Charles University

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

The Volatility Patterns and Correlation of Cryptocurrencies: Overcoming the Bitcoin's primacy

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, July 31, 2017

Signature

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Abstract

The thesis focuses at the evolution of cryptocurrencies or more precisely at the competition process between them in expanding to broader usage. The first main goal of the work is to find out, whether Bitcoin, as the first and still most capitalized cryptocurrency, has an advantage of higher maturity than alternative cryptocurrencies. The second goal is to analyze whether the individual cryptocurrencies are perceived individually by market participants, which could grant the alternative cryptocurrencies an option to compete with Bitcoin by offering better features as safer technology or faster transaction. The analysis of volatility patterns in their exchange rates via various GARCH models suggests that Bitcoin still has advantage in higher maturity. The analysis of the correlation between various alternative cryptocurrencies and Bitcoin finds positive correlation and thus suggests that the cryptocurrencies are rather perceived together.

JEL Classification	G17, G19, E40, E41
Keywords	cryptocurrencies, volatility, GARCH, money, correlation

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Abstrakt

Tato diplomová práce se soustředí na vývoj kryptoměn, či přesněji, na proces konkurence mezi nimi při expanzi do širšího používání. Prvním cílem práce je zjistit, zda Bitcoin, jakožto první a stále nejvíce kapitalizovaná kryptoměna, má výhodu ve větší dospělosti trhu, než alternativní kryptoměny. Druhým cílem je analyzovat, zda jsou jednotlivé kryptoměny tržními účastníky vnímány individuálně, což by nabízelo alternativním kryptoměnám možnost konkurovat Bitcoinu lepšími rysy jako je bezpečnější technologie nebo rychlejší transakce. Analýza vzorců ve volatilitě jejich směnných kurzů různými variantami GARCH modelů naznačuje, že Bitcoin má stále výhodu ve větší dospělosti. Analýza korelace mezi různými alternativními měnami a Bitcoinem nachází pozitivní korelaci a tedy naznačuje, že kryptoměny jsou vnímány spíše společně.

Klasifikace	G17, G19, E40, E41
Klíčová slova	kryptoměny, volatilita, GARCH, peníze, korelace

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Acronyms

ARCH Autoregressive Conditional Heteroscedasticity

ARMA Autoregressive Moving Average

BTC currency code for Bitcoin

CNY currency code for Chinese yuan renminbi

DAO Decentralised Autonomous Organisation

DASH currency code for Dash

EUR currency code for Euro

GBP currency code for Great Britain pound sterling

ILP Interledged Protocol

LTC currency code for Litecoin

USD currency code for United States dollar

XMR currency code for Monero

XRP currency code for Ripple

Master's Thesis Proposal

Author:	Bc. Tomáš Šembera
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Defense Planned:	September 2017

Proposed Topic:

Volatility Patterns and Correlation of Cryptocurrencies: Overcoming the Bitcoin's primacy

Motivation:

Cryptocurrencies as Bitcoin, Dash or Monero present an interesting topic of study for economics. If cryptocurrencies succeeded in becoming money, the alternative monetary system would propose a very interesting field of study for economists.

The value of traditional currencies can be explained by tracking it back through history to commodity money and hence to non-monetary value and by commitment of the central banks to keep the value at some level. Both these explanations cannot be applied to cryptocurrencies. Therefore the major part of the economic research focuses on the question of the determinants of cryptocurrencies (mainly bitcoin's) value. ◦On one hand Kristoufek (2015) shows that the major part of the demand for bitcoins is associated with speculative motives, on the other hand in the long term also its usage as a currency affects its price. Moreover, according to Glaser et col. (2014) especially not well informed users have speculative reasons to hold bitcoins.

For cryptocurrencies, one of the major obstacles in becoming generally accepted medium of exchange is their high volatility. Therefore many studies were focused on modeling mainly bitcoin's volatility and its evolution. Bouoiyour and Selmi (2016) analyzed the bitcoin's volatility by fitting GARCH and its variants to subsamples of the exchange rate development since 2010 to 2016. The earliest subsample (2010 – 2014) showed more volatile pattern with higher positive leverage effect of negative price events and higher volatility persistence than the following subsample. Also the usage of specific GARCH variants show that the volatility patterns in bitcoin price evolved to less volatile ones.

So far, most of the research was focused on Bitcoin as the most famous and the oldest cryptocurrency and almost no studies were carried out on other cryptocurrencies. From one point of view it makes sense because the primacy of Bitcoin can be interpreted in the way that this relatively well established cryptocurrency is also the one which has the best chance to become generally accepted. From the other point of view, this primacy can also mean that more than other cryptocurrencies, bitcoins are held generally for speculative reasons. One way or the other, more research should focus on other cryptocurrencies.

Hypotheses:

1. Hypothesis #1: Being the oldest cryptocurrency, the patterns in volatility of Bitcoin's exchange rate show higher degree of maturity than in case of alternative cryptocurrencies.
2. Hypothesis #2: Market participants differentiate between individual cryptocurrencies, therefore the correlation between Bitcoin and alternative cryptocurrencies is negative.
3. Hypothesis #3: The correlation is stronger during the price bubbles.

Methodology:

The thesis will be based upon analyzing the patterns in cryptocurrenices‘ price volatilities using volatility models as the variants of GARCH model. Various parameters of GARCH models are discussed and used for evaluation of cryptocurrencies‘ maturity to confirm or reject the first hypothesis.

For testing the second and the third hypotheses the multivariate volatility models, namely the BEKK models,are estimated to measure correlation between Bitcoin, fiat currencies and alternative cryptocurrencies. As stated above, it is expected the correlation is negative and stronger, both in case it is found negative or positive, in periods of price surges. To test this, the sample is divided into subsamples with price surges and without, the average correlation coefficients for subsamples are computed and used for comparison.

The time series of cryptocurrencies for this thesis are supposed to be obtained from websites as cryptocompare.com, coinmarketcap.com or poloniex.com. The data for fiat currencies come from the database of the Bank of England.

Expected Contribution:

The thesis is supposed to grant some insight into the future of cryptocurrencies, more precisely it should answer the question, whether alternative cryptocurrencies have a chance to succes in the market dominated so far by Bitcoin. Excluding that, the estimated models can be used for predictions of their exchange rates and volatilities which can beuseful in managing portfolios containing cryptocurrencies.

