading volumes of cryptocurrencies and Google Trends queries, for the variables of trading volumes, we found very similar results as for the third model with trading volumes only.

For the variables of Google Trends queries, we found that BTC query has relatively strong explaining power in all variables but ETC query variable. There are also some small shares of variations explained by trading volumes.

According to Forecast error variance decomposition, we found that Ethereum and Ethereum Classic are not significantly correlated in either of our four models. Thus, our results do not support the hypothesis of [13]. He suggested a hypothesis that two cryptocurrencies, such that one has forked from the second one, could behave similarly. He [13] also found robust positive association among Bitcoin, Litecoin, Ethereum Classic and Ethereum. Our results supports these findings. We found some correlation among prices, volumes and Google Trends queries, individually.

Our results supports the previous finding of [39] that one of the factors for the price formation of cryptocurrency is cryptocurrency‘s popularity, which can be captured in Google Trends queries.

The results of our thesis indicates that investors who are trading one cryptocurrency, are probably also trading some other cryptocurrencies, or at least following their developments.

8 Conclusions and suggestions for further research

Limitations of our research

At the same time, we are aware of several limitations of our thesis. We applied four relatively basic models based on prices, trading volumes and Google Trends queries regarding the four chosen cryptocurrencies. For getting the information about cryptocurrencies from Google Trends, we used only four elementary names of the four chosen cryptocurrencies. We admit that we could give more attention to choosing, which queries to use in our model.

Suggestions for further research

In the further research, we suggest to enrich our models by adding various new variables such as the price of electricity, due to the relatively high consumption of electricity during mining the cryptocurrencies. Further, we suggest to add some global financial indicators to our model, e.g. the growth of world GDP, interest rates, the price of crude oil, the price of gold, DJIA, NASDAQ or another important stock index. We also suggest to utilize other searching tools or social networks, e.g. The Yahoo!, GitHub, Facebook or Twitter. Moreover, the basic idea of our model perhaps could be utilized to build an investment portfolio.

Conclusions

We regard the results of our thesis as an interesting addition to the previous results of research utilizing web searches in order to examine the behaviour of cryptocurrencies. Now, let us answer our research questions, mentioned in Section 1. According to our results, the answer for the first question is yes, there are some relationships among prices of cryptocurrencies. According to FEVD results for the first model, BTC price significantly influence all other prices in the log-difference transformation. LTC price influence LTC, ETC and ETH price in the log-difference transformation. ETC price influence the

ETH price in log-difference transformation.

The answer to the second question is yes, Google Trends queries slightly help to explain the variation of price but very slightly. According to the FEVD results for the second model, there are greater interconnections among prices variables and among Google Trends queries variables than between these two groups.

The answer for the third question is yes, there are some relationships among daily trading volumes of cryptocurrencies in log-difference transformation. Similarly as for the first model with prices, BTC volume influence all the volumes in log-difference transformation. LTC volume influence ETC and ETH volumes and ETH volume influence ETC volume in log-difference transformation.

The answer for the fourth question is yes, Google Trends queries slightly help to explain the variation of volumes of cryptocurencies. According to the FEVD results of the fourth model with daily trading volumes and Google Trends queries, there are greater interconnections among volumes variables and among Google Trends queries variables than between these two groups. There is also the dominant explaining power of BTC volume for volumes and BTC query for BTC queries.

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10 Appendix

In this section, we present all tables and plots that are not presented in the main text of this thesis. Firstly, 2 tables with results of ADF, KPSS and PP tests for time series of daily trading volumes and time series of Google Trends queries of cryptocurrencies. Then, we present 4 tables with results of IRF and 4 tables with results of FEVD for the first model. Then we present 8 tables with results of IRF and 8 tables with results of FEVD for the second model. Then, we present the results for the third and fourth model in the same scope as for the first and second model, respectively. Then we present the boxplots and density plots of daily trading volumes and daily Google Trends hits. Then, we attach time series plots of daily opening prices, daily trading volumes and daily Google Trends hits for each cryptocurrency. At the end of the appendix, we attach 1 FEVD plot for the first model, 2 FEVD plots for the second model, 1 FEVD plot for the third model and 2 FEVD plots for the fourth model.

Table 9: Results of testing stationarity of time series of volumes

	BTC			LTC			ETC			ETH		
	test	lag	p	test	lag	p	test	lag	p	test	lag	p
level												
ADF	-1.69	9	0.71	-0.54	9	0.98	-5.57	9	0.01	-3.11	9	0.11
KPSS	3.79	7	0.01	3.87	7	0.01	5.54	7	0.01	6.88	7	0.01
PP	-7.29	7	0.01	-7.47	7	0.01	-11.38	7	0.01	-11.30	7	0.01
diff												
ADF	-13.94	9	0.01	-13.26	9	0.01	-13.01	9	0.01	-13.37	9	0.01
KPSS	0.06	7	0.1	0.10	7	0.1	0.01	7	0.1	0.04	7	0.1
PP	-44.91	7	0.01	-45.59	7	0.01	-46.41	7	0.01	-48.73	7	0.01
log												
ADF	-2.49	9	0.37	-3.01	9	0.15	-3.33	9	0.06	-2.86	9	0.21
KPSS	5.33	7	0.01	4.89	7	0.01	8.81	7	0.01	10.48	7	0.01
PP	-4.24	7	0.01	-4.69	7	0.01	-4.61	7	0.01	-6.45	7	0.01
log-diff												
ADF	-12.65	9	0.01	-11.88	9	0.01	-12.05	9	0.01	-13.43	9	0.01
KPSS	0.03	7	0.1	0.03	7	0.1	0.03	7	0.1	0.02	7	0.1
PP	-42.25	7	0.01	-41.88	7	0.01	-42.90	7	0.01	-51.58	7	0.01

Table 10: Results of testing stationarity of time series of Google Trends queries

	BTC			LTC			ETC			ETH		
	test	lag	p	test	lag	p	test	lag	p	test	lag	p
level												
ADF	-3.74	9	0.02	-6.46	9	0.01	-5.36	9	0.01	-4.24	9	0.01
KPSS	1.20	7	0.01	0.57	7	0.03	0.70	7	0.01	1.17	7	0.01
PP	-5.84	7	0.01	-9.69	7	0.01	-9.87	7	0.01	-4.36	7	0.01
diff												
ADF	-12.79	9	0.01	-12.45	9	0.01	-13.99	9	0.01	-10.22	9	0.01
KPSS	0.01	7	0.1	0.01	7	0.1	0.03	7	0.1	0.02	7	0.1
PP	-33.49	7	0.01	-34.60	7	0.01	-37.24	7	0.01	-28.18	7	0.01
log												
ADF	-3.18	9	0.09	-3.76	9	0.02	-13.99	9	0.01	-2.80	9	0.24
KPSS	4.00	7	0.01	3.68	7	0.01	0.03	7	0.1	2.23	7	0.01
PP	-3.70	7	0.02	-4.64	7	0.01	-37.24	7	0.01	-3.28	7	0.07
log-diff												
ADF	-11.23	9	0.01	-11.65	9	0.01	-13.99	9	0.01	-11.05	9	0.01
KPSS	0.03	7	0.1	0.02	7	0.1	0.03	7	0.1	0.03	7	0.1
PP	-29.20	7	0.01	-37.85	7	0.01	-37.24	7	0.01	-38.07	7	0.01

Table 11: IRF results for impulse from BTC price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0.042	0.037	0.033	0.034
-0.0002	0.0004	-0.001	-0.0002
0.00000	0.0001	0.0001	0.0001
-0.00001	-0.00000	-0.00000	0.00000
-0.00000	-0.00000	-0.00000	-0.00000
-0.00000	-0.00000	-0.00000	-0.00000
0	-0	-0	-0
0	0	-0	-0
0	0	0	0
0	0	0	0
-0	0	0	0
-0	-0	0	0
-0	-0	-0	-0
-0	-0	-0	-0
0	-0	-0	-0
0	0	-0	-0
0	0	0	0
0	0	0	0
-0	0	0	0
-0	-0	-0	0
-0	-0	-0	-0

Table 12: IRF results for impulse from LTC price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0	0.050	0.022	0.016
-0.002	0.001	0.0003	0.002
-0.0003	-0.0002	0.00003	0.0001
-0.00002	-0.00004	-0.00001	-0.00001
-0.00000	-0.00000	-0.00000	-0.00000
0.00000	-0.00000	-0.00000	-0.00000
0.00000	0	0	-0
0	0	0	0
-0	0	0	0
-0	0	0	0
-0	-0	-0	0
-0	-0	-0	-0
0	-0	-0	-0
0	0	-0	-0
0	0	0	0
0	0	0	0
-0	0	0	0
-0	-0	0	0
-0	-0	-0	-0
-0	-0	-0	-0
0	-0	-0	-0

Table 13: IRF results for impulse from ETC price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0	0	0.057	0.016
-0.003	-0.007	-0.005	-0.004
0.0002	-0.0001	0.00005	-0.0002
0.00002	0.00001	-0.00001	-0.00001
0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000
-0	0	0	0
-0	-0	-0	0
-0	-0	-0	-0
-0	-0	-0	-0
0	-0	-0	-0
0	0	0	-0
0	0	0	0
-0	0	0	0
-0	0	0	0
-0	-0	-0	0
-0	-0	-0	-0
0	-0	-0	-0
0	0	-0	-0
0	0	0	0
0	0	0	0

Table 14: IRF results for impulse from ETH price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0	0	0	0.042
-0.002	-0.002	0.001	-0.0002
-0.0001	-0.0003	-0.0001	-0.0001
0.00001	-0.00001	-0.00000	-0.00001
0.00000	0.00000	-0.00000	-0.00000
0.00000	0.00000	0.00000	0.00000
0	0	0	0
-0	0	0	0
-0	-0	0	0
-0	-0	-0	-0
-0	-0	-0	-0
0	-0	-0	-0
0	0	-0	-0
0	0	0	0
0	0	0	0
-0	0	0	0
-0	-0	-0	0
-0	-0	-0	-0
-0	-0	-0	-0
0	-0	-0	-0
0	0	0	-0

Table 15: FEVD for BTC price in price model

BTC_price	LTC_price	ETC_price	ETH_price
1	0	0	0
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002
0.991	0.003	0.004	0.002

Table 16: FEVD for LTC price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0.360	0.640	0	0
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001
0.355	0.632	0.012	0.001

Table 17: FEVD for ETC price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0.223	0.097	0.681	0
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001
0.222	0.096	0.682	0.0001

Table 18: FEVD for ETH price in price model

BTC_price	LTC_price	ETC_price	ETH_price
0.334	0.070	0.076	0.520
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517
0.332	0.071	0.080	0.517

Table 19: IRF results for impulse from BTC price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.041	0.037	0.032	0.033	0.005	0.009	-0.123	-0.005
0.040	0.036	0.031	0.032	0.010	0.007	-0.089	-0.005
0.040	0.038	0.034	0.033	0.001	-0.005	0.037	0.003
0.040	0.038	0.034	0.031	-0.004	0.015	0.106	0.008
0.037	0.037	0.033	0.030	-0.008	0.022	0.035	0.002
0.037	0.037	0.033	0.029	-0.005	0.019	0.031	0.005
0.037	0.037	0.033	0.028	-0.002	0.028	0.037	0.010
0.037	0.036	0.033	0.028	0.001	0.029	0.019	0.009
0.037	0.037	0.033	0.027	0.002	0.030	0.042	0.009
0.037	0.036	0.032	0.027	0.002	0.029	0.032	0.008
0.036	0.036	0.032	0.026	0.003	0.029	0.024	0.006
0.036	0.036	0.031	0.025	0.004	0.028	0.025	0.005
0.036	0.036	0.031	0.025	0.004	0.027	0.025	0.004
0.036	0.036	0.031	0.025	0.005	0.027	0.024	0.003
0.036	0.036	0.031	0.024	0.005	0.026	0.023	0.002
0.036	0.035	0.030	0.024	0.006	0.026	0.022	0.001
0.036	0.035	0.030	0.024	0.006	0.026	0.022	0.001
0.036	0.035	0.030	0.023	0.007	0.025	0.022	0.0002
0.036	0.035	0.030	0.023	0.007	0.025	0.021	-0.0003
0.035	0.035	0.030	0.023	0.008	0.025	0.021	-0.001
0.035	0.035	0.029	0.023	0.008	0.025	0.020	-0.001

Table 20: IRF results for impulse from LTC price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0.048	0.021	0.015	0.002	-0.001	0.107	0.014
-0.002	0.049	0.021	0.018	0.002	0.017	0.153	0.009
-0.001	0.047	0.020	0.017	0.011	0.038	0.125	0.025
0.001	0.050	0.020	0.018	0.009	0.055	0.101	0.015
0.002	0.053	0.021	0.015	-0.009	0.124	0.080	0.009
0.003	0.053	0.023	0.015	-0.004	0.104	0.133	0.028
0.003	0.054	0.023	0.014	0.0003	0.105	0.170	0.032
0.003	0.054	0.022	0.012	-0.0004	0.112	0.066	0.027
0.003	0.054	0.022	0.011	0.003	0.121	0.079	0.029
0.003	0.054	0.022	0.011	0.002	0.113	0.121	0.026
0.002	0.054	0.021	0.010	-0.0003	0.112	0.116	0.021
0.002	0.053	0.021	0.009	-0.001	0.111	0.084	0.020
0.002	0.053	0.020	0.008	-0.001	0.109	0.094	0.019
0.001	0.053	0.020	0.008	-0.002	0.106	0.102	0.016
0.001	0.053	0.020	0.008	-0.003	0.105	0.099	0.015
0.001	0.053	0.019	0.007	-0.003	0.103	0.094	0.014
0.001	0.053	0.019	0.007	-0.004	0.101	0.094	0.012
0.0003	0.052	0.019	0.006	-0.004	0.100	0.094	0.011
0.00004	0.052	0.019	0.006	-0.005	0.098	0.094	0.010
-0.0002	0.052	0.018	0.006	-0.005	0.097	0.093	0.009
-0.0004	0.052	0.018	0.006	-0.006	0.095	0.091	0.008

Table 21: IRF results for impulse from ETC price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0.055	0.016	-0.006	0.006	0.181	0.006
-0.003	-0.007	0.050	0.012	-0.004	0.014	0.059	0.016
-0.003	-0.010	0.047	0.011	-0.001	0.004	0.114	0.015
-0.003	-0.011	0.049	0.013	0.001	-0.009	0.116	0.038
-0.004	-0.012	0.047	0.014	-0.005	-0.009	0.327	0.049
-0.003	-0.012	0.047	0.014	-0.001	-0.013	0.184	0.038
-0.003	-0.012	0.048	0.015	0.003	-0.013	0.188	0.042
-0.003	-0.011	0.048	0.016	0.004	-0.007	0.203	0.048
-0.002	-0.011	0.049	0.017	0.007	-0.002	0.210	0.048
-0.002	-0.011	0.049	0.017	0.008	-0.003	0.219	0.050
-0.001	-0.011	0.050	0.018	0.010	0.001	0.215	0.053
-0.001	-0.011	0.050	0.018	0.011	0.005	0.207	0.055
-0.0005	-0.011	0.050	0.019	0.013	0.006	0.216	0.057
-0.0001	-0.010	0.051	0.019	0.014	0.009	0.219	0.059
0.0002	-0.010	0.051	0.019	0.015	0.012	0.216	0.060
0.001	-0.010	0.051	0.020	0.017	0.014	0.217	0.062
0.001	-0.010	0.051	0.020	0.018	0.016	0.220	0.064
0.001	-0.010	0.052	0.020	0.018	0.018	0.222	0.065
0.001	-0.010	0.052	0.020	0.019	0.020	0.223	0.066
0.002	-0.010	0.052	0.021	0.020	0.022	0.224	0.068
0.002	-0.009	0.053	0.021	0.021	0.024	0.225	0.069

Table 22: IRF results for impulse from ETH price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0.040	-0.001	0.004	-0.183	-0.009
-0.002	-0.002	0.001	0.038	-0.009	0.004	-0.030	-0.0004
-0.002	-0.004	0.006	0.039	-0.010	0.003	0.070	0.028
-0.004	-0.006	0.005	0.039	-0.009	0.004	0.098	0.039
-0.004	-0.007	0.005	0.041	-0.014	-0.017	0.130	0.051
-0.005	-0.007	0.005	0.040	-0.013	-0.015	0.019	0.042
-0.006	-0.008	0.005	0.039	-0.013	-0.022	0.020	0.037
-0.007	-0.008	0.005	0.039	-0.014	-0.026	0.045	0.039
-0.007	-0.009	0.004	0.039	-0.014	-0.030	0.025	0.035
-0.008	-0.009	0.003	0.038	-0.015	-0.033	0.002	0.031
-0.008	-0.009	0.003	0.037	-0.015	-0.035	-0.003	0.030
-0.009	-0.010	0.002	0.037	-0.015	-0.037	-0.004	0.028
-0.009	-0.010	0.002	0.036	-0.015	-0.039	-0.010	0.025
-0.009	-0.010	0.002	0.035	-0.015	-0.040	-0.016	0.024
-0.009	-0.010	0.001	0.035	-0.014	-0.042	-0.021	0.022
-0.010	-0.011	0.001	0.034	-0.014	-0.043	-0.022	0.021
-0.010	-0.011	0.001	0.034	-0.013	-0.044	-0.024	0.020
-0.010	-0.011	0.0002	0.034	-0.013	-0.045	-0.027	0.019
-0.010	-0.011	-0.0001	0.033	-0.013	-0.046	-0.029	0.018
-0.010	-0.011	-0.0004	0.033	-0.012	-0.046	-0.030	0.017
-0.011	-0.011	-0.001	0.032	-0.012	-0.047	-0.031	0.016

Table 23: IRF results for impulse from BTC query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0.180	0.152	0.080	0.124
0.0002	0.006	0.004	0.004	0.187	0.149	0.032	0.131
-0.002	0.007	0.003	0.006	0.165	0.135	0.133	0.103
-0.001	0.004	0.001	0.007	0.156	0.123	0.074	0.092
-0.001	0.005	0.003	0.008	0.137	0.094	0.107	0.082
-0.001	0.005	0.004	0.010	0.123	0.099	0.065	0.081
-0.0002	0.006	0.004	0.012	0.116	0.094	0.064	0.084
-0.00003	0.007	0.006	0.014	0.111	0.084	0.094	0.086
-0.0001	0.008	0.007	0.016	0.104	0.084	0.089	0.086
-0.00001	0.008	0.008	0.017	0.098	0.084	0.081	0.088
-0.00001	0.009	0.009	0.019	0.093	0.080	0.094	0.090
-0.0001	0.009	0.010	0.020	0.087	0.077	0.099	0.089
-0.0001	0.010	0.010	0.021	0.081	0.075	0.093	0.090
-0.0002	0.010	0.011	0.022	0.077	0.073	0.093	0.091
-0.0003	0.010	0.011	0.023	0.072	0.070	0.095	0.091
-0.0004	0.011	0.012	0.024	0.068	0.068	0.094	0.091
-0.001	0.011	0.012	0.024	0.064	0.065	0.093	0.091
-0.001	0.011	0.013	0.025	0.061	0.062	0.092	0.090
-0.001	0.011	0.013	0.025	0.057	0.060	0.091	0.090
-0.001	0.011	0.013	0.026	0.054	0.058	0.090	0.089
-0.001	0.012	0.013	0.026	0.051	0.055	0.088	0.088

Table 24: IRF results for impulse from LTC query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0	0.264	0.004	0.045
0.0003	-0.001	0.003	-0.0001	0.010	0.185	0.061	0.063
-0.001	0.001	0.004	-0.003	0.012	0.180	0.323	0.073
-0.003	-0.001	0.001	-0.007	0.008	0.181	0.021	0.069
-0.004	-0.003	0.001	-0.011	0.012	0.185	0.071	0.071
-0.006	-0.003	-0.001	-0.012	0.003	0.158	0.129	0.052
-0.008	-0.004	-0.003	-0.015	-0.005	0.151	0.133	0.037
-0.010	-0.005	-0.005	-0.017	-0.008	0.139	0.057	0.033
-0.011	-0.006	-0.006	-0.018	-0.012	0.128	0.073	0.026
-0.013	-0.006	-0.008	-0.020	-0.017	0.119	0.077	0.017
-0.014	-0.007	-0.009	-0.022	-0.020	0.110	0.072	0.011
-0.015	-0.008	-0.010	-0.023	-0.023	0.101	0.061	0.005
-0.016	-0.009	-0.012	-0.024	-0.026	0.094	0.054	-0.001
-0.017	-0.009	-0.013	-0.026	-0.029	0.087	0.049	-0.006
-0.018	-0.010	-0.014	-0.027	-0.031	0.081	0.047	-0.011
-0.019	-0.010	-0.015	-0.028	-0.033	0.074	0.041	-0.016
-0.020	-0.011	-0.016	-0.029	-0.035	0.069	0.034	-0.020
-0.021	-0.012	-0.017	-0.030	-0.036	0.064	0.030	-0.024
-0.022	-0.012	-0.018	-0.031	-0.038	0.059	0.027	-0.028
-0.022	-0.012	-0.019	-0.032	-0.039	0.054	0.022	-0.032
-0.023	-0.013	-0.019	-0.033	-0.040	0.050	0.018	-0.035

Table 25: IRF results for impulse from ETC query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0	0	3.654	0.014
-0.002	-0.002	0.00002	0.0001	0.008	0.012	0.289	-0.011
-0.002	0.0004	-0.0002	0.001	0.010	0.008	-0.033	-0.027
-0.002	0.002	0.001	0.001	0.003	0.015	0.125	-0.022
-0.002	0.003	0.004	0.003	-0.001	-0.002	0.600	-0.042
-0.001	0.005	0.006	0.003	-0.008	-0.013	0.278	-0.054
-0.001	0.006	0.006	0.004	-0.010	-0.007	0.007	-0.052
-0.001	0.006	0.006	0.004	-0.011	-0.001	0.012	-0.052
-0.0002	0.007	0.007	0.005	-0.013	-0.006	0.128	-0.055
0.00004	0.008	0.008	0.005	-0.014	-0.003	0.087	-0.057
0.0003	0.008	0.008	0.006	-0.014	-0.001	0.014	-0.055
0.001	0.008	0.008	0.006	-0.014	0.001	0.009	-0.054
0.001	0.009	0.009	0.006	-0.014	0.002	0.028	-0.054
0.001	0.009	0.009	0.007	-0.015	0.004	0.027	-0.054
0.001	0.009	0.009	0.007	-0.015	0.004	0.013	-0.053
0.001	0.009	0.010	0.007	-0.015	0.005	0.008	-0.053
0.001	0.009	0.010	0.007	-0.015	0.006	0.011	-0.052
0.001	0.010	0.010	0.007	-0.015	0.007	0.013	-0.052
0.002	0.010	0.010	0.008	-0.015	0.007	0.011	-0.051
0.002	0.010	0.010	0.008	-0.015	0.008	0.009	-0.051
0.002	0.010	0.010	0.008	-0.015	0.008	0.010	-0.050

Table 26: IRF results for impulse from ETH query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0	0	0	0.276
-0.001	0.002	0.002	-0.001	0.008	0.007	0.178	0.193
-0.002	0.003	0.002	-0.004	0.006	-0.003	0.102	0.122
-0.001	0.005	0.005	-0.001	0.016	0.010	0.182	0.176
-0.002	0.003	0.003	-0.002	0.019	0.033	0.019	0.173
-0.003	0.002	0.001	-0.005	0.018	0.018	0.077	0.156
-0.002	0.003	0.001	-0.006	0.021	0.020	0.138	0.165
-0.003	0.002	0.001	-0.007	0.022	0.025	0.098	0.164
-0.003	0.002	0.0001	-0.008	0.025	0.022	0.070	0.159
-0.003	0.002	-0.001	-0.009	0.027	0.021	0.082	0.158
-0.003	0.001	-0.001	-0.010	0.028	0.022	0.085	0.157
-0.004	0.001	-0.002	-0.011	0.030	0.021	0.081	0.155
-0.004	0.001	-0.002	-0.011	0.031	0.020	0.079	0.154
-0.004	0.0003	-0.003	-0.012	0.033	0.020	0.076	0.153
-0.004	0.00004	-0.003	-0.013	0.034	0.020	0.076	0.152
-0.004	-0.0002	-0.003	-0.013	0.035	0.020	0.077	0.151
-0.004	-0.0004	-0.004	-0.014	0.036	0.020	0.076	0.150
-0.004	-0.001	-0.004	-0.014	0.038	0.020	0.074	0.150
-0.004	-0.001	-0.004	-0.014	0.039	0.020	0.075	0.149
-0.004	-0.001	-0.004	-0.015	0.040	0.020	0.075	0.149
-0.004	-0.001	-0.005	-0.015	0.041	0.021	0.074	0.149

Table 27: FEVD for BTC price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
1	0	0	0	0	0	0	0
0.993	0.001	0.002	0.002	0.00002	0.00003	0.001	0.0001
0.990	0.001	0.003	0.002	0.001	0.0004	0.002	0.001
0.986	0.001	0.004	0.004	0.001	0.001	0.002	0.001
0.981	0.002	0.005	0.006	0.001	0.003	0.002	0.001
0.973	0.003	0.005	0.008	0.001	0.007	0.002	0.002
0.965	0.003	0.005	0.010	0.001	0.012	0.002	0.002
0.956	0.004	0.005	0.013	0.0005	0.018	0.002	0.002
0.947	0.004	0.005	0.015	0.0004	0.025	0.001	0.003
0.937	0.004	0.005	0.017	0.0004	0.033	0.001	0.003

Table 28: FEVD for LTC price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.369	0.631	0	0	0	0	0	0
0.358	0.629	0.007	0.0004	0.005	0.00005	0.0004	0.0005
0.364	0.613	0.014	0.001	0.007	0.0001	0.0003	0.001
0.359	0.611	0.018	0.003	0.006	0.0001	0.001	0.002
0.347	0.617	0.021	0.005	0.006	0.0005	0.001	0.002
0.340	0.620	0.023	0.006	0.006	0.001	0.002	0.002
0.333	0.623	0.024	0.008	0.006	0.001	0.003	0.002
0.328	0.625	0.024	0.009	0.007	0.002	0.004	0.002
0.323	0.626	0.025	0.010	0.008	0.002	0.004	0.002
0.320	0.626	0.025	0.010	0.008	0.003	0.005	0.002

Table 29: FEVD for ETC price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.232	0.095	0.673	0	0	0	0	0
0.240	0.103	0.654	0.0001	0.002	0.001	0.00000	0.001
0.261	0.104	0.628	0.003	0.002	0.002	0.00000	0.001
0.266	0.104	0.622	0.003	0.001	0.002	0.0001	0.002
0.271	0.106	0.613	0.004	0.002	0.002	0.001	0.002
0.273	0.110	0.605	0.005	0.002	0.001	0.002	0.002
0.273	0.113	0.601	0.005	0.002	0.001	0.003	0.002
0.272	0.114	0.599	0.005	0.003	0.002	0.004	0.001
0.271	0.115	0.596	0.005	0.004	0.003	0.005	0.001
0.268	0.115	0.595	0.005	0.005	0.004	0.006	0.001

Table 30: FEVD for ETH price in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.336	0.071	0.081	0.512	0	0	0	0
0.338	0.088	0.067	0.505	0.003	0.00000	0.00000	0.0002
0.342	0.090	0.057	0.502	0.006	0.001	0.0001	0.002
0.334	0.093	0.057	0.500	0.008	0.005	0.0002	0.002
0.323	0.089	0.057	0.506	0.011	0.012	0.001	0.002
0.315	0.086	0.058	0.505	0.014	0.018	0.001	0.003
0.306	0.082	0.061	0.502	0.018	0.025	0.002	0.004
0.297	0.078	0.063	0.498	0.023	0.033	0.002	0.005
0.289	0.073	0.066	0.492	0.029	0.041	0.003	0.007
0.280	0.069	0.068	0.485	0.036	0.049	0.003	0.009

Table 31: FEVD for BTC query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.001	0.0002	0.001	0.0001	0.998	0	0	0
0.002	0.0001	0.001	0.001	0.993	0.001	0.001	0.001
0.001	0.001	0.001	0.002	0.989	0.002	0.002	0.001
0.001	0.002	0.0005	0.002	0.988	0.003	0.001	0.003
0.001	0.002	0.001	0.003	0.983	0.003	0.001	0.005
0.002	0.002	0.001	0.004	0.981	0.003	0.001	0.007
0.001	0.002	0.001	0.005	0.978	0.003	0.002	0.009
0.001	0.002	0.001	0.005	0.975	0.003	0.002	0.011
0.001	0.002	0.001	0.006	0.971	0.004	0.003	0.013
0.001	0.002	0.001	0.007	0.965	0.005	0.004	0.016

Table 32: FEVD for LTC query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.001	0.00002	0.0003	0.0002	0.247	0.751	0	0
0.001	0.002	0.002	0.0002	0.301	0.693	0.001	0.0003
0.001	0.009	0.001	0.0002	0.314	0.674	0.001	0.0003
0.001	0.019	0.001	0.0002	0.309	0.666	0.002	0.001
0.003	0.064	0.001	0.001	0.278	0.647	0.001	0.004
0.003	0.086	0.002	0.002	0.269	0.632	0.002	0.004
0.005	0.104	0.002	0.003	0.261	0.619	0.002	0.005
0.006	0.123	0.002	0.004	0.253	0.605	0.001	0.006
0.008	0.143	0.002	0.005	0.246	0.589	0.001	0.006
0.009	0.157	0.002	0.007	0.243	0.575	0.001	0.007

Table 33: FEVD for ETC query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.001	0.001	0.002	0.002	0.0005	0.00000	0.993	0
0.002	0.003	0.003	0.003	0.001	0.0003	0.987	0.002
0.002	0.004	0.004	0.003	0.002	0.008	0.975	0.003
0.003	0.004	0.005	0.004	0.002	0.008	0.970	0.005
0.003	0.005	0.012	0.005	0.003	0.008	0.960	0.005
0.003	0.006	0.014	0.005	0.003	0.009	0.955	0.006
0.003	0.008	0.016	0.005	0.003	0.010	0.948	0.007
0.003	0.008	0.019	0.005	0.004	0.010	0.944	0.007
0.003	0.008	0.022	0.005	0.005	0.011	0.939	0.008
0.003	0.009	0.025	0.005	0.005	0.011	0.934	0.008

Table 34: FEVD for ETH query in price and query model

BTC_price	LTC_price	ETC_price	ETH_price	BTC_query	LTC_query	ETC_query	ETH_query
0.0003	0.002	0.0004	0.001	0.163	0.021	0.002	0.810
0.0003	0.002	0.002	0.0005	0.211	0.039	0.002	0.743
0.0003	0.005	0.003	0.005	0.231	0.060	0.005	0.691
0.001	0.005	0.009	0.010	0.220	0.068	0.006	0.682
0.0005	0.004	0.016	0.018	0.206	0.075	0.012	0.670
0.0005	0.006	0.018	0.021	0.200	0.074	0.019	0.661
0.001	0.008	0.021	0.022	0.196	0.069	0.024	0.659
0.001	0.009	0.024	0.024	0.194	0.064	0.028	0.656
0.001	0.010	0.027	0.024	0.192	0.060	0.033	0.652
0.001	0.011	0.030	0.024	0.192	0.056	0.037	0.650