Outline:

1. Cryptocurrencies and their history: The first part will start with brief description how cryptocurrencies work. Then the work will sumarize their history with ephasis on events, which had influence on their value. This part will also decribe the development of their usage. This historical part should help explain the process of formation of prices of cryptocurrencies and their volatility.
2. Theoretical foundations: The second part of the thesis will summarize the theoretical basics about medium of exchange with focus on the origin of value and its formation in time. This part should encompass the discussion between more schools of economics.
3. Studies on cryptocurrencies prices: Third part should summarize the results of previous studies on cryptos usage, price formation and volatility.
4. Data: I will describe the dataset.
5. Methods: I will describe the volatility models used (GARCH and its variants)
6. Model and results: I will discuss the variables and models used and analyse the results.

7. Concluding remarks: I will summarize my findings and their implications for the future of cryptocurrencies and for future research

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Author **Supervisor**

1. Introduction

Since John Adam Smith's edition of possibly the most famous economic book *An Inquiry into the Nature and Causes of the Wealth of Nations*, usually shortened to *Wealth of Nations*, the idea of the power of a free market, of an invisible hand coordinating millions of people driven by self-interest to fulfill the needs of others, reached a solid position in the economic science. With a little exception which is a field of this science focusing on the origin and function of money – the monetary economics. While in the case of other sectors the markets are believed to coordinate individuals to provide goods in economically effective way, fulfilling both the criteria of demanded numbers and quality, in case of money most economists follow the idea that to provide a stable monetary system the state interventions in the form of central banks are needed. The discussion about this topic does not nearly exist and is led in alternative schools of economics only as for example by scholars of the Austrian school of economics, represented in the past by Friedrich August von Hayek (1990) or Murray N. Rothbard (1981) and currently represented by Jesús Huerta de Soto (2009). One of the reasons why this discussion is at the bottom of scientific interest is that the current economics focus on empirical methods borrowed from other sciences. Given that today only fiat currencies are used to the extent that allows economists to create empirical studies about various phenomena related to money an economist who would like to study the topic of free market money would have to restrict his attention either to a theoretical analysis only, which is something not very favored in the mainstream economics, or to an analysis using historical data of pre-central-banking period, which would expose his conclusions to arguments that they are not valid in current economic system. In this context, the emergence of cryptocurrencies might cause at least small return of attention to monetary economics. Needless to say that there is still a long way for cryptocurrencies to be used in such extent that they could grant some insight into the monetary topics as inflation, business cycles etc.

This thesis therefore does not attempt to analyze such important economic topics but rather focuses at the process of evolution of cryptocurrencies and competition between them. One of the propositions almost and maybe all economists throughout all schools of economic thought (this time including the Austrian school of economics) agree on is that for an asset to be a good money the stability of its value is vital. The high volatility of cryptocurrencies is one of the most serious obstacles as a good whose value often changes in a large scale cannot be very suitable to be used in economic calculation. Cryptocurrencies are rather new phenomena so it is not surprising that their exchange rates underwent very rough development. There are many factors which can cause the high volatility – security problems of the exchanges, weaknesses in their protocols, attacks at the network, speculation bubbles etc. Because this work is economical and the author is not an expert in information technologies it does not focuses at the particular causes of volatility but rather at the way of forecasting it, analyzing its structure and analyzing the relationships between the cryptocurrencies themselves, as it can grants some insights about their future development. To be more precise, the work focuses at the relation between the age of the cryptocurrency and its volatility and at the co-movements of their prices, since it can help better understand whether the cryptocurrencies compete with each other or are rather perceived as whole.

The Chapter 2 introduces some basic functional aspects of cryptocurrencies to help understand what exactly individuals obtain when they buy coins at cryptocurrency exchanges. Because Bitcoin was the first cryptocurrency introduced and because it is still the most important one in terms of capitalization it is used for this basic description. The later cryptocurrencies, because of the primacy and until recently completely prevailing capitalization of Bitcoin called alternative cryptocurrencies, are then introduced with focus on the major improvements and differences from Bitcoin. The Chapter 3 summarizes the recent literature about the volatility and value of cryptocurrencies. While value itself, or more precisely the character of demand for cryptocurrencies, is not the main objective of the thesis, it is of great importance for understanding the evolution the coins underwent and for understanding the factors which might have impact on its volatility. The Chapter 4 describes the methods used for analyzing and forecasting the volatility, more precisely the conditional variance models based on autoregressive conditional heteroscedasticity framework. The Chapter 5 describes the data used in the estimation, generally the exchange rates of cryptocurrencies and few most traded fiat currencies. The Chapter 6 presents and comments the results of the estimation processes. Finally the Chapter 7 concludes the findings and propose the further direction of research on the topic of cryptocurrencies.

2. Blockchain technology

This part of the thesis describes technological features of cryptocurrencies and their usage. Bitcoin was the first and therefore, the most innovative. Other cryptocurrencies are more or less derived of its technology. For this reason, the basics of the technology are explained on the example of Bitcoin and the differences of alternate cryptocurrencies are described in the last section of the chapter.

In October 2008 Satoshi Nakamoto (2008) published a white paper called *Bitcoin: A Peer-to-Peer Electronic Cash System*, describing the function of the most known cryptocurrency – Bitcoin. The major invention of this paper was a solution of the problem of double-spending without using a trusted central intermediary. This brought forth the creation of Bitcoin and other alternate cryptocurrencies, based on the same or similar technology. The market of cryptocurrencies is evolving very fast with high dynamics which is nicely illustrated by the fact that in the beginning of writing this thesis, which was the December 2016, the capitalization of 5 most capitalized cryptocurrencies was 13,235,527,805 USD, with Bitcoin capitalization creating the largest part - 12,088,518,801 USD (circa 91 %), while in the time the thesis was being finalized, which was the end of July 2017, the capitalization of the top 5 was already 78.6 billion USD with 45.09 billion USD held by Bitcoin (57.4 %) ("Crypto-Currency Market Capitalizations," n.d.).

2.1. Transactions

In his white paper Nakamoto (2008) defined digital coin as follows:

> "We define an electronic coin as a chain of digital signatures. Each owner transfers the coin to the next by digitally signing a hash of the previous transaction and the public key of the next owner and adding these to the end of the coin. A payee can verify the signatures to verify the chain of ownership (ibid., p. 2)."

The transactions are stored in publicly known ledger called blockchain, secured by public-private key cryptography. In the ledger, every unit of currency is associated to a public key. When somebody owns some cryptocurrency coin, it means that he knows a combination of public and private keys and in the ledger it is written that this public key received the coins in previous transactions. Böhme, Christin, Edelman, & Moore (2015) describes the process as follows:

> “Suppose that Alice has three bitcoins that she wants to give to Bob. She publishes a message in the Bitcoin network indicating that she is transferring three of her existing bitcoins, along with a reference to the transaction where she had received those bitcoins. Part of this message is encrypted by Alice’s private key to prove that the instruction came from her, in a method akin to a signature on a paper check. Later, if Bob wants to send bitcoins to Charlie, he publishes a message, again encrypted with his private key, indicating that he got his bitcoins from Alice and what he wants to send to whom. The Bitcoin network identifies Alice, Bob, and Charlie only by their public keys, which serve as account numbers (ibid., p. 217).”