Table 35: IRF results for impulse from BTC volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0.344	0.203	-0.002	0.190
0.260	0.149	-0.004	0.134
0.177	0.108	-0.001	0.082
0.168	0.107	0.015	0.055
0.177	0.102	0.140	0.059
0.139	0.091	0.112	0.041
0.152	0.121	0.071	0.076
0.171	0.093	0.074	0.068
0.174	0.090	0.059	0.066
0.164	0.099	0.047	0.067
0.168	0.102	0.072	0.063
0.160	0.092	0.073	0.052
0.159	0.098	0.064	0.059
0.165	0.102	0.065	0.066
0.168	0.100	0.066	0.068
0.165	0.098	0.059	0.065
0.165	0.100	0.061	0.065
0.164	0.098	0.067	0.063
0.164	0.098	0.067	0.063
0.164	0.100	0.065	0.064
0.165	0.100	0.065	0.064

Table 36: IRF results for impulse from LTC volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0	0.354	0.006	0.088
0.011	0.273	0.016	0.071
-0.017	0.194	0.006	0.028
-0.008	0.189	0.020	0.049
0.005	0.205	0.123	0.049
0.016	0.185	0.122	0.045
0.002	0.192	0.064	0.023
-0.006	0.170	0.072	0.014
0.001	0.175	0.081	0.021
-0.002	0.183	0.083	0.023
-0.005	0.188	0.080	0.020
-0.006	0.181	0.080	0.018
-0.004	0.181	0.078	0.024
-0.001	0.182	0.081	0.027
-0.001	0.184	0.083	0.025
-0.002	0.182	0.083	0.022
-0.003	0.182	0.084	0.021
-0.002	0.181	0.087	0.021
-0.002	0.182	0.087	0.021
-0.002	0.182	0.087	0.021
-0.002	0.182	0.087	0.021

Table 37: IRF results for impulse from ETC volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0	0	0.398	0.017
-0.003	-0.007	0.258	0.006
0.006	0.018	0.193	0.025
0.025	-0.0002	0.142	0.037
0.015	-0.012	0.150	0.010
-0.017	-0.014	0.140	0.0004
-0.002	0.004	0.158	-0.001
-0.024	-0.012	0.156	-0.008
-0.010	-0.001	0.122	0.022
-0.004	0.004	0.105	0.031
0.002	0.005	0.102	0.036
-0.007	0.0001	0.092	0.028
-0.007	0.006	0.096	0.031
-0.008	0.002	0.101	0.029
-0.008	0.005	0.096	0.032
-0.005	0.008	0.087	0.036
-0.003	0.009	0.084	0.039
-0.005	0.007	0.080	0.038
-0.005	0.008	0.078	0.039
-0.006	0.008	0.079	0.039
-0.006	0.009	0.078	0.039

Table 38: IRF results for impulse from ETH volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0	0	0	0.393
-0.022	-0.017	0.026	0.212
-0.036	-0.014	0.035	0.154
-0.006	-0.021	0.044	0.160
-0.010	-0.011	0.148	0.147
-0.0005	-0.011	0.103	0.148
0.008	-0.022	0.111	0.127
0.022	0.008	0.093	0.136
0.006	-0.010	0.098	0.145
-0.010	-0.020	0.107	0.135
-0.005	-0.016	0.112	0.130
-0.011	-0.020	0.125	0.128
-0.005	-0.017	0.123	0.136
-0.003	-0.016	0.116	0.136
-0.001	-0.020	0.120	0.133
-0.001	-0.019	0.119	0.130
-0.002	-0.017	0.124	0.130
-0.003	-0.019	0.128	0.128
-0.004	-0.019	0.128	0.127
-0.003	-0.019	0.129	0.128
-0.002	-0.019	0.130	0.129

Table 39: FEVD results for BTC volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
1	0	0	0
0.997	0.001	0.00003	0.003
0.990	0.002	0.0002	0.008
0.988	0.002	0.003	0.007
0.988	0.002	0.003	0.007
0.987	0.003	0.004	0.006
0.988	0.003	0.004	0.006
0.986	0.002	0.005	0.007
0.986	0.002	0.005	0.006
0.987	0.002	0.005	0.006

Table 40: FEVD results for LTC volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0.247	0.753	0	0
0.240	0.759	0.0002	0.001
0.239	0.758	0.001	0.002
0.239	0.757	0.001	0.003
0.234	0.762	0.001	0.003
0.230	0.766	0.002	0.003
0.235	0.760	0.002	0.003
0.235	0.760	0.002	0.003
0.233	0.762	0.002	0.003
0.233	0.762	0.001	0.004

Table 41: FEVD results for ETC volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0.00002	0.0002	1.000	0
0.0001	0.001	0.996	0.003
0.0001	0.001	0.991	0.007
0.001	0.003	0.983	0.013
0.054	0.043	0.832	0.070
0.076	0.072	0.766	0.086
0.080	0.074	0.743	0.104
0.084	0.078	0.727	0.111
0.085	0.085	0.709	0.122
0.084	0.092	0.689	0.135

Table 42: FEVD results for ETH volume in model with volumes

BTC_vol	LTC_vol	ETC_vol	ETH_vol
0.182	0.039	0.001	0.778
0.203	0.048	0.001	0.748
0.203	0.046	0.003	0.748
0.193	0.048	0.007	0.752
0.188	0.052	0.007	0.754
0.179	0.053	0.006	0.761
0.184	0.052	0.006	0.759
0.185	0.049	0.006	0.760
0.183	0.047	0.006	0.763
0.184	0.046	0.008	0.762

Table 43: IRF results for impulse from BTC volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.333	0.193	-0.003	0.187	0.002	0.011	0.019	0.007
0.246	0.142	-0.005	0.131	0.009	0.012	-0.265	0.017
0.165	0.105	-0.004	0.084	0.023	0.016	-0.145	0.035
0.157	0.106	0.013	0.060	0.057	0.051	0.154	0.082
0.163	0.101	0.132	0.061	0.102	0.074	0.262	0.106
0.129	0.094	0.104	0.043	0.092	0.061	-0.125	0.074
0.145	0.123	0.069	0.081	0.081	0.063	-0.345	0.065
0.163	0.095	0.076	0.074	0.076	0.054	0.059	0.073
0.169	0.097	0.059	0.074	0.063	0.049	0.276	0.062
0.157	0.099	0.042	0.064	0.059	0.052	0.050	0.059
0.160	0.099	0.066	0.055	0.070	0.062	0.063	0.075
0.158	0.095	0.071	0.057	0.075	0.065	0.034	0.085
0.160	0.100	0.071	0.069	0.072	0.061	0.132	0.078
0.164	0.101	0.065	0.072	0.072	0.063	0.088	0.074
0.168	0.103	0.060	0.075	0.073	0.067	0.056	0.076
0.165	0.098	0.061	0.072	0.071	0.068	0.053	0.077
0.164	0.096	0.067	0.068	0.071	0.068	0.112	0.079
0.162	0.094	0.071	0.066	0.073	0.070	0.096	0.083
0.162	0.095	0.073	0.066	0.074	0.072	0.078	0.084
0.164	0.097	0.070	0.068	0.073	0.072	0.059	0.084
0.166	0.097	0.069	0.069	0.073	0.071	0.088	0.084

Table 44: IRF results for impulse from LTC volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0.347	0.007	0.089	-0.004	0.009	0.267	0.003
0.011	0.263	0.016	0.073	0.001	0.025	0.029	0.016
-0.017	0.187	0.007	0.038	-0.0005	0.040	-0.017	0.014
-0.009	0.180	0.019	0.055	0.002	0.071	0.101	0.020
0.006	0.197	0.120	0.055	0.013	0.150	0.314	0.041
0.019	0.179	0.119	0.052	0.012	0.151	0.059	0.048
0.004	0.181	0.064	0.027	-0.0004	0.128	0.234	0.039
-0.006	0.157	0.075	0.018	-0.008	0.121	0.228	0.031
0.007	0.160	0.085	0.024	-0.003	0.126	0.213	0.050
0.002	0.171	0.085	0.028	-0.006	0.116	0.129	0.046
-0.002	0.175	0.079	0.022	-0.010	0.109	0.129	0.031
-0.008	0.160	0.076	0.020	-0.011	0.106	0.148	0.034
-0.006	0.158	0.079	0.032	-0.013	0.103	0.228	0.032
-0.004	0.159	0.081	0.036	-0.017	0.100	0.185	0.023
-0.005	0.158	0.082	0.032	-0.018	0.100	0.128	0.025
-0.008	0.154	0.081	0.032	-0.019	0.099	0.145	0.026
-0.009	0.154	0.083	0.033	-0.020	0.095	0.179	0.025
-0.007	0.154	0.085	0.034	-0.022	0.092	0.187	0.027
-0.007	0.155	0.084	0.033	-0.022	0.092	0.156	0.027
-0.007	0.155	0.085	0.034	-0.023	0.091	0.135	0.026
-0.007	0.155	0.087	0.035	-0.024	0.089	0.170	0.026

Table 45: IRF results for impulse from ETC volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0.387	0.017	-0.003	-0.008	0.308	0.016
-0.004	-0.008	0.247	0.009	0.008	-0.004	0.200	0.015
0.003	0.013	0.186	0.027	0.010	-0.017	0.160	0.004
0.023	-0.005	0.134	0.039	0.021	0.013	0.138	0.014
0.013	-0.017	0.144	0.017	0.020	0.024	0.064	0.030
-0.017	-0.016	0.139	0.014	0.020	0.016	0.089	0.023
0.005	0.007	0.155	0.015	0.025	0.015	0.178	0.023
-0.014	-0.009	0.153	0.001	0.029	0.027	-0.009	0.032
0.005	0.005	0.122	0.029	0.027	0.024	0.108	0.026
0.017	0.013	0.107	0.036	0.026	0.029	0.093	0.025
0.023	0.012	0.109	0.038	0.030	0.037	0.111	0.031
0.012	0.004	0.101	0.032	0.030	0.042	0.100	0.029
0.013	0.012	0.103	0.033	0.036	0.045	0.100	0.034
0.016	0.010	0.107	0.033	0.041	0.049	0.112	0.040
0.015	0.011	0.102	0.037	0.041	0.052	0.088	0.040
0.017	0.014	0.091	0.040	0.041	0.051	0.046	0.039
0.021	0.016	0.089	0.042	0.042	0.053	0.103	0.040
0.021	0.014	0.087	0.042	0.042	0.054	0.095	0.041
0.020	0.015	0.084	0.042	0.042	0.055	0.096	0.041
0.021	0.016	0.084	0.042	0.044	0.056	0.088	0.043
0.022	0.016	0.084	0.044	0.045	0.058	0.092	0.044

Table 46: IRF results for impulse from ETH volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0.380	0.009	0.012	-0.506	0.009
-0.017	-0.010	0.033	0.200	0.009	0.009	0.009	0.024
-0.031	-0.004	0.044	0.142	0.011	0.032	0.130	0.038
0.0002	-0.008	0.050	0.143	0.024	0.039	0.114	0.077
-0.001	0.004	0.150	0.127	0.035	0.025	0.293	0.130
0.006	0.006	0.104	0.128	0.020	0.031	0.060	0.117
0.017	-0.001	0.115	0.105	0.017	0.038	0.263	0.121
0.035	0.033	0.098	0.116	0.036	0.047	0.043	0.130
0.031	0.029	0.105	0.129	0.032	0.037	0.391	0.102
0.014	0.007	0.112	0.111	0.035	0.041	0.220	0.105
0.012	0.006	0.116	0.096	0.045	0.044	0.252	0.111
0.002	0.006	0.131	0.101	0.051	0.053	0.193	0.102
0.002	0.007	0.126	0.101	0.051	0.049	0.230	0.101
0.001	0.010	0.111	0.097	0.048	0.045	0.217	0.099
0.004	0.011	0.109	0.097	0.046	0.044	0.232	0.095
0.009	0.017	0.107	0.095	0.045	0.044	0.186	0.098
0.006	0.019	0.109	0.095	0.046	0.046	0.225	0.097
0.006	0.019	0.111	0.092	0.048	0.047	0.224	0.096
0.007	0.021	0.112	0.091	0.050	0.051	0.214	0.101
0.008	0.022	0.113	0.093	0.052	0.055	0.207	0.100
0.009	0.022	0.113	0.092	0.052	0.056	0.208	0.098

Table 47: IRF results for impulse from BTC query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0.167	0.130	-0.013	0.098
-0.006	0.016	0.024	0.019	0.164	0.124	-0.037	0.095
-0.018	-0.004	0.038	0.006	0.146	0.117	0.191	0.078
-0.014	-0.011	0.018	0.001	0.140	0.107	0.121	0.063
-0.009	0.004	0.017	0.026	0.126	0.079	0.051	0.054
-0.018	-0.013	0.020	0.030	0.113	0.096	-0.204	0.062
-0.018	-0.017	0.001	-0.002	0.110	0.079	-0.024	0.062
-0.001	-0.001	0.002	0.028	0.115	0.080	0.104	0.082
-0.004	-0.009	0.018	0.035	0.111	0.083	0.026	0.078
-0.011	-0.019	0.017	0.036	0.105	0.080	-0.024	0.071
-0.007	-0.021	0.008	0.043	0.100	0.076	0.038	0.072
-0.001	-0.025	0.028	0.050	0.099	0.078	0.053	0.075
-0.009	-0.035	0.025	0.049	0.096	0.076	0.010	0.075
-0.008	-0.035	0.021	0.051	0.093	0.070	0.047	0.077
-0.007	-0.038	0.026	0.050	0.093	0.070	0.030	0.081
-0.007	-0.041	0.031	0.052	0.090	0.066	0.048	0.083
-0.008	-0.042	0.028	0.055	0.086	0.061	0.048	0.081
-0.006	-0.042	0.030	0.057	0.084	0.058	0.053	0.081
-0.006	-0.046	0.032	0.058	0.082	0.056	0.054	0.082
-0.007	-0.047	0.033	0.060	0.080	0.054	0.065	0.082
-0.007	-0.049	0.035	0.061	0.079	0.052	0.066	0.081

Table 48: IRF results for impulse from LTC query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0	0.260	-0.024	0.039
-0.009	-0.011	-0.002	0.004	0.007	0.170	0.024	0.051
0.012	-0.0002	0.010	-0.013	0.010	0.168	0.220	0.062
0.030	0.016	0.023	-0.020	0.007	0.167	-0.099	0.062
0.023	0.010	0.035	-0.013	0.010	0.163	-0.013	0.056
0.011	0.029	0.010	-0.029	0.005	0.132	0.021	0.046
0.017	0.024	0.020	-0.025	0.004	0.128	0.042	0.035
-0.011	-0.010	0.009	-0.045	0.002	0.121	0.005	0.036
-0.011	0.007	0.012	-0.027	0.001	0.105	-0.052	0.016
-0.011	0.010	0.009	-0.022	-0.002	0.098	-0.055	0.002
-0.016	0.001	0.012	-0.023	-0.008	0.085	-0.007	-0.003
-0.020	0.003	-0.013	-0.022	-0.014	0.072	-0.049	-0.011
-0.017	0.008	-0.008	-0.016	-0.017	0.062	-0.011	-0.018
-0.019	0.004	-0.006	-0.018	-0.018	0.059	-0.027	-0.016
-0.023	0.007	-0.010	-0.017	-0.021	0.052	-0.036	-0.020
-0.023	0.010	-0.009	-0.015	-0.022	0.046	-0.041	-0.024
-0.021	0.011	-0.006	-0.013	-0.023	0.042	-0.010	-0.024
-0.023	0.010	-0.008	-0.012	-0.024	0.038	-0.031	-0.028
-0.024	0.011	-0.009	-0.011	-0.026	0.033	-0.020	-0.032
-0.024	0.011	-0.007	-0.012	-0.026	0.031	-0.020	-0.031
-0.026	0.010	-0.006	-0.013	-0.026	0.028	-0.011	-0.033

Table 49: IRF results for impulse from ETC query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0	0	3.479	0.013
-0.024	-0.039	0.020	-0.033	0.006	0.006	0.230	-0.010
-0.038	-0.046	0.043	-0.055	0.013	0.012	-0.061	-0.021
-0.019	-0.022	0.029	0.002	0.008	0.016	0.104	-0.015
-0.020	-0.013	0.017	-0.003	0.004	-0.010	0.487	-0.031
-0.026	-0.010	-0.002	-0.008	-0.005	-0.023	0.123	-0.043
-0.036	-0.012	-0.024	-0.035	-0.009	-0.016	0.126	-0.039
-0.039	-0.008	-0.004	-0.032	-0.005	-0.012	-0.170	-0.034
-0.045	-0.020	0.034	-0.027	-0.009	-0.014	0.194	-0.038
-0.042	-0.018	0.025	-0.022	-0.013	-0.012	0.078	-0.039
-0.039	-0.015	0.006	-0.023	-0.013	-0.009	-0.010	-0.045
-0.030	-0.012	0.001	-0.013	-0.015	-0.006	-0.018	-0.047
-0.033	-0.019	0.001	-0.016	-0.017	-0.007	0.030	-0.045
-0.039	-0.021	0.002	-0.019	-0.017	-0.009	0.032	-0.045
-0.040	-0.021	0.006	-0.023	-0.015	-0.007	0.017	-0.043
-0.039	-0.018	0.006	-0.022	-0.013	-0.004	-0.042	-0.039
-0.039	-0.018	0.002	-0.018	-0.014	-0.006	-0.018	-0.042
-0.036	-0.017	-0.002	-0.015	-0.016	-0.008	-0.002	-0.043
-0.036	-0.018	-0.003	-0.016	-0.016	-0.007	-0.010	-0.043
-0.036	-0.018	-0.003	-0.016	-0.016	-0.006	-0.015	-0.043
-0.037	-0.018	-0.003	-0.016	-0.016	-0.006	-0.015	-0.043

Table 50: IRF results for impulse from ETH query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0	0	0	0	0	0	0	0.264
0.010	0.021	0.039	0.020	0.0001	-0.003	0.167	0.169
0.024	0.036	0.025	0.005	-0.006	-0.017	0.115	0.097
0.022	0.030	0.031	0.010	-0.004	-0.016	0.160	0.147
0.048	0.032	0.051	0.022	-0.004	0.007	0.017	0.154
0.045	0.015	0.054	0.007	-0.001	-0.005	-0.033	0.146
0.041	0.017	0.043	0.007	0.006	0.0002	0.213	0.161
0.002	-0.008	0.047	-0.006	0.019	0.017	0.036	0.133
0.013	0.009	0.044	-0.008	0.020	0.006	-0.023	0.146
0.026	0.020	0.038	0.0005	0.015	-0.003	0.093	0.154
0.022	0.016	0.034	0.003	0.014	-0.004	-0.023	0.133
0.013	0.012	0.018	-0.001	0.010	-0.012	-0.016	0.131
0.021	0.021	0.018	0.005	0.011	-0.004	0.081	0.139
0.022	0.018	0.022	-0.001	0.014	-0.002	0.037	0.135
0.024	0.024	0.018	0.003	0.014	-0.004	0.020	0.139
0.021	0.023	0.017	0.006	0.015	-0.001	0.017	0.137
0.022	0.021	0.020	0.005	0.017	0.001	0.020	0.135
0.024	0.024	0.015	0.005	0.017	-0.0002	0.037	0.139
0.025	0.026	0.015	0.007	0.017	0.002	0.028	0.137
0.023	0.024	0.014	0.004	0.018	0.002	-0.0003	0.137
0.023	0.025	0.013	0.005	0.018	0.001	0.028	0.139

Table 51: FEVD results for BTC volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
1	0	0	0	0	0	0	0
0.993	0.001	0.0001	0.002	0.0002	0.001	0.003	0.001
0.976	0.002	0.0001	0.006	0.002	0.001	0.010	0.003
0.968	0.002	0.002	0.005	0.002	0.005	0.010	0.005
0.958	0.002	0.003	0.005	0.002	0.006	0.011	0.013
0.947	0.003	0.004	0.005	0.003	0.006	0.012	0.020
0.939	0.003	0.003	0.005	0.004	0.007	0.016	0.023
0.935	0.003	0.004	0.008	0.004	0.007	0.019	0.021
0.932	0.003	0.003	0.010	0.003	0.006	0.022	0.020
0.928	0.002	0.004	0.010	0.003	0.006	0.025	0.020

Table 52: FEVD results for LTC volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.237	0.763	0	0	0	0	0	0
0.230	0.760	0.0003	0.0004	0.001	0.0005	0.006	0.002
0.229	0.751	0.001	0.0004	0.001	0.0004	0.012	0.006
0.232	0.745	0.001	0.0005	0.001	0.001	0.012	0.008
0.228	0.748	0.001	0.0005	0.001	0.001	0.011	0.009
0.226	0.748	0.002	0.0005	0.001	0.003	0.010	0.009
0.234	0.740	0.002	0.0005	0.002	0.004	0.009	0.009
0.236	0.738	0.002	0.002	0.002	0.004	0.009	0.008
0.237	0.735	0.002	0.004	0.002	0.004	0.009	0.008
0.238	0.734	0.002	0.004	0.002	0.004	0.009	0.008

Table 53: FEVD results for ETC volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.0001	0.0003	1.000	0	0	0	0	0
0.0002	0.001	0.982	0.005	0.003	0.00002	0.002	0.007
0.0002	0.001	0.961	0.012	0.008	0.0004	0.009	0.008
0.001	0.002	0.944	0.020	0.009	0.002	0.011	0.011
0.049	0.042	0.792	0.078	0.007	0.005	0.009	0.016
0.068	0.070	0.728	0.093	0.007	0.005	0.008	0.020
0.071	0.072	0.703	0.112	0.007	0.005	0.008	0.022
0.076	0.076	0.685	0.120	0.006	0.005	0.008	0.024
0.077	0.084	0.662	0.132	0.006	0.005	0.009	0.026
0.075	0.091	0.641	0.145	0.006	0.005	0.010	0.027

Table 54: FEVD results for ETH volume in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.186	0.042	0.002	0.770	0	0	0	0
0.207	0.052	0.002	0.732	0.001	0.0001	0.004	0.002
0.208	0.051	0.004	0.719	0.001	0.001	0.014	0.001
0.200	0.056	0.009	0.717	0.001	0.002	0.013	0.002
0.197	0.061	0.009	0.713	0.003	0.002	0.012	0.003
0.189	0.065	0.009	0.713	0.006	0.004	0.012	0.003
0.197	0.063	0.009	0.703	0.005	0.006	0.014	0.003
0.199	0.060	0.008	0.696	0.007	0.011	0.016	0.003
0.200	0.058	0.010	0.692	0.009	0.012	0.017	0.003
0.200	0.057	0.012	0.688	0.012	0.012	0.017	0.003

Table 55: FEVD results for BTC query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.0001	0.001	0.0003	0.003	0.996	0	0	0
0.002	0.0003	0.001	0.003	0.993	0.001	0.001	0.00000
0.008	0.0002	0.002	0.004	0.981	0.002	0.003	0.0005
0.038	0.0002	0.006	0.009	0.942	0.002	0.003	0.001
0.110	0.001	0.008	0.016	0.860	0.002	0.002	0.001
0.150	0.002	0.009	0.016	0.818	0.002	0.002	0.0005
0.171	0.002	0.012	0.016	0.795	0.002	0.002	0.001
0.182	0.002	0.015	0.021	0.774	0.002	0.002	0.002
0.184	0.002	0.017	0.024	0.765	0.002	0.002	0.004
0.186	0.002	0.018	0.027	0.757	0.002	0.003	0.005

Table 56: FEVD results for LTC query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.001	0.001	0.001	0.002	0.200	0.795	0	0
0.002	0.006	0.001	0.002	0.248	0.741	0.0003	0.0001
0.003	0.013	0.002	0.007	0.262	0.710	0.001	0.002
0.014	0.033	0.002	0.013	0.256	0.679	0.002	0.002
0.030	0.104	0.004	0.012	0.222	0.624	0.002	0.002
0.036	0.154	0.004	0.013	0.213	0.575	0.003	0.002
0.042	0.179	0.004	0.015	0.205	0.550	0.003	0.002
0.045	0.195	0.005	0.019	0.200	0.530	0.003	0.002
0.046	0.213	0.006	0.020	0.198	0.511	0.003	0.002
0.048	0.225	0.007	0.022	0.197	0.494	0.004	0.002

Table 57: FEVD results for ETC query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.00003	0.006	0.008	0.020	0.00001	0.00005	0.966	0
0.006	0.006	0.011	0.020	0.0001	0.0001	0.956	0.002
0.007	0.006	0.012	0.021	0.003	0.004	0.944	0.003
0.009	0.006	0.014	0.022	0.004	0.005	0.935	0.005
0.014	0.013	0.014	0.028	0.004	0.004	0.918	0.005
0.015	0.014	0.014	0.028	0.007	0.004	0.913	0.005
0.023	0.017	0.016	0.032	0.007	0.004	0.892	0.008
0.023	0.021	0.016	0.032	0.008	0.004	0.888	0.008
0.028	0.023	0.016	0.042	0.008	0.004	0.871	0.008
0.028	0.024	0.017	0.045	0.008	0.005	0.865	0.009

Table 58: FEVD results for ETH query in model with volumes and queries

BTC_vol	LTC_vol	ETC_vol	ETH_vol	BTC_query	LTC_query	ETC_query	ETH_query
0.001	0.0001	0.003	0.001	0.118	0.019	0.002	0.856
0.003	0.002	0.004	0.005	0.151	0.034	0.002	0.799
0.011	0.003	0.003	0.015	0.169	0.055	0.005	0.739
0.044	0.005	0.004	0.043	0.151	0.063	0.005	0.686
0.078	0.010	0.006	0.100	0.126	0.060	0.008	0.612
0.083	0.016	0.007	0.129	0.117	0.057	0.012	0.579
0.082	0.018	0.007	0.151	0.110	0.052	0.015	0.565
0.085	0.018	0.009	0.173	0.113	0.048	0.016	0.537
0.085	0.022	0.010	0.179	0.115	0.044	0.017	0.529
0.084	0.024	0.010	0.184	0.114	0.040	0.019	0.526