2.2. Double-spending problem

The public-private key cryptography gives the payee assurance that the payer was in the transaction chain of the unit of cryptocurrency, but it does not have to mean that the payer had been the last element of the chain before the transaction took place. In other words, the payee cannot be sure that the payer did not spend the money before and then used the same public key and private key combination to create second transaction (Nakamoto, 2008). This problem is called double-spending. Until Bitcoin, this problem had to be solved by including a trusted central party which was aware of all transaction and therefore was able to decide which transaction had been the first one. Solution of double spending without inclusion of the central party is the main innovation of Bitcoin.

The consensus about the sequence of transactions in bitcoin network is achieved through collecting the block of transactions and transforming them into hash which is timestamped and published. To avoid the creation of a block with invalid transactions, the proof of work is implemented in the process of hashing. Nakamoto (2008) describes it as follow:

> “For our timestamp network, we implement the proof-of-work by incrementing a nonce in the block until a value is found that gives the block's hash the required zero bits. Once the CPU effort has been expended to make it satisfy the proof-of-work, the block cannot be changed without redoing the work. As later blocks are chained after it, the work to change the block would include redoing all the blocks after it.

The proof-of-work also solves the problem of determining representation in majority decision making. If the majority were based on one-IP-address-one-vote, it could be subverted by anyone able to allocate many IPs. Proof-of-work is essentially one-CPU-one-vote. The majority decision is represented by the longest chain, which has the greatest proof-of-work effort invested in it. If a majority of CPU power is controlled by honest nodes, the honest chain will grow the fastest and outpace any competing chains. To modify a past block, an attacker would have to redo the proof-of-work of the block and all blocks after it and then catch up with and surpass the work of the honest nodes (ibid., pg. 3)."

For the common user this means that when connecting to the bitcoin network, the node recognizes those blocks of transactions as valid which are a part of the longest chain (ibid.).

2.3. Mining

To participate in a transaction, it is not needed to participate in the whole block validation process. To keep the users interested also in participating the proof of work process, there are incentives build in bitcoin protocol. The node which solves the cryptographic problem first and creates a block is rewarded by adding certain amount of bitcoins to his address. According to Nakamoto (2008) this has two functions:

"By convention, the first transaction in a block is a special transaction that starts a new coin owned by the creator of the block. This adds an incentive for nodes to support the network, and provides a way to initially distribute coins into circulation, since there is no central authority to issue them. The steady addition of a constant of amount of new coins is analogous to gold miners expending resources to add gold to circulation. In our case, it is CPU time and electricity that is expended (ibid., pg. 4)."

The second source of incentives for miners are transaction fees. The payer can set the transaction in the way that part of the amount will not be transferred to a payee. After adding the transaction to a new block, this remaining balance will be transferred to the miner's address (ibid.).

The bitcoin protocol is programmed to adjust the difficulty of creating new block according to the total computational power in the network, so the average time of finding new block is 10 minutes ("Controlled supply - Bitcoin Wiki," n.d.). The amount of bitcoins obtained as a reward is programmed to decrease by 50 % after every

210,000 blocks. The total amount of bitcoins is therefore expected to never exceed 21 million (ibid.).

2.3.1 Proof-of-work and Proof-of-stake

As described above, the proof-of-work means that a miner has to invest some computational effort to create a block and win a reward. If more than 50 % of the computational power is centralized, the monopoly problem arises. This means that the monopolist could chose to create a new fork of blocks, which could, because he owns majority of the power and is therefore faster in creating blocks, after some time grow longer than the original chain. In this way, the monopolist would be able to double-spend or stop transactions from being processed ("Proof of Stake - Bitcoin Wiki," n.d.). Proof-of-stake technology is designed to counter this problem in the way that it is holding some amount of the currency, i.e. having a stake in the currency, what allows a miner to create a block. This counters the monopoly problem in two ways. Firstly, undermining the confidence in the network would result in a large fall of its value. In the proof-of-stake system, the monopolist would therefore face immense losses. Secondly, because being a monopolist in the mining process of proof-of-stake currency means owning more than a half of all coins, it is much more costly to attain this position (ibid.).

2.4. Cryptocurrencies

Alternative cryptocurrencies (altcoins) were created from various reasons. Some were released to provide a better medium of exchange than bitcoins in terms of privacy, security of the network or scalability as for example Monero or Dash. Others were created to provide various non-monetary functions keeping the blockchain coins only as a necessary complement of the network providing incentives to miners to provide the security. The following text aims to describe the main characteristics of several altcoins and propose some relations between them which could affect co-movements in prices and volatility.

2.4.1 Bitcoin

As already written above, Bitcoin was the first decentralized cryptocurrency created and its goal was to offer a decentralized currency with limited supply. As the first currency it has the major advantage against others in the network effect, which means that it is accepted by more market participants than altcoins. As further discussed in Chapter 3 the higher level of acceptance of the currency is a very important characteristics affecting the individual's choice of an asset to be used as a medium of exchange, because the more widespread the usage of the asset is, the higher is its marketability. Furthermore, the widespread usage means relatively smaller changes in total demand which results in lower volatility of the value.

2.4.2 Dash

Dash was released in January 2014 as Xcoin, shortly afterwards renamed to Darkcoin and finally rebranded to Dash in March 2015. The main innovation of Dash is usage of second tier of nodes in mining called masternodes. This second tier enable functions as PrivateSend (private transactions achieved by mixing), InstantX (instant transactions) or Dash evolution (decentralized payment processor) ("Masternode Network - Official Documentation - Confluence," n.d.). To run a masternode the user must invest 1000 Dash as a collateral. In compensation the masternode network receives 45 % of the network mining rewards ("Dash-WhitepaperV1.pdf," n.d.). Dash is a decentralized autonomous organization (DAO), which means that decision making about future development or projects regarding the network is distributed to users, in case of Dash it is to the masternodes. To finance this development the protocol is programmed to allocate 10 % of the mining rewards to the DAO's budget ("Masternode Network - Official Documentation - Confluence," n.d.). As of 28.6.2017 the average time between blocks is 3 minutes 41 seconds and block size is 9.409 Kbytes ("Dash (DASH) statistics - Price, Blocks Count, Difficulty, Hashrate, Value," n.d.). The Dash was created to be anonymous medium of exchange, therefore it could be expected that it would behave as a substitute to Bitcoin.