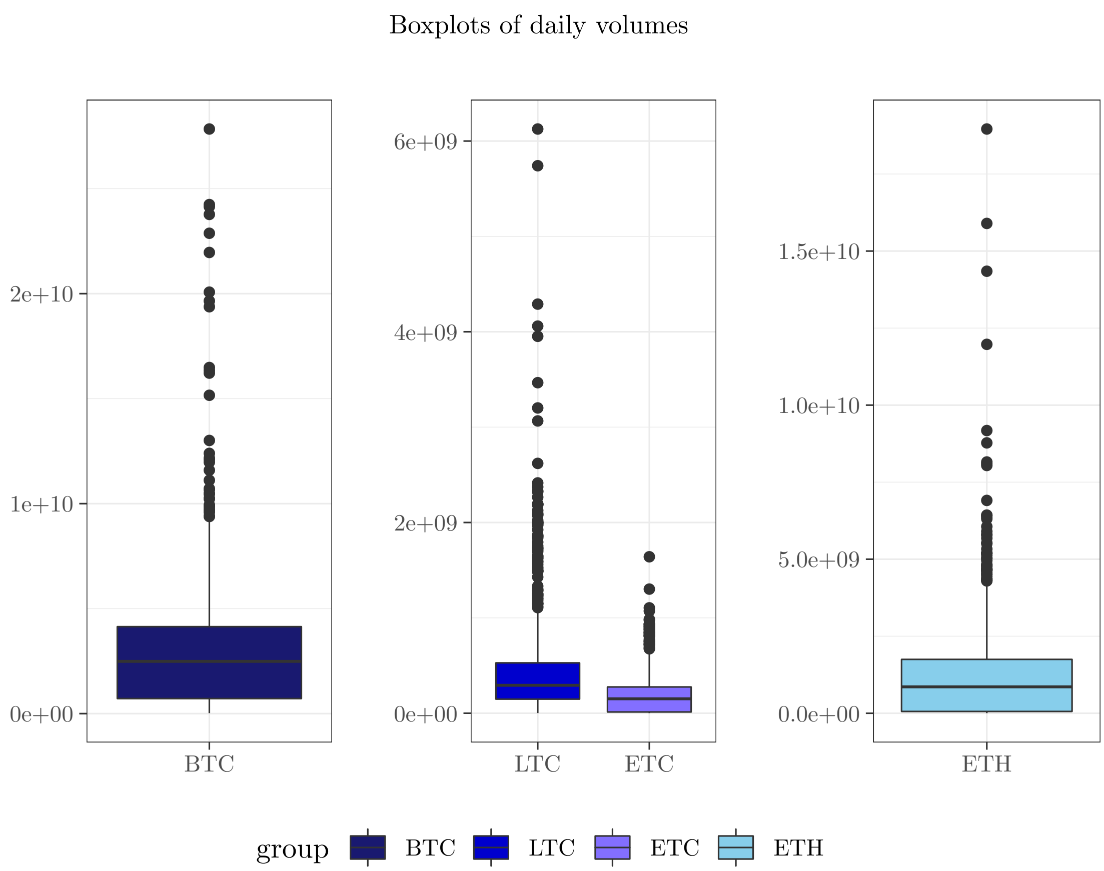

Figure 3: Boxplots of daily trading volumes of cryptocurrencies

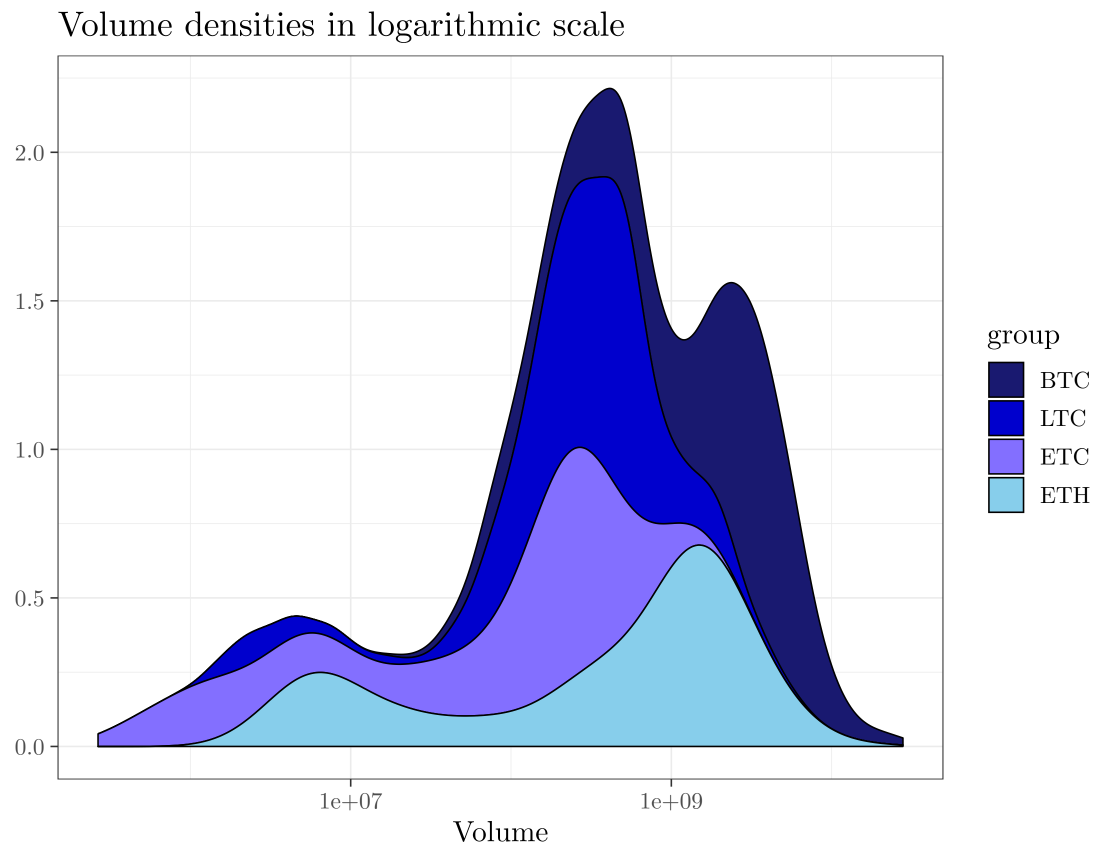

Figure 4: Densities of daily trading volumes of cryptocurrencies

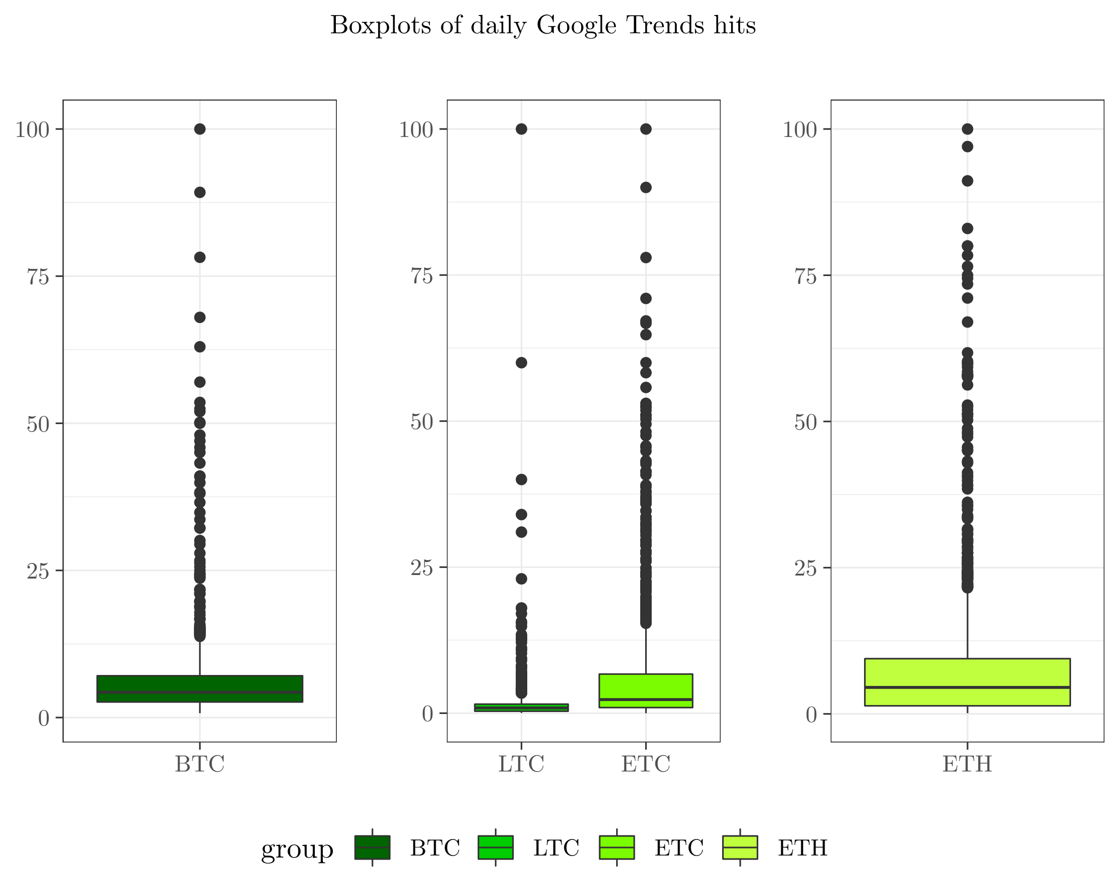

Figure 5: Boxplots of daily Google Trends hits of cryptocurrencies

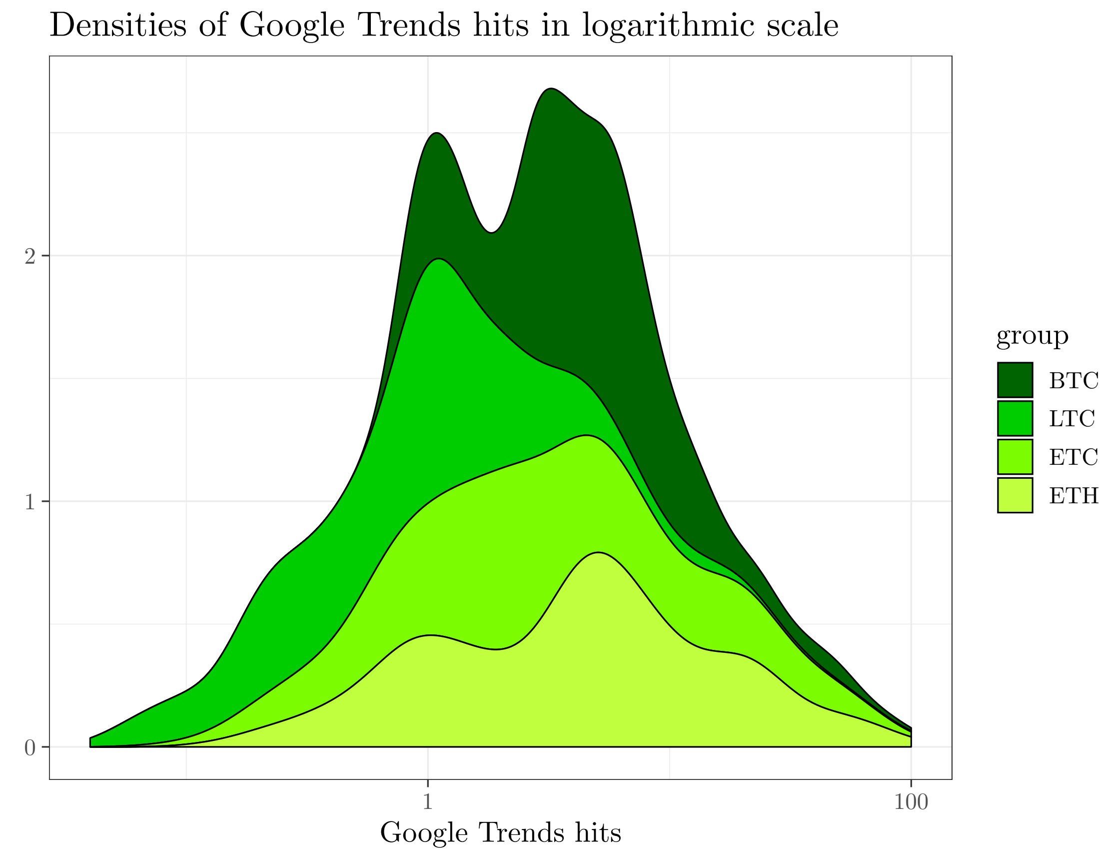

Figure 6: Densities of daily Google Trends hits of cryptocurrencies

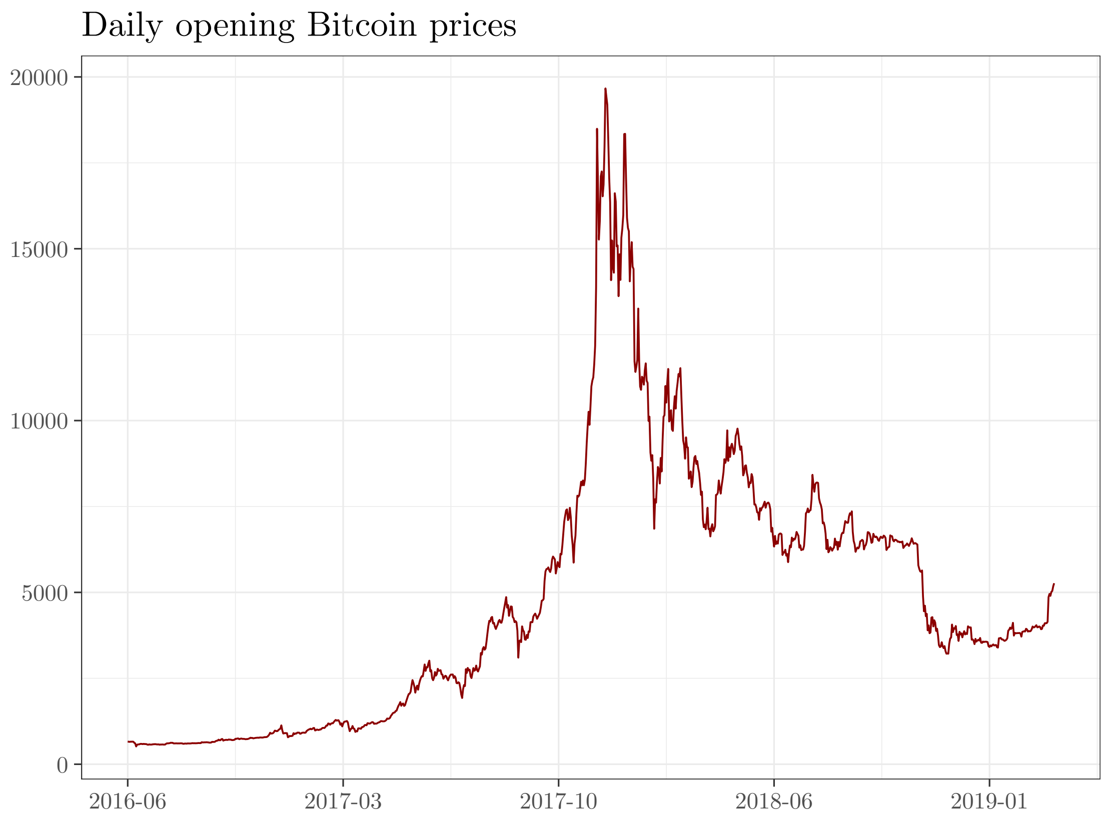

Figure 7: Time series plot of BTC daily opening prices in USD

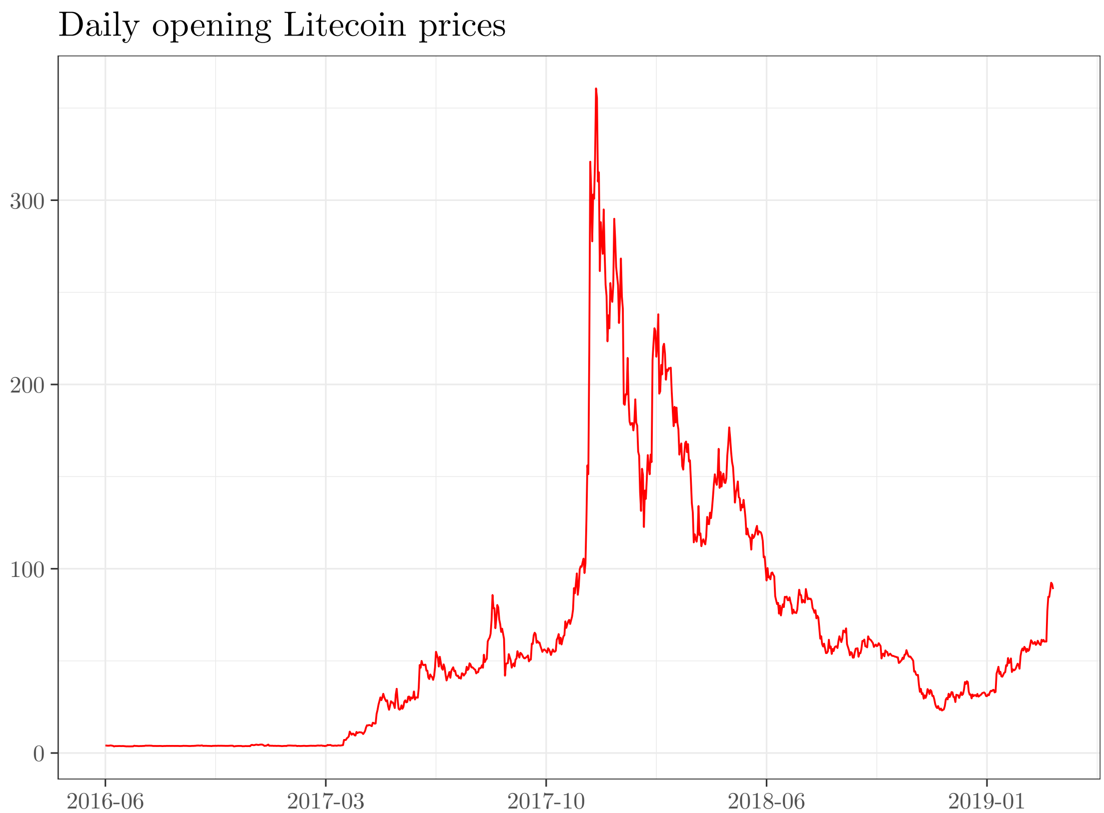

Figure 8: Time series plot of LTC daily opening prices in USD