2.4.3 Litecoin

According to its developers, Litecoin's purpose is to be the Bitcoin's silver. That means there is higher supply of litecoins and transaction confirmation time is lower. As of 28.6.2017 it is in average 2 minutes 23 seconds so it suits better for smaller transactions than Bitcoin ("Litecoin (LTC) statistics - Price, Blocks Count, Difficulty, Hashrate, Value," n.d.). It uses different cryptography to ensure decentralization of mining which relies on scrypt algorithm rather than SHA256 as in case of Bitcoin ("User:Iddo/Comparison between Litecoin and Bitcoin - Litecoin Wiki," n.d.). This was originally proposed to prevent the development of "application-specific integrated circuits" (ASICs) which is very specialized hardware greatly increasing the chance to find the block, making other lower tier hardware devices as GPUs or CPUs almost unable to ever mine a block. However, this goal was not achieved since today there are ASICs for mining cryptocurrencies based on scrypt algorithm too. Needless to say that because even according to its developers intentions to create "silver" to Bitcoin, Litecoin should behave as its substitute.

2.4.4 Monero

While Bitcoin is often referred to as an untraceable or anonymous payment network it is not exactly true. Bitcoin is rather pseudonymous, because the chain of transactions is public, in other words it is visible which addresses participated the transactions. Monero was created to offer unlinkable transactions. While there are public addresses in Monero too, they are never associated with existing funds. Instead when somebody sends the funds to user's public address, a new one-time address is created, completely under the control of the receiver, so his public address cannot be associated with this transaction in the blockchain. To prevent senders from finding when the receivers use the funds they obtained the protocol uses so called ring signatures. When money is being sent, the network chooses several other addresses which are used as a cover in the transaction which means that it is not possible to find which one of these addresses was the source of the funds ("A low-level explanation of the mechanics of Monero vs Bitcoin in plain English," n.d.). One of the advantages of Monero is its continuous development adding new features as "Ring Confidential Transactions" hiding what exact amount is being sent or "Kovri", which is a currently in development feature that will allow users to hide Monero usage itself from network monitoring (ibid.).

The block size limit is automatically adaptive so the network is able to process any number of transactions per block, avoiding scalability problems recently observed in the Bitcoin network. As of 28.6.2017 the block size is 100.274 Kbytes ("Monero (XMR) statistics - Price, Blocks Count, Difficulty, Hashrate, Value," n.d.). The average time for a block to be mined is 2 minutes so it takes in average one minute for a transaction to be visible in block chain. After another 2 minutes the transaction is confirmed by appearing in a following block and after in total 21 minutes the transaction is considered to be completely valid by the network and it is possible to spend the funds (ibid.). The protocol is set to provide fungibility and the CryptoNight proof-of-work algorithm aims to keep the mining decentralized.

The question of being a substitute or complement is not so simple in case of Monero. From one point of view it could be argued that because its purpose is to serve as medium of exchange only it should be a substitute. However, Monero could be used to anonymously buy bitcoins, thus combining the advantage of anonymity with network effect of Bitcoin. In this point of view, the two cryptocurrencies would be in complementary relation.

2.4.5 Ripple

Ripple is the third most capitalized cryptocurrency reaching over 11 billion USD as of 14.6.2017 (CryptoCurrency Market Capitalizations," n.d.). Ripple is based on

Interledged Protocol (ILP) which enables to process transaction of almost any asset. Antony Lewis ("Ripple Explained," 2014) finds it similar to medieval hawala network. The hawala network enable transactions to be settled without the need of moving the asset. The system is based on network of trusted agents. When an individual A needs to pay to individual B he comes to his agent and gives him the money or anything what is used to settle the transaction. The agent sends an order to the individual B's agent to pay the amount of the asset to person B, which can be certain person or anybody who proves his claim by for example some password. So asset was transferred from A to B and a debt between the two agents was created. The debt can be cleared by opposite transaction or by direct payment. Of course, to transaction to occur, the agents must trust each other that the counterparty will repay its obligations. If there is no trust between agents of the two individuals, the transaction can still occur by involving other agents, creating the chain of trust. In the Ripple network the agents are called gateways and work in the same manner as the hawala network. In this way anything can be transacted via Ripple with the condition that there are gateways with chain of trust between themselves offering to trade the particular asset. The network's coin XRP is used when there is no chain of trust between the gateways. All gateways trade assets for XRP so creating the debt, which implies the condition of chain of trust, is avoided because the individual A can sell the transferred asset to his gateway for XRPs, send them to person B who uses them for buying the asset from his gateway. As Bitcoin's block chain keeps track of the ownership of the coins, the Ripple's block chain keeps track of all the debts and transactions. (ibid) The transactions are settled in 4 seconds and 1000 transactions per second can be processed ("XRP," n.d.).

3. Value and Volatility

The purpose of this chapter is to attempt to define the category of cryptocurrencies in the framework of economics. More precisely, it analyses a question, whether the cryptocurrencies are really monies and whether there is a chance they can become them. This is related to the structure of their demand and to their volatility which are the topics analyzed in the sections below.

3.1. Cryptocurrencies in context of money emergence

There are two generally accepted definitions of money. The empirical definition claims that money are such assets whose usage in prediction of events which are supposed to be explained by money grants the most precise and useful predictions. The theoretical one claims that money is a generally accepted medium of exchange. (Rothbard, 2009) From both points of view it can be stated that cryptocurrencies are not money yet. Their usage is limited to small number of individuals when related to the whole economy so they can hardly have significant effect on macroeconomic events. Based on the same reason they are not money from the theoretical point of view, because however vague the term "generally accepted" is, given that most of the people have even never heard of cryptocurrencies, it can be hardly said they are generally accepted. Nevertheless, the theoretical definition shows that in order to analyze the possibility of becoming money, we must pay attention to the ways how some asset can become generally accepted medium of exchange.

According to Wray (2000) there are two main streams in the economic theory of money origin. The first one is the chartalism which attributes the emergence of money to authorities as states and their power to create and enforce liabilities As Wray writes:

> "…but the critical point is that governments impose fees, fines, and taxes to move resources to the government sector, and that for many thousands of years, governments have imposed these liabilities in the form of a monetary liability. Originally, the money liability was always in terms of a unit of account as represented by a certain number of grains of wheat or barley. In fact, all the early money units were weight units for grain --the mina, the shekel, the lira, the pound. Once the state has imposed the tax liability, the taxed population has got to get hold of something the state will accept in payment of taxes. This can be

> anything the state wishes: It can be clay tablets, hazelwood tallies, iron bars, or precious metal coins. This, in turn, means the state can buy whatever is offered for sale merely by issuing that thing it accepts in payment of taxes (Wray, 2000, p. 4)."

Applied to cryptocurrencies, this means the issuer would have to fulfill two conditions. Firstly, he would have to be able to grant some "intrinsic" value to the token. In the case of the state money it is possibility to replace certain amount of commodity usually used to pay taxes by given amount of tokens. In the case of cryptocurrencies this means this token would have to be fixed to something of a real value to the users, such as computational power, data storage etc. As described in the previous chapter this is not the case of the cryptocurrencies analyzed in this work. While there are such cryptocurrencies whose value is pegged to something of a nonmonetary value such as Peerplays their timeline is still too short to be included in the empirical analysis in the empirical part. Secondly, this value have to be recognized by large amount of users, as in the case of state money, where the tokens become valuable for all taxpayers. Applied to cryptocurrencies, this condition could be again fulfilled by for example offering computational power or data storage.

The second approach is the metalism which states that money emerged from the competition between various mediums of exchange (Rothbard, 2009). As Rothbard describes (2009) it is in interest of every individual to exchange the goods for most marketable commodities. Rothbard explains as follows:

> "Tending to increase the marketability of a commodity are its demand for use by more people, its divisibility into small units without loss of value, its durability, and its transportability over large distances. It is evident that people can vastly increase the extent of the market for their own products and goods by exchanging them for more marketable commodities and using the latter as media to exchange for goods that they desire (p. 190)."

And further he continues:

> "For commodities, in so far as they are used as media, have an additional component in the demand for them—not only the demand for their direct use, but also a demand for their use as a medium of indirect exchange. This demand for their use as a medium is superimposed on the demand for their direct use, and this increase in the composite demand for the selected media greatly increases their marketability (ibid., 191)."

Applied to cryptocurrencies this can be interpreted that to become generally accepted, cryptocurrencies must offer some advantages to their users which compensate the lower marketability stemming from usage of other monies like national fiat currencies. According to the literature the most widely recognized advantages of cryptocurrencies are its decentralization, low transaction fees, low-cost international payments or certain degree of anonymity (Böhme, Christin, Edelman, & Moore, 2015).

At this point it must be mentioned that individuals can use these advantages by using particular cryptocurrency as payment system only. This is for example the case of foreign remittances as Bohme et. col. describe it (2015). When foreign workers want to send money home, they just have to convert their USD balances to bitcoin and then almost instantly trade bitcoin for the local currency. Because such transaction involves middlemen, it is of course more expensive than only peer-to-peer transaction. This work therefore differentiate between usage of cryptocurrency as payment system and as a medium of exchange which implicates that it is held as a part of money balances. This explains why this work focuses on volatility. The advantages as low-cost and fast transactions can be used without holding the coins as money balances, therefore when the purpose of the study is to analyze the chances of becoming money, the volatility is of great importance, for as of now the high volatility is one of the most serious disadvantage of cryptocurrencies.

3.2. Value of cryptocurrencies

The value of cryptocurrency, or more precisely, the demand which stands behind its value, is of real importance for the analysis of its volatility. Unfortunately, most studies about the value of cryptocurrencies take bitcoins only as a subject of analysis. However, as analyzed in the previous chapter, most cryptocurrencies are the same as Bitcoin in the meaning that there is no fixed connecting link between the amount of coins and their usage, or in other words, the amount of coins user needs to hold is given by its value. The studies of bitcoins value can therefore grant some insights about the value determinants of altcoins too.

The main topic of many economic papers on Bitcoin is the nature of its demand, or more precisely the question whether it is a speculation or a transactional demand what drives the price of the cryptocurrency. Kristoufek (2013) analyzed the speculation motive measured by the interest in Bitcoin on internet and found bidirectional causality between price and the interest with tendency toward pro-bubble behavior. This was later confirmed in Kristoufek's another study which analyzed the determinants of bitcoin price using the wavelet analysis (Kristoufek, 2015). He found that in the long term the bitcoin price is driven by its usage in transactions and by the interest. In the short term the interest drives the prices up during the explosive phases but during the depreciation phases it causes further depreciation. Bouoiyour and Selmi (2014) described the interest – price relationship little differently. According to them the interest drives bitcoin price in short and long term, but the granger causality is reverse in lower frequencies. Bolt and Oordt (2016) found that both speculative motives and transaction usage affects the exchange rate of bitcoin and the spread of its adoption diminish the impact of speculation on the price. The dominance of speculation motive was confirmed by Kancs et al. (2015), however according to the authors the speculative demand is not inherently a burden for Bitcoin, because as they argue short-term speculative behavior provides liquidity to the market.

3.3. Volatility of cryptocurrencies

As cryptocurrency goes through the different phases of its life cycle, it can be expected that the volatility patterns of the cryptocurrency change, responding to the increasing liquidity, changing character of the demand incentives etc. Again most of the literature focuses on Bitcoin, as the first and most capitalized cryptocurrency.

Gronwald (2014) analyzes the bitcoin's USD exchange rate at Mt. Gox exchange via jump-intensity GARCH model, which allows to measure effect of large price movements on volatility. The best fitting model to the data from the period of 7.2.2011 to 24.2.2014 is an autoregressive version of jump-intensity GARCH, which allows the intensity of jumps vary over time. The volatility share of jump induced volatility is 60 % which Gronwald attributes to the immaturity of the Bitcoin market. The immaturity of the market was also confirmed by Bouoiyour and Selmi (2015) who applied set of GARCH variants to fit the data from December 2010 to June 2015. The best fitting model for the whole period was threshold – GARCH, however the analysis revealed shift to EGARCH for the period from January 2015 to June 2015. The former revealed strong persistence of volatility, for the later one the persistence decreased, however the asymmetric reaction to shocks, which is according to authors a sign of immaturity, remained. This conclusion was also confirmed by their later research. In this later study authors analyzed the volatility patterns in two periods. The first was from December 2010 to December 2014 and was best described by CMT – GARCH. The results implied strong persistence and asymmetric reactions to shocks. The second period, ranging from January 2015 to July 2016, was best described by asymmetric power GARCH and implied lower persistency (Bouoiyour & Selmi, 2016). This contradicts to the research led by Bourri, Azzi and Haubo Dyhrberg (2016) who found an exactly opposite asymmetric return-volatility relationship in the period prior to price crash in 2013. According to them the increase of volatility after positive price shocks was a sign of safe haven property.