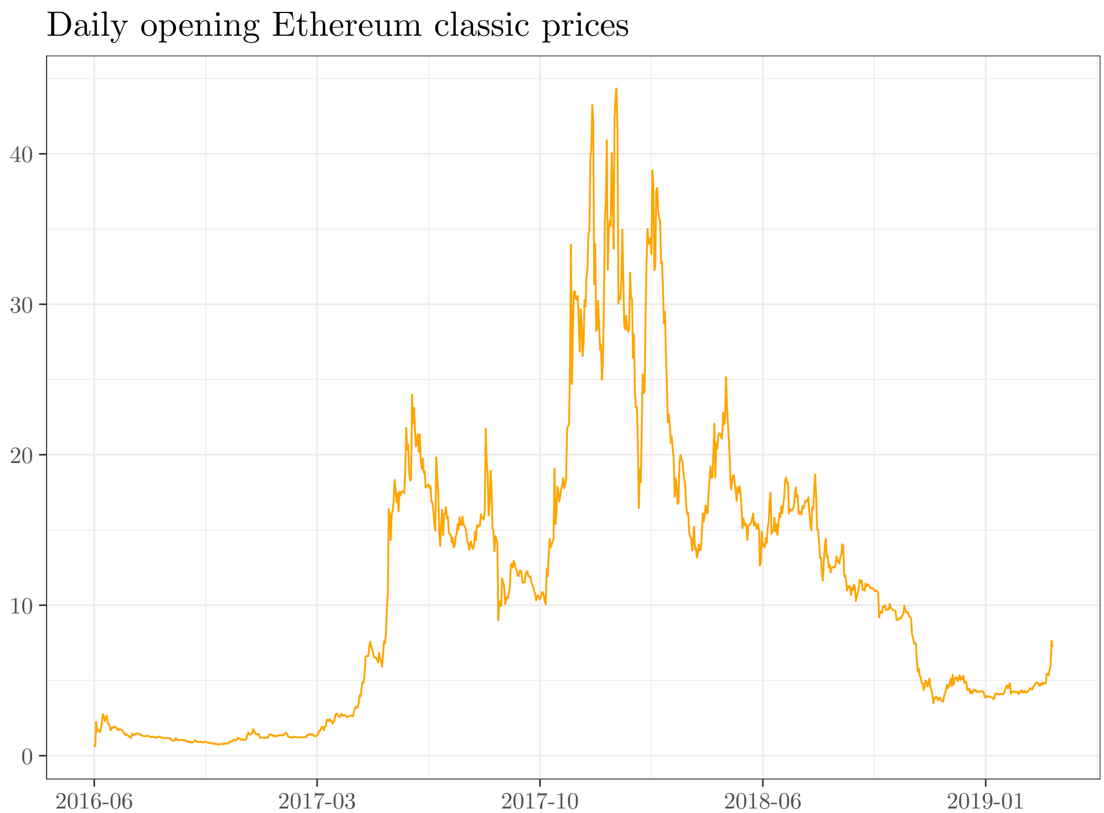

Figure 9: Time series plot of ETC daily opening prices in USD

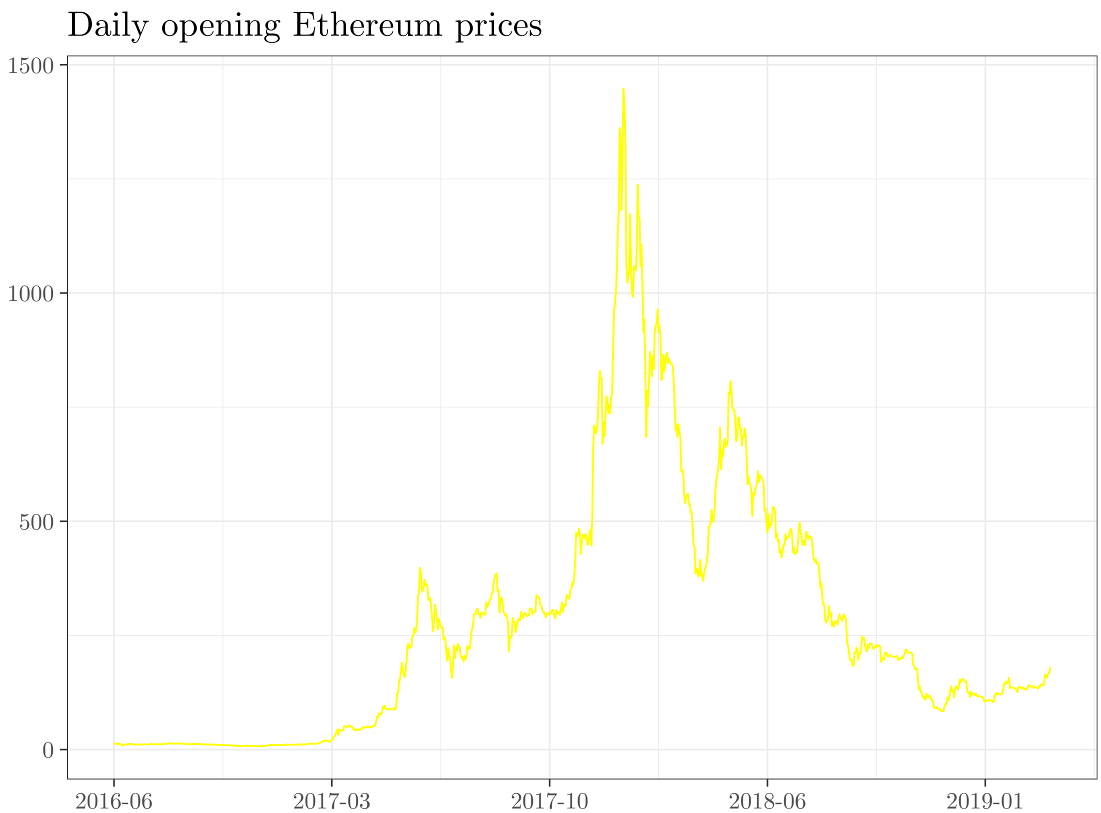

Figure 10: Time series plot of ETH daily opening prices in USD

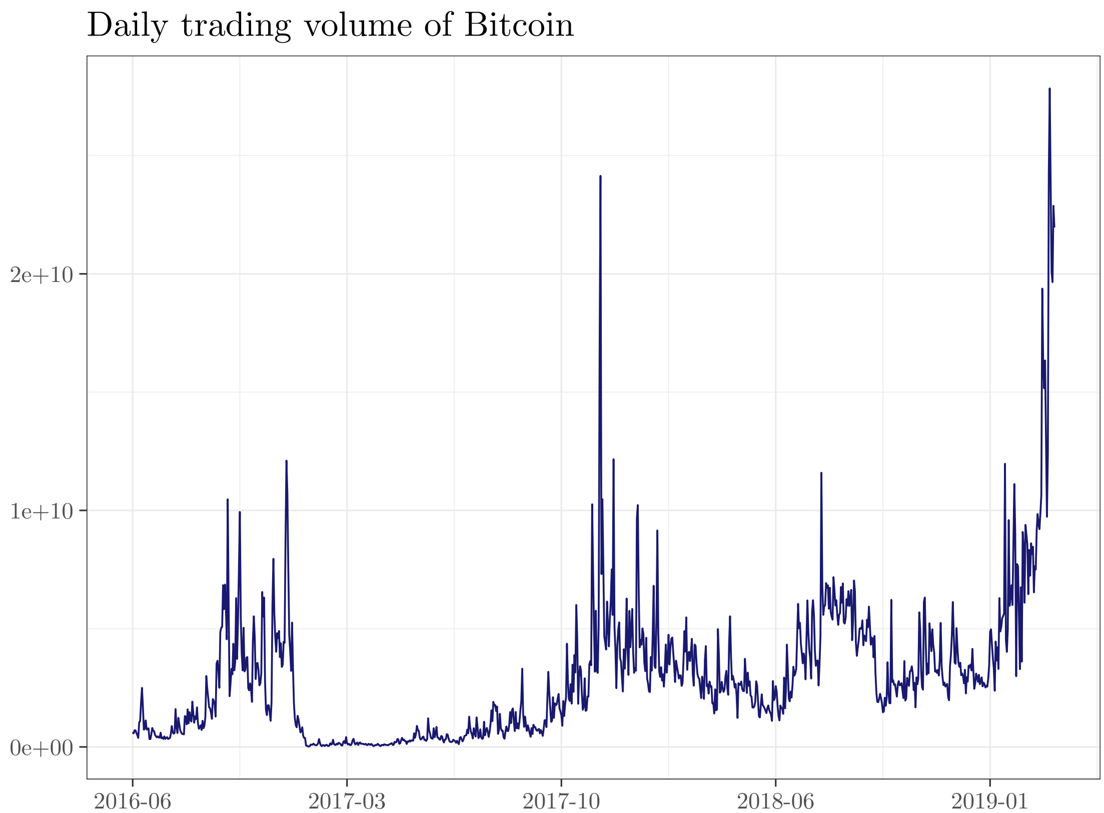

Figure 11: Time series plot of BTC daily trading volumes in USD

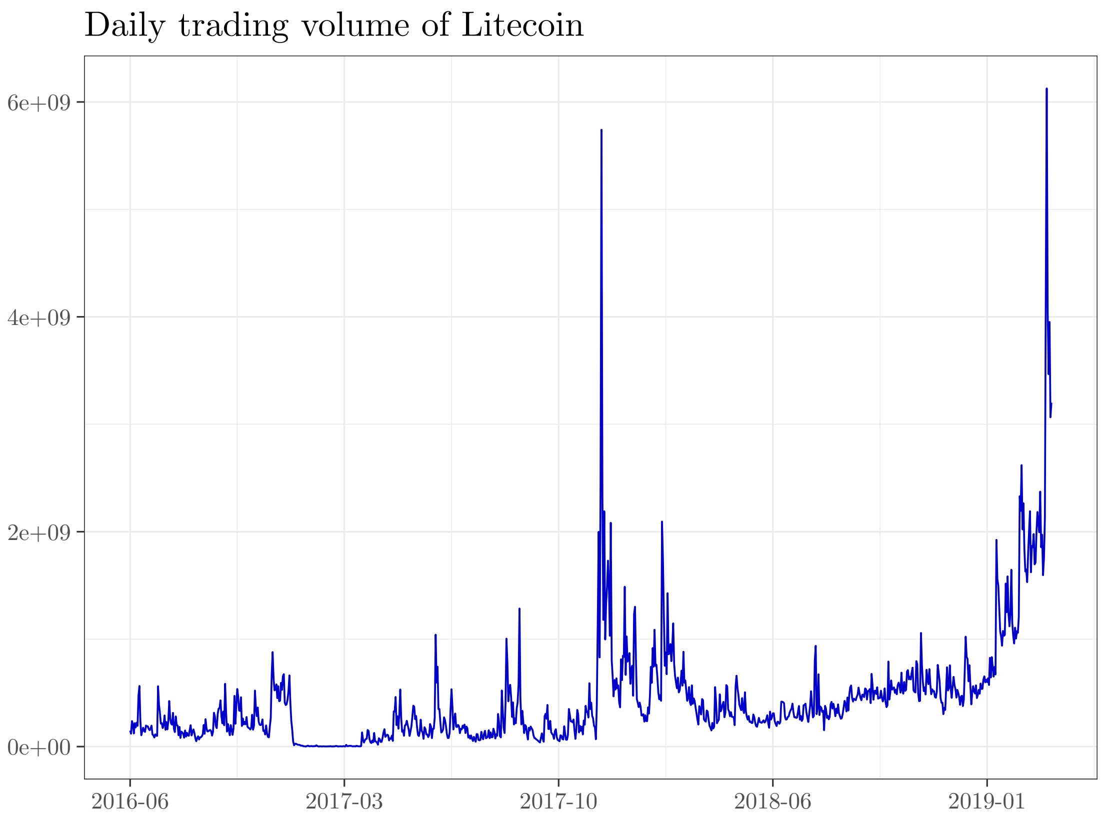

Figure 12: Time series plot of LTC daily trading volumes in USD

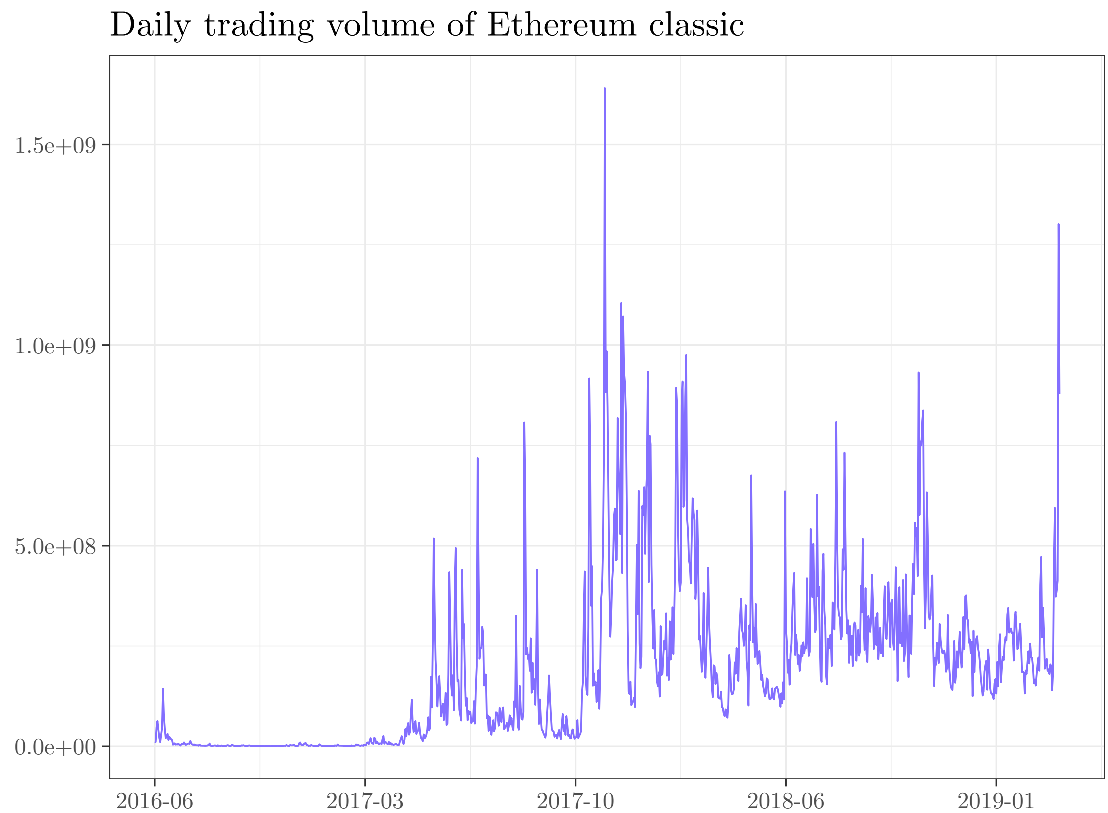

Figure 13: Time series plot of ETC daily trading volumes in USD

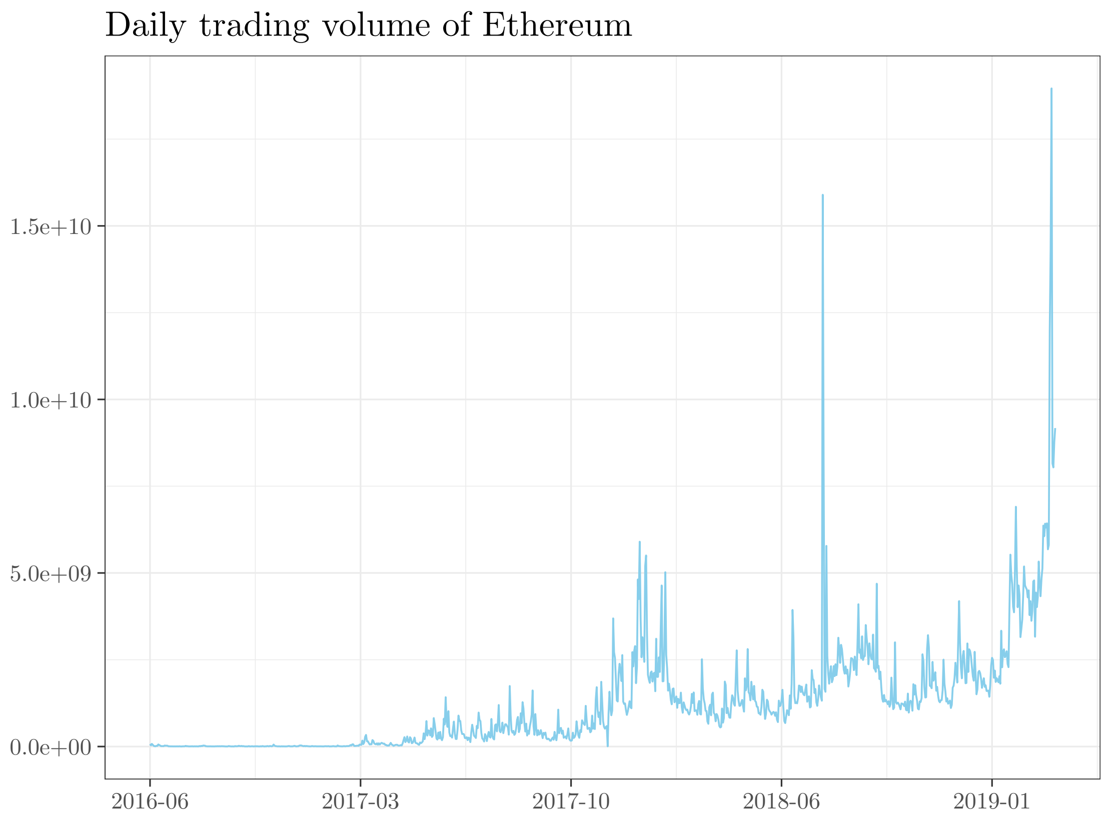

Figure 14: Time series plot of ETH daily trading volumes in USD

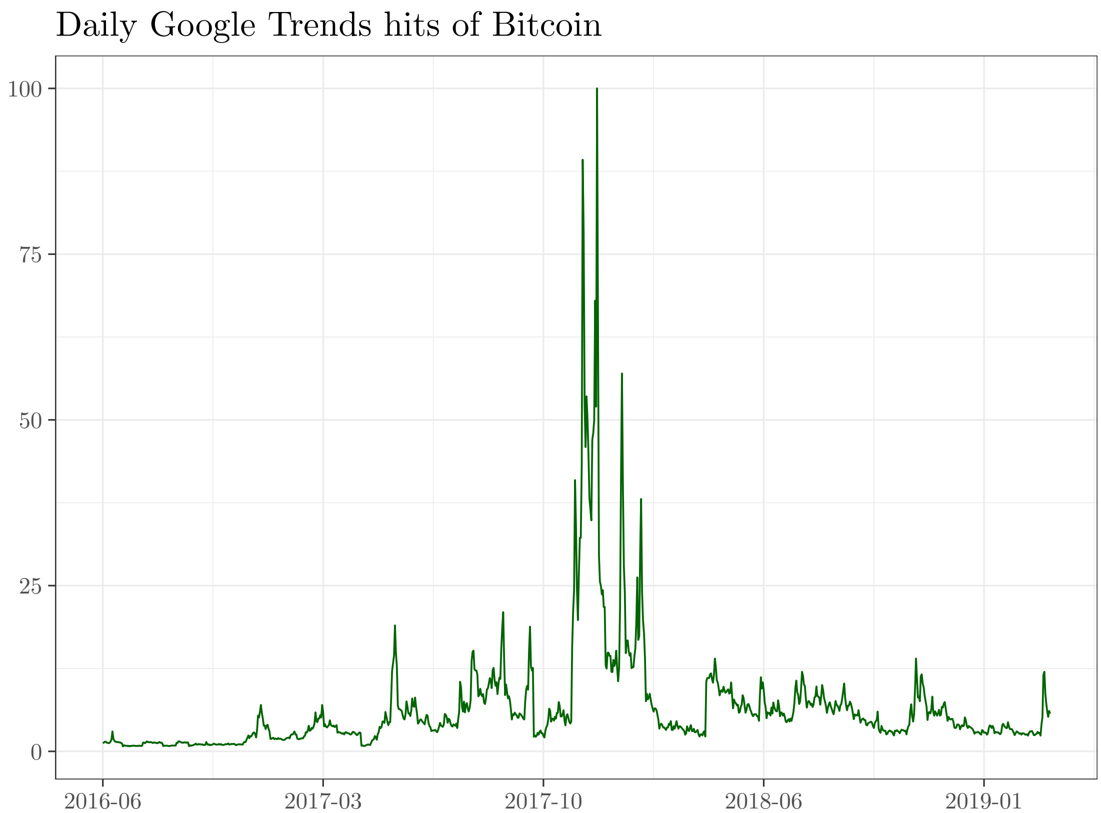