The above mentioned studies imply two conclusions. Firstly, the price of Bitcoin, but this could be extended to other cryptocurrencies as well, is to a large extent driven by speculative motives. The reason is quite clear. The growing market of cryptocurrencies offer very high profits when investor's expectations appear to be in line with reality. Regarding volatility, the findings suggest the market is very immature but it is slowly changing. However, there is disagreement in interpretation of some results as the direction of leverage effect in conditional volatility.

4. Methodology

The question that arises when considering which cryptocurrency has the highest chance to become money is whether other cryptocurrencies are doomed to follow the same or similar phases of development in price and volatility as Bitcoin or whether Bitcoin cleared them the way for faster evolution. This depends on the way the cryptocurrencies are perceived by public. Whether they are perceived together as one market or rather individually as independent currencies with their own advantages and problems. The thesis therefore focuses at three hypotheses. The first one states that Bitcoin, as the oldest one, is supposed to be more mature than others. As the interpretation of the leverage effect in conditional volatility showed to be ambiguous, another measure is implemented – unconditional variance. The logic behind this is that one of the factors influencing this unchanging part of variance is stability of expectations. If the cryptocurrencies are perceived independently, it could be assumed that the unconditional variance of younger currencies should be higher. Another measure to test the perception of cryptocurrencies is the analysis of their correlation. If they were perceived independently, then given that all of analyzed coins are supposed to serve as medium of exchange, they should be negatively correlated, since they should behave as substitutes. On the other hand it they are perceived together, the correlation should be positive. In both cases, it can be assumed that during the price surges of one of them, the correlation should be stronger no matter the direction is.

The empirical part is therefore divided into two sections. The first one estimates the univariate variance models to analyze the maturity and the second one estimates multivariate covariance models to analyze the correlation. In the following sections the models used in estimations are presented.

4.1. Univariate conditional heteroscedasticity models

The empirical part of the work consists of modeling volatility of cryptocurrencies by family of conditional heteroscedasticity models. The first part consists of specification and estimation of univariate volatility models to grant some insight into the volatility patterns of particular cryptocurrencies to assess their maturity. The process of model specifications consists of three steps. In the first step the time series are diagnosed by series of test for presence of unit roots by the Augmented Dickey-Fuller test and KPSS test and for presence of autocorrelation process in residuals. The Augmented Dickey-Fuller (ADF) test tests the null hypothesis of unit root. The test regression is:

$$y_t = \beta' D_t + \phi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t \tag{3.1}$$

Where D_t is a vector of terms such as constant or trend, p denotes the number of lags of differenced values with ψ being their parameters. The symbol ϕ denotes the unit root and in case of null hypothesis of unit root it is equal to one (Said, Dickey, 1984). The test statistics is given by:

$$ADF_t = t_{\phi=1} = \frac{\hat{\phi} - 1}{SE(\phi)} \tag{3.2}$$

The test used in the practical part includes both constant and time trend. The KPSS test assumes the time series is given by:

$$y_t = \xi t + r_t + \varepsilon_t \tag{3.3}$$

$$r_t = r_{t-1} + u_t \tag{3.4}$$

t denotes the time trend variable, u_t has zero mean and r_0 is fixed. The null hypothesis is that the variance of u_t is 0. In that case $r_t = r_0$ and the series y_t is therefore given by the trend, the constant r_0 and the error process ε_t. The case when ξ is zero the null hypothesis is that the series is level stationary, if not the hypothesis is the series is trend stationary (Kwiatkowski, Phillips, Schmidt, Shin, 1992). Both tests are used in the work.

The second step consist in estimation of ARMAX-GARCH(1,1) model to determine the level of ARMA process by resulting parameters' significance and by testing the models for presence of autocorrelation among standardized residuals and their squares. In case more models meet these conditions the best fitting model is selected by ordering the models according to the information criteria (Akaike, Bayesian, Hannan – Quinn and Shibata), summing the order and choosing the model with the lowest sum. In the third step the proper ARCH form is specified by using ARMA specification from the second step and varying the volatility specification. The methodology of this step is the same as in step two. The next section describes the models used in the estimation.

4.1.1 ARMA model

The autoregressive-moving-average model with exogenous variables (ARMAX) is given by:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \psi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i} \tag{3.5}$$

Where X_t denotes the time series, ε_t is an error term, ψ_i is vector of autoregressive (AR) parameters, θ_i is the vector of moving average (MA) parameters, η_i denotes the vector of parameters for exogenous variables d_i such as constant, trend or ARCH-in-mean parameter. (Box, Jenkins, 1968)

4.1.2 ARCH

The conditional volatility of cryptocurrencies' exchange rates will be modeled by the variants of autoregressive conditional heteroscedasticity models. The original model introduced in 1982 by Engle is called ARCH – autoregressive conditional heteroscedasticity model. The model deals with volatility clustering in time series by including weighted average of lagged squared error terms into the variance equation. The innovation of this model was in estimating these weights parametrically (Engle, 2001). ARCH (p) model is described by the following formulas:

$$r_t = \mu + \varepsilon_t \tag{3.6}$$

$$\varepsilon_t = \sigma_t z_t \tag{3.7}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{3.8}$$

$$\sigma^2 = \frac{\widehat{\omega}}{1 - \widehat{P}} \tag{3.9}$$

$$\widehat{P} = \sum_{i=1}^{p} \alpha_j \tag{3.10}$$

The first formula is the mean equation. The return at time t is given by the expected return μ and the error term ε which follows the white noise with zero mean. Second equation denotes the error process which is given by conditional standard deviation denoted by Greek letter sigma and standard residuals denoted by letter z_t ("GARCH Documentation," n.d.). σ^2 without time index denotes unconditional variance which is the variance the series tends to when conditional volatility caused by shocks dies out. Moreover, the model imposes several conditions.

$$\hat{P} < 1 \tag{3.11}$$

$$\alpha, \omega > 0 \tag{3.12}$$

The parameters must be non-negative and the sum of alpha parameters must be lower than one, otherwise the volatility would follow exploding process. (Engle, 1982)

4.1.3 GARCH

The generalized autoregressive conditional heteroscedasticity model (GARCH) introduced in 1986 by Bollerslev enhances the ARCH model by implementing past conditional variance into the variance equation. As Bollerslev (1986) stated the generalization of the ARCH model was needed to avoid arbitrary selection of lags in case the volatility of a time series follows long memory process. Adding conditional variance of previous period implies that the model includes all past squared residuals with declining weights (Engle, 2001). The GARCH model is given by the formulas:

$$r_t = \mu + \varepsilon_t \tag{3.13}$$

$$\varepsilon_t = \sigma_t z_t \tag{3.14}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j-1}^{q} \beta_j \sigma_{t-j}^2 \tag{3.15}$$

$$\hat{P} = \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j \tag{3.16}$$

$$\sigma^2 = \frac{\widehat{\omega}}{1 - \hat{P}} \tag{3.17}$$

The meaning of the variables is the same as in case of ARCH, the only new parameter is β, denoting the effect of previous conditional variance on current the current one. Conditions are again as follows:

$$\hat{P} < 1 \tag{3.18}$$

$$\alpha, \beta, \omega > 0 \tag{3.19}$$

Interpretation of conditions is the same as for ARCH model. Persistence must be lower than 1 to avoid explosive process and parameters must be higher than 0.