Figure 15: Time series plot of BTC daily Google Trends hits scaled between 0 and 100

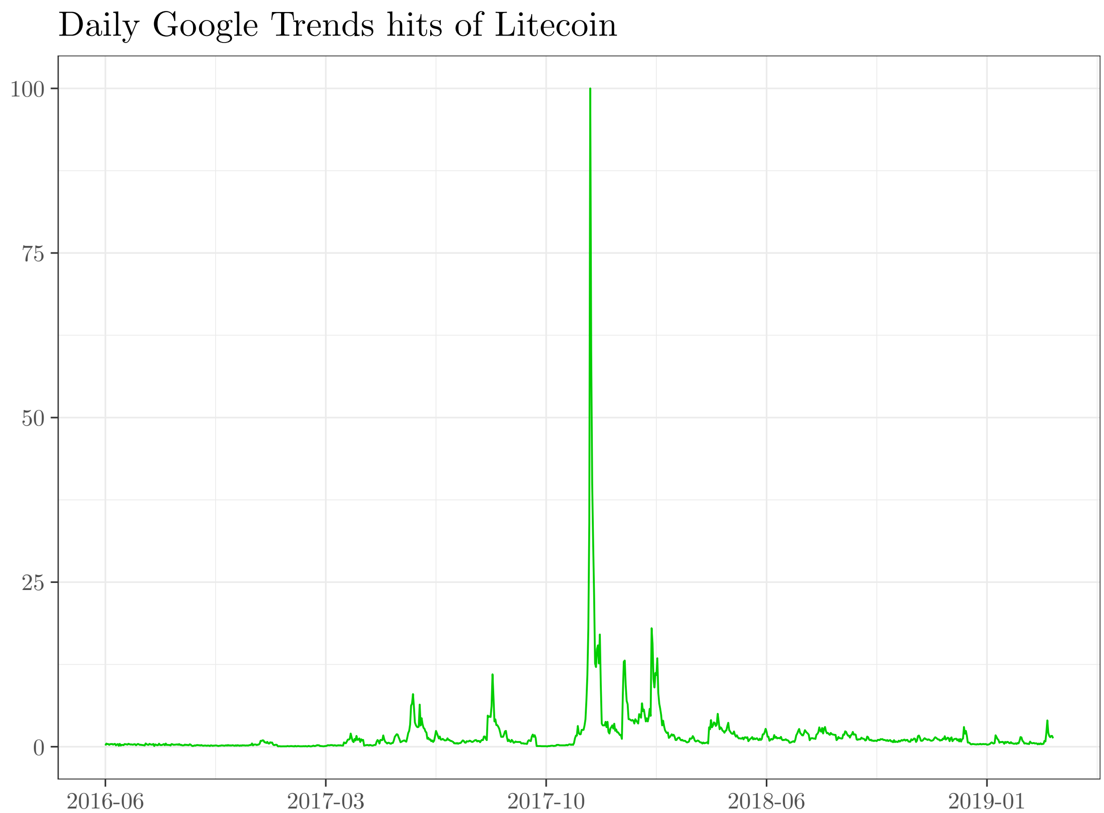

Figure 16: Time series plot of LTC daily Google Trends hits scaled between 0 and 100

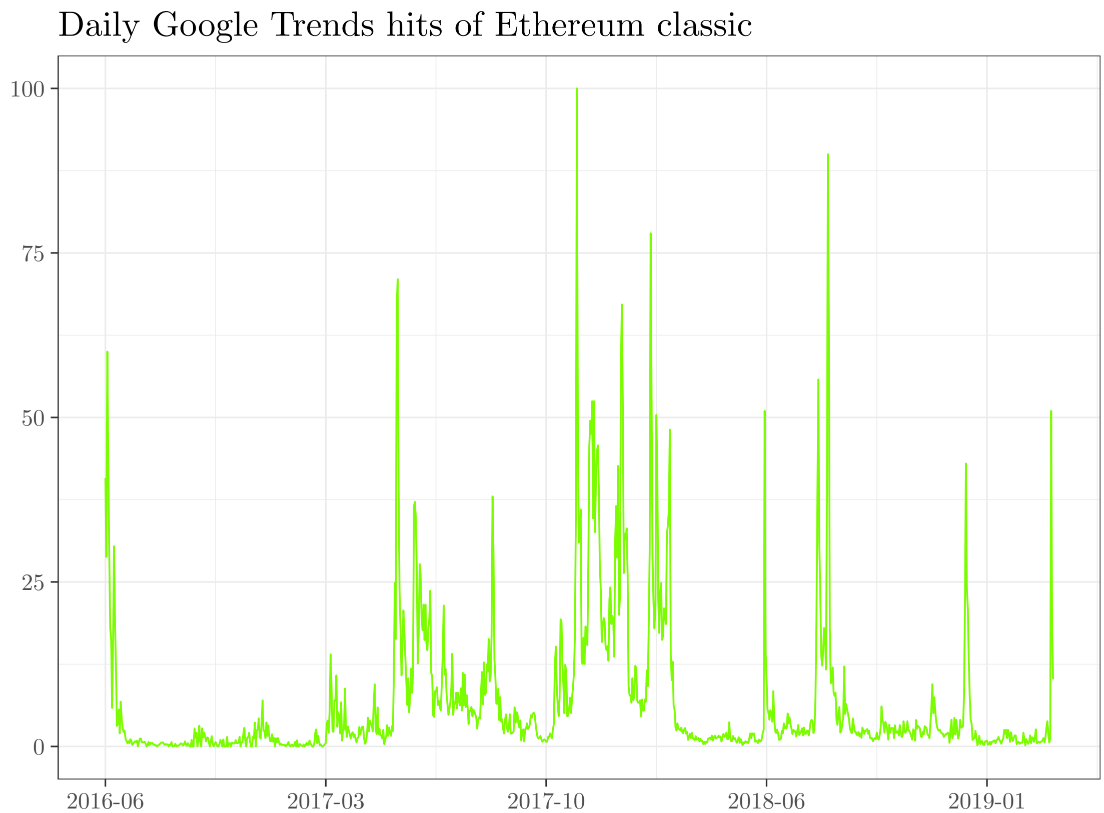

Figure 17: Time series plot of ETC daily Google Trends hits scaled between 0 and 100

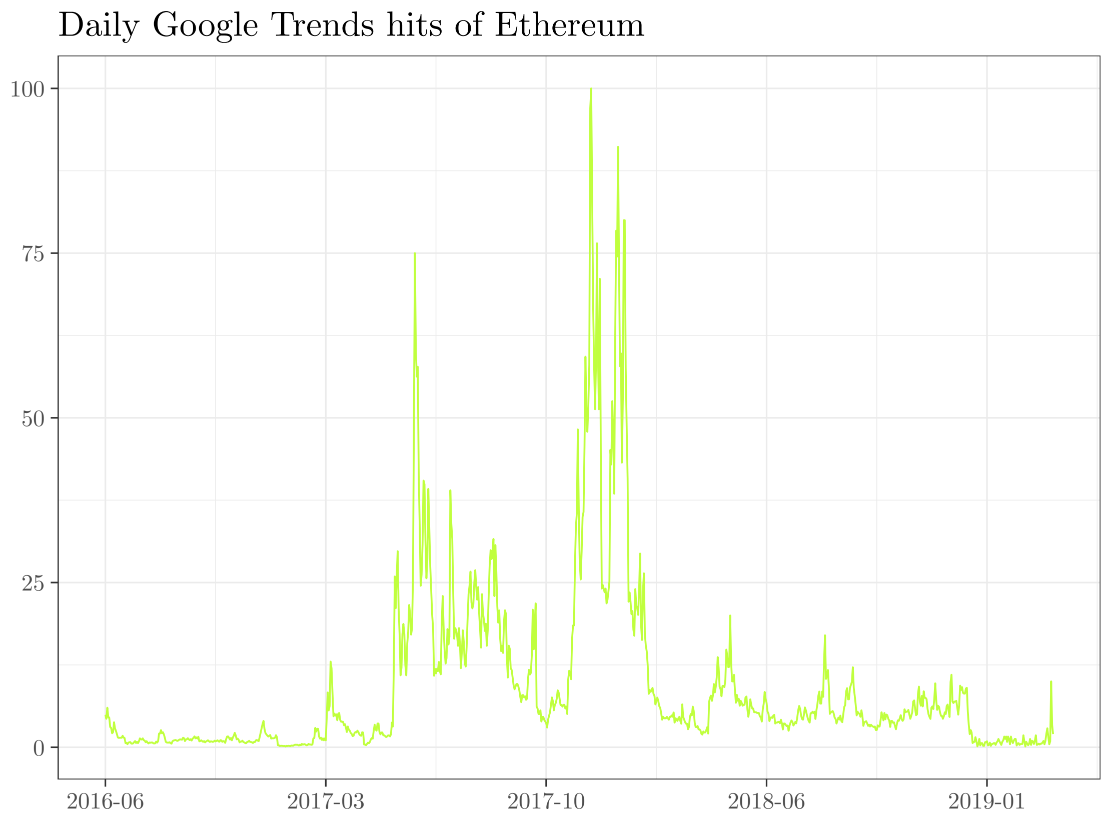

Figure 18: Time series plot of ETH daily Google Trends hits scaled between 0 and 100

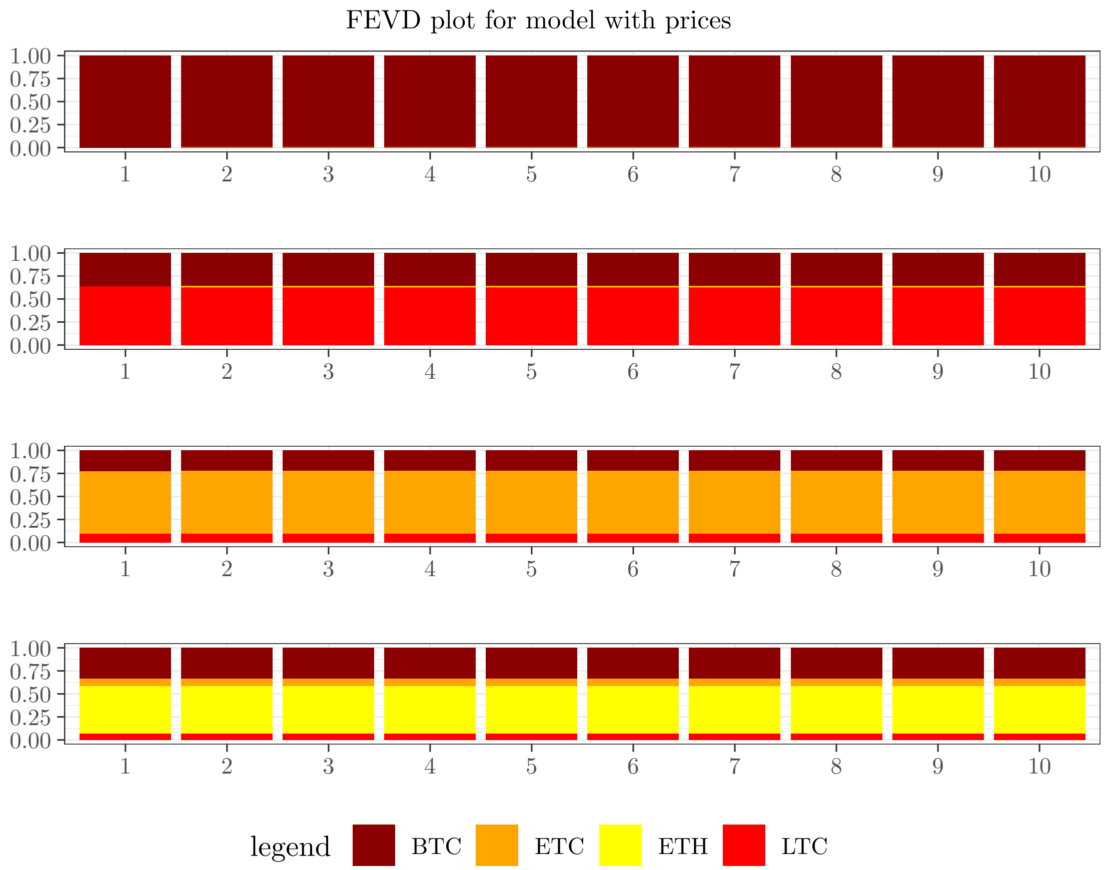

Figure 19: FEVD results for prices in model with prices. Horizontal blocks are ordered as follows: BTC price, LTC price, ETC price and ETH price.