4.1.4 IGARCH

The integrated GARCH is a special case of GARCH model, where the sum of alpha and beta parameters is equal to one. This implies that there is no unconditional variance for this model, since in the equation there would be zero in the denominator.

4.1.5 EGARCH

Exponential GARCH model developed by Nelson (1991) avoids non-negativity constraints on parameters by setting logarithm of variance as dependent variable which ensures the positivity of the variance itself. Another innovation of the model is distinguishing between the effects of positive and negative shocks on volatility. The phenomena of higher volatility after negative shock is called leverage effect. At such case the parameter gamma is negative. (“EGARCH Documentation,” n.d.)

$$r_t = \mu + \varepsilon_t \tag{3.20}$$

$$\varepsilon_t = \sigma_t z_t \tag{3.21}$$

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \{\alpha_i(|z_{t-i}| - \mathrm{E}[|z_{t-i}|]) + \gamma_i z_{t-i}\} + \sum_{j-1}^{q} \beta_j ln(\sigma_{t-j}^2) \tag{3.22}$$

$$\hat{P} = \sum_{j=1}^{p} \beta_j \tag{3.23}$$

The parameters of EGARCH model do not need any restrictions because the logarithmic form ensures positivity of the variance. Another difference from previous models is the persistence equation which includes sum of beta parameters only.

4.1.6 GJR–GARCH

GJR–GARCH model introduced in 1993 by Glosten, Jagannathanand Runkle (therefore GJR–GARCH) implements dummy variable for negative shocks into the GARCH equation with parameter gamma.

$$r_t = \mu + \varepsilon_t \tag{3.24}$$

$$\varepsilon_t = \sigma_t z_t \tag{3.25}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-i}^2 + \sum_{j-1}^{q} \beta_j \sigma_{t-j}^2 \tag{3.26}$$

$$I_{t-i} = \begin{matrix} 0 \text{ if } r_{t-i} \geq \mu \\ 1 \text{ if } r_{t-i} < \mu \end{matrix} \tag{3.27}$$

$$\hat{P} = \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j + \sum_{i=1}^{p} \gamma_i \kappa \tag{3.28}$$

$$\sigma^2 = \frac{\widehat{\omega}}{1 - \hat{P}} \tag{3.29}$$

The model is enhanced by dummy variable I_t which equals 0 when the error in appropriate lag is positive and 1 when it is negative. Gamma measures the size and direction of the leverage effect. Positive gamma means higher volatility increase after negative shock. Conditions for parameters stay the same as in GARCH model. The persistence must not be higher than 1 and all parameters must be non-negative ("GJR-GARCH Documentation," n.d.). The letter κ in the persistence equation denotes the probability the standardized residual is under zero (Ghalanos, 2015). The conditions are standardly persistence under 1 and alpha, beta, omega and gamma parameters over zero.

$$\hat{P} < 1 \tag{3.30}$$

$$\alpha, \beta, \gamma, \omega > 0 \tag{3.31}$$

4.1.7 APARCH

Asymmetric power GARCH is another generalization of GARCH models. It was developed to capture long memory process of returns in time series where there was autocorrelation between powers of residuals' absolute values (Ding, Granger, and Engle, 1993). The model is specified by these equations:

$$r_t = \mu + \varepsilon_t \tag{3.32}$$

$$\varepsilon_t = \sigma_t z_t \tag{3.33}$$

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j-1}^{q} \beta_j \sigma_{t-j}^\delta \tag{3.34}$$

Persistence and unconditional variance equations are:

$$\hat{P} = \sum_{j=1}^{q} \beta_j + \sum_{i=1}^{p} \alpha_i \kappa \tag{3.35}$$

$$\sigma^2 = \left(\frac{\widehat{\omega}}{1 - \hat{P}}\right)^{2/\delta} \tag{3.36}$$

The conditions are as usual. All parameters except gamma must be higher than 0, gamma's absolute value must be lower than 1.

$$\hat{P} < 1 \tag{3.37}$$

$$\alpha, \beta, \delta, \omega > 0 \tag{3.38}$$

$$-1 < \gamma < 1 \tag{3.39}$$

4.1.8 CGARCH

The component GARCH model was introduced by Lee and Engle (1999). According to the model the conditional variance consists of permanent and transitory parts. The model is specified by the following equations:

$$r_t = \mu + \varepsilon_t \tag{3.40}$$

$$\varepsilon_t = \sigma_t z_t \tag{3.41}$$

$$\sigma_t^2 = q_t + \sum_{i=1}^{p} \alpha_i(\varepsilon_{t-i}^2 - q_{t-i}) + \sum_{j=1}^{q} \beta_j\left(\sigma_{t-j}^2 - q_{t-j}\right) \tag{3.42}$$

$$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{3.43}$$

The constant parameter omega used in previous models is here replaced by time varying permanent component qt. The sum of alpha and beta parameters must be lower than 1 as well as the persistence parameter ρ. The equations of the conditions and unconditional variance are below.