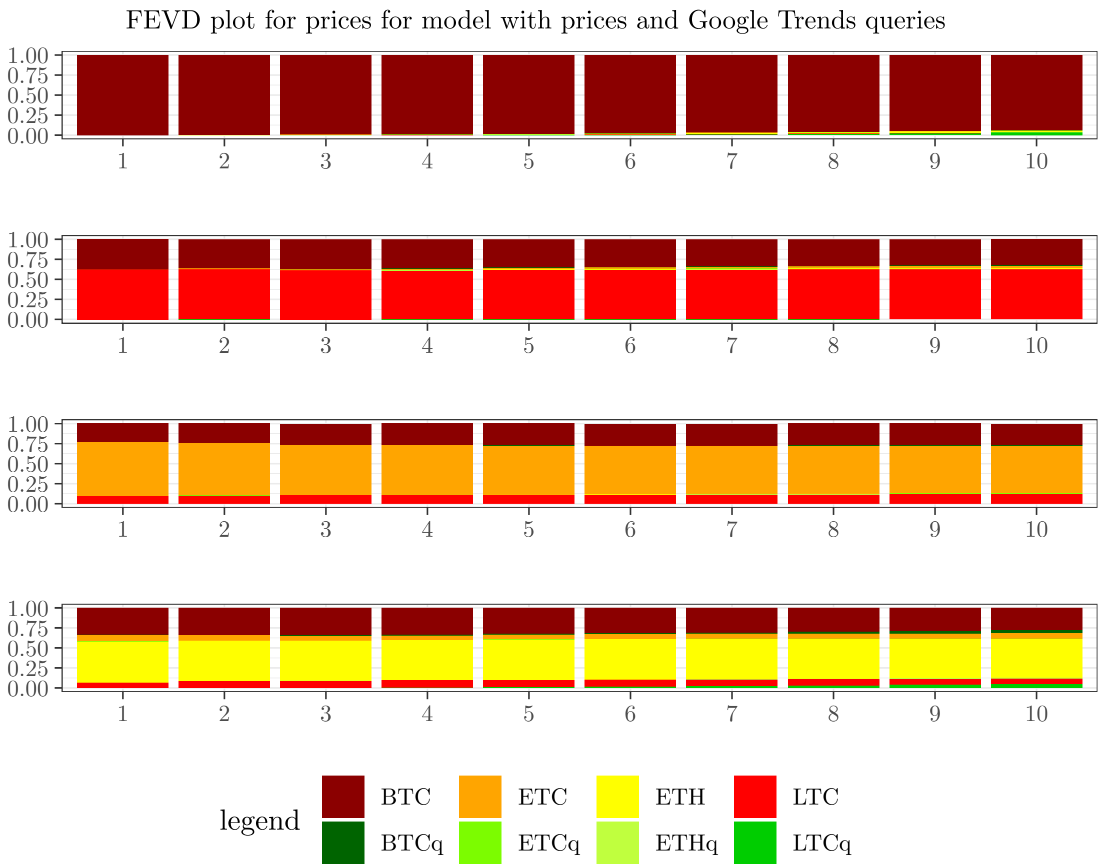

Figure 20: FEVD results for prices in model with prices and Google Trends queries. Horizontal blocks are ordered as follows: BTC price, LTC price, ETC price and ETH price.

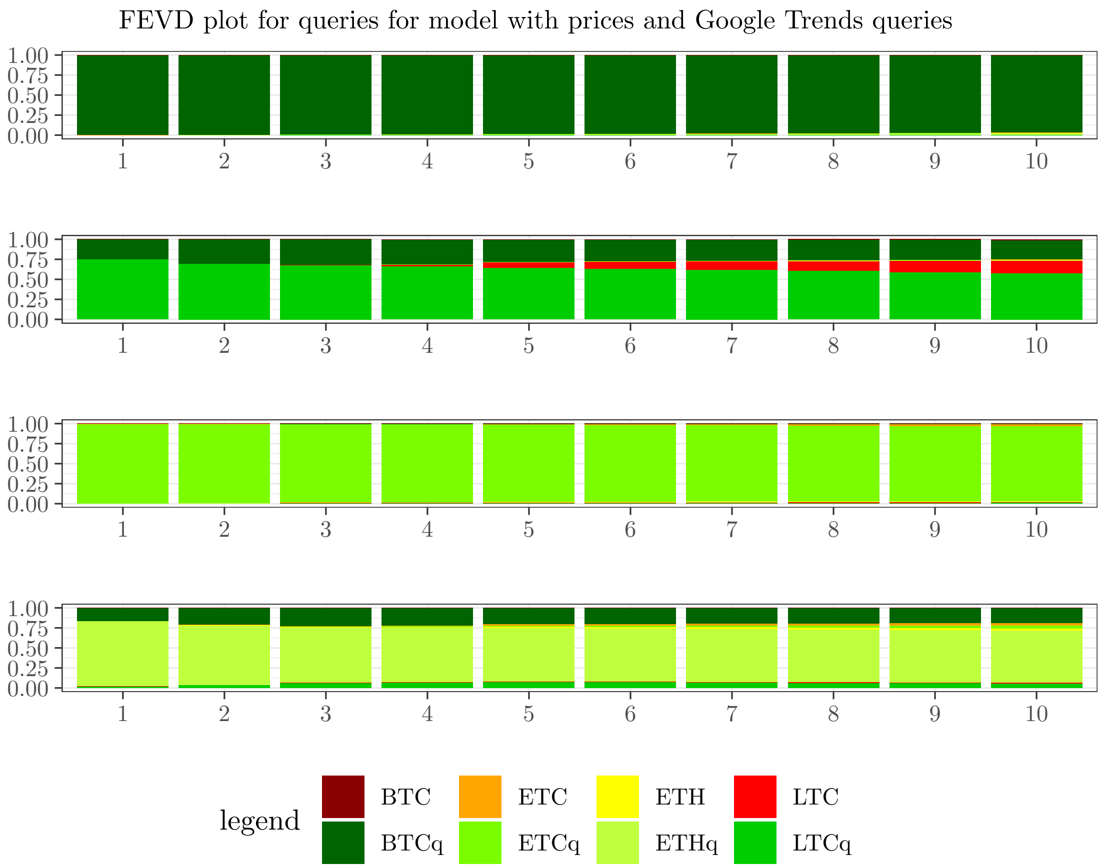

Figure 21: FEVD results for Google Trends queries in model with prices and Google Trends queries. Horizontal blocks are ordered as follows: BTC query, LTC query, ETC query and ETH query.

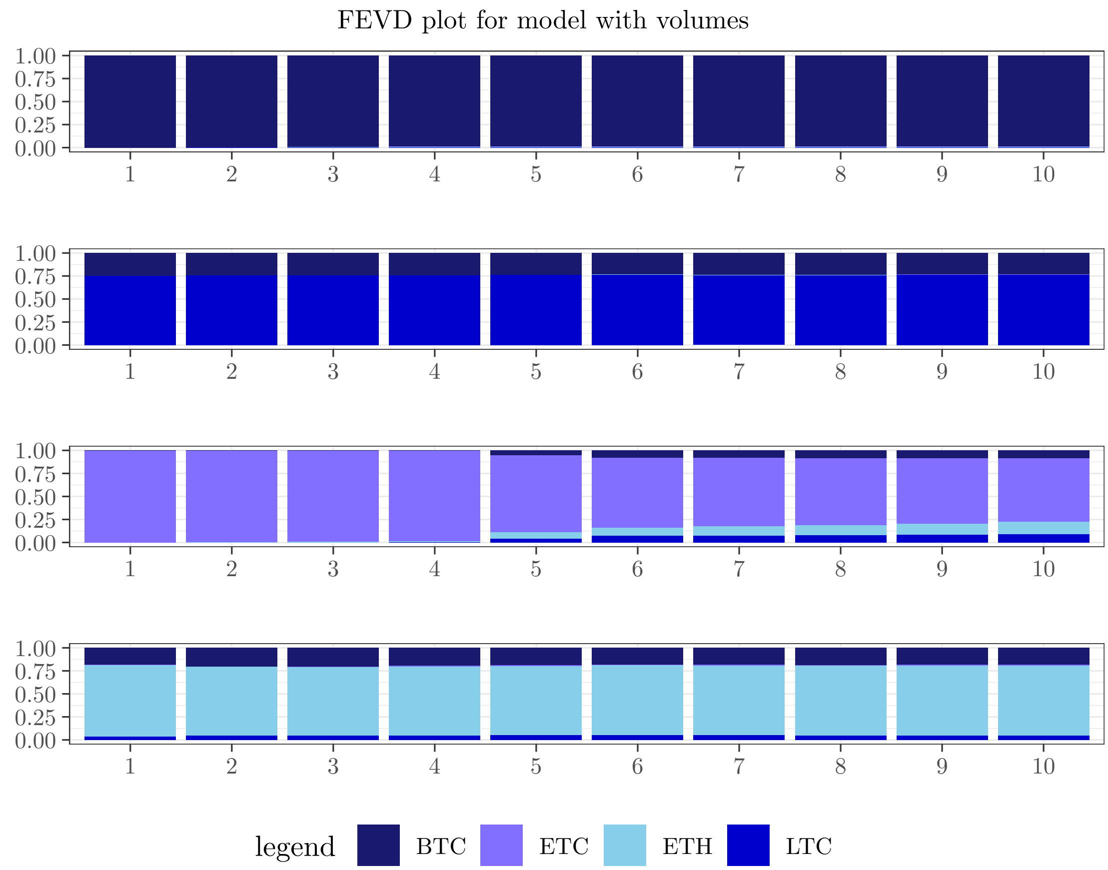

Figure 22: FEVD results for volumes in model with volumes. Horizontal blocks are ordered as follows: BTC volume, LTC volume, ETC volume and ETH volume.

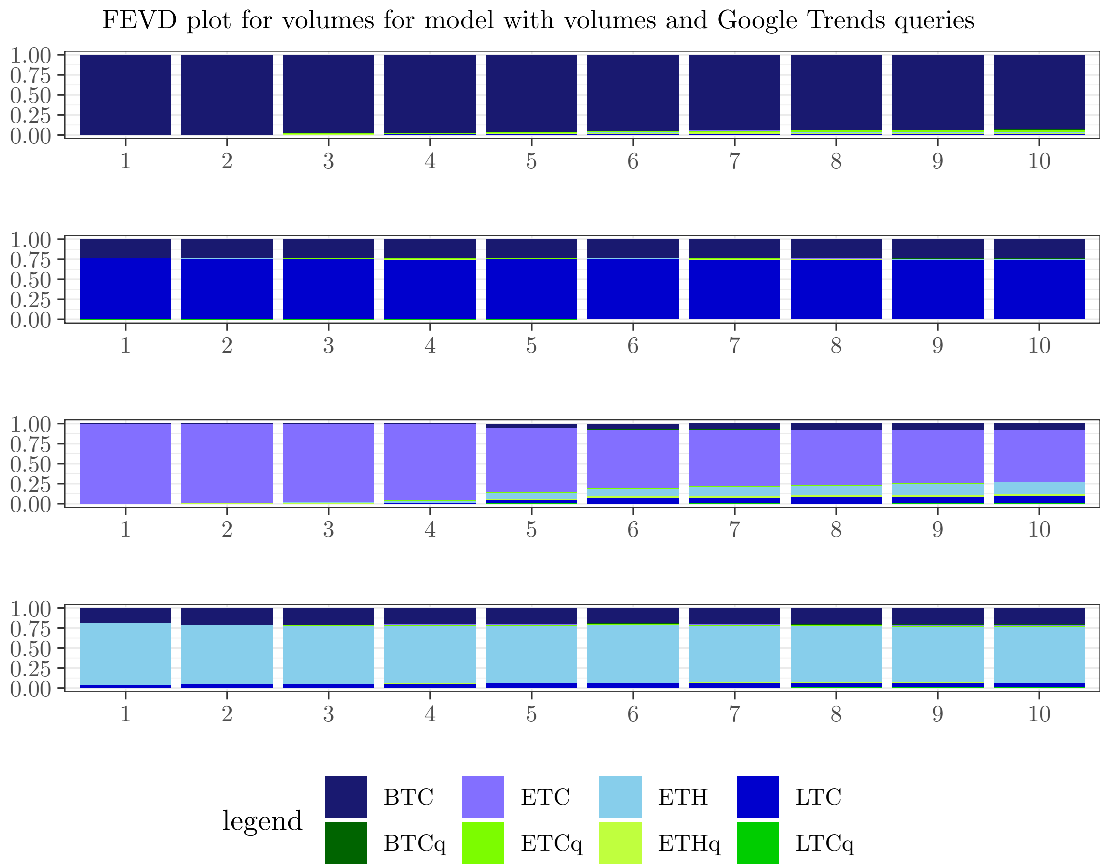

Figure 23: FEVD results for volumes in model with volumes and Google Trends queries. Horizontal blocks are ordered as follows: BTC volume, LTC volume, ETC volume and ETH volume.

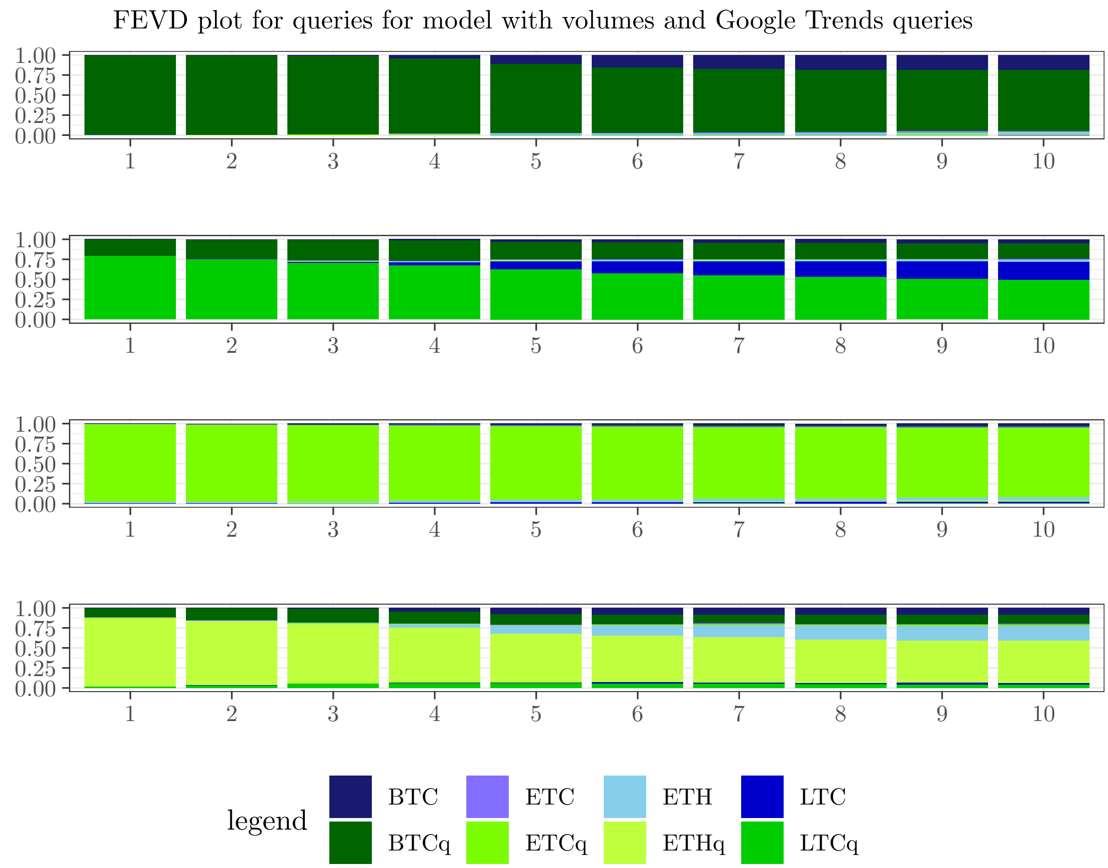

Figure 24: FEVD results for Google Trends queries in model with volumes and Google Trends queries. Horizontal blocks are ordered as follows: BTC query, LTC query, ETC query and ETH query.