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1 \tag{3.44}$$

$$\rho < 1 \tag{3.45}$$

$$\sigma^2 = \frac{\omega}{1-\rho} \tag{3.46}$$

4.2. Multivariate GARCH models

As the title suggest the family of multivariate GARCH models takes into account not only particular variances, but also covariance between returns of multiple assets. This is of great importance because according to the CAPM model both variances and covariance are involved in evaluation of portfolio. (Bollerslev, Engle, Wooldridge, 1988)

4.2.1 VECH model

The VECH – GARCH model is a generalization of GARCH. The model is given by equations:

$$r_t = \mu + \varepsilon_t \tag{3.47}$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \tag{3.48}$$

εt denotes the n-dimensional vector of residuals with zero mean and conditional covariance matrix H_t which depends on the information set Ω_{t-1}. Each element thus depends on q lagged values of cross products and squares of residuals and on p lagged values of H_t (Engle, Kroner, 1995). The formula for variance-covariance matrix is given by:

$$\varepsilon_t = H_t^{1/2} \eta_t \tag{3.49}$$

$$vech(H_t) = C + \sum_{i=1}^{q} A_j vech\left(r_{t-j} r_{t-j}^{i}\right) + \sum_{j-1}^{p} B_j vech\left(H_{t-j}\right) \tag{3.50}$$

Where *vech* is an operator stacking the columns of the matrix. C is an n^2 x 1 vector, A_j and B_j are n^2 x n^2 parameter matrices, representing the multivariate form of univariate alphas and betas. The bivariate GARCH(1,1) form without exogenous variables is in detail given by:

$$\begin{aligned} h_t = \begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{01} \\ c_{02} \\ c_{03} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} \\ + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \end{aligned} \tag{3.51}$$

Assuming that elements of covariance matrix depend only on its past realizations and either squared residuals in case of variances and cross products of residuals in case of covariance the formula for GARCH(1,1) model can be rewritten to:

$$h_{ijt} = \gamma_{ij} + \alpha_{ij}\varepsilon_{it-1}\varepsilon_{jt-1} + \beta_{ij}h_{ijt-1} \tag{3.52}$$

$$i, j = 1, \dots, N \tag{3.53}$$

4.2.2 BEKK

In VECH-GARCH model it is hard to ensure the covariance matrix to be positive definite. Therefore it can be adjusted to BEKK parameterization which ensures the positive definiteness while disallowing only few models from the original VECH parameterization (Engle, Kroner, 1995). Full model without exogenous variables is given by formula:

$$H_t = C_0^{*\prime}C_0^* + \sum_{k=1}^{K}\sum_{i=1}^{q} A_{ik}^{*\prime}\varepsilon_{t-i}\varepsilon_{t-i}^{\prime}A_{ik}^* + \sum_{k=1}^{K}\sum_{i=1}^{p} B_{ik}^{*\prime}H_{t-i}B_{ik}^* \tag{3.54}$$

C is a triangular *n* x *n* matrix, *A* and *B* denote *n* x *n* parameter matrices and *K* determines the generality of the model (ibid.). The BEKK (1, 1) without exogenous variables takes form:

$$r_{it} = \mu_i + \varepsilon_{it} \tag{3.55}$$

$$H_t = C_0^{*\prime}C_0^* + A_{11}^{*\prime}\varepsilon_{t-1}\varepsilon_{t-1}^{\prime}A_{11}^* + B_{11}^{*\prime}H_{t-1}B_{11}^* \tag{3.56}$$

The bivariate case of BEKK-GARCH(1,1) is given by:

$$\begin{aligned} H_t = C_0^{*\prime}C_0^* &+ \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix}^{\prime} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix} \\ &+ \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix}^{\prime} H_{t-1} \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix} \end{aligned} \tag{3.57}$$

According to Sheppard (2003) the BEKK model suffers from the large number of parameters to be estimated in case high dimensional structure and the interpretation of parameters can be problematic. However in this study it is assumed that if there are any volatility spillovers between exchange rates of cryptos or traditional currencies, it is enough to include only Bitcoin as the most capitalized and traded crypto and yuan/US dollar exchange rate. Therefore the dimension stays in low numbers.

5. Data

5.1. Exchange rates - cryptocurrencies

The exchange rates of cryptocurrencies were obtained from two various websites - cryptocompare.com and poloniex.com. Cryptocompare is a website providing large scale of information about cryptocurrencies as explanations of the technology, information about exchanges, wallets and mining pools and most importantly it provides data as exchange rates on multiple exchanges, volume, capitalization etc. Daily prices from cryptocompare.com are in the form of cryptocompare index. This index is computed via volume weighted average price (VWAP) with reduction on time – the index is weighted average of prices from all reliable exchanges followed on the website using volume from past 24 hours as weights. Reduction on time is involved to avoid using outdated prices in case some of the exchanges go offline. This is done through decreasing particular volume to 80 % if the time since last trade was between 5 and 10 minutes, to 60 % for time between 10 and 15 minutes, to 40 % for 15 – 20 minutes and to 20 % for 20 – 25 minutes. Above 25 minutes only 0.1 % is taken into account. ("How does the CryptoCompare Aggregated Index Work," n.d.). The exchange rates are downloadable in form of candlestick data – the daily maximum, daily minimum, the opening price and the close price. Because most of the cryptocurrency exchanges work on 24/7 principle, the close price equals the open price of the next day and is taken at 24:00 GMT.

Unfortunately the price data from cryptocompare does not contain full or the largest possible history of some cryptocurrencies. Because in order to make proper statistical inference especially the multivariate models need the time series to be as long as possible, other sources had to be included. Poloniex is one of the largest cryptocurrency exchanges and it runs on 24/7 principle. The poloniex data were obtained via the poloniex API and as in case of cryptocompare they are in the form of candlestick data taken at 24:00 GMT.

As a result the cryptocompare.com website is the source of price data for Bitcoin only. Data for Dash, Litecoin, Monero and Ripple were obtained from Poloniex.

To provide comparable results of volatility analysis the exchange rates of all cryptocurrencies must be measured against the same currency. Because the thesis also analyses the influence of some fiat currencies' price movements to cryptocurrencies' prices their exchange rates must be denominated in different currency than are the analyzed ones. From this reason the prices are denominated in pound sterling (GBP). Not all analyzed cryptocurrencies are traded against pound sterling and even if they are the volume is lower than volume of trade against U.S. dollar or bitcoin. Based on this it can be expected that liquidity for GBP pairs is lower and volatility therefore higher than volatility of more traded pairs. To mitigate this illiquidity effect cryptocurrency/GBP exchange rates are computed by using the exchange rate of most traded currency and converting it via its rate to pound sterling. Given that data from Poloniex come in BTC prices only, in the end this methodology applies for Bitcoin only. Other exchange rates are converted into pound sterling via BTC/GBP exchange rate. The dataset comprises of observations from 14.8.2014 to 26.5.2017.

5.1.1 Bitcoin

In this section the development of exchange rates and their returns is discussed. To include as long timeline as possible the data for the cryptocurrencies come from two sources. The first one is already discussed cryptocompare.com which was used for Bitcoin data, the second source is a similar site, coinmarketcap.com, which is used for other cryptocurrencies. To include a very interesting development in prices in spring and summer 2017 the last observation is from 17.7.2017. However, the range of data used in the further estimations stays the same as mentioned above.

From BTC/USD exchange rate and its daily returns depicted in Figure 5.1 and Figure 5.2 the Bitcoin's timeline can be divided into four periods.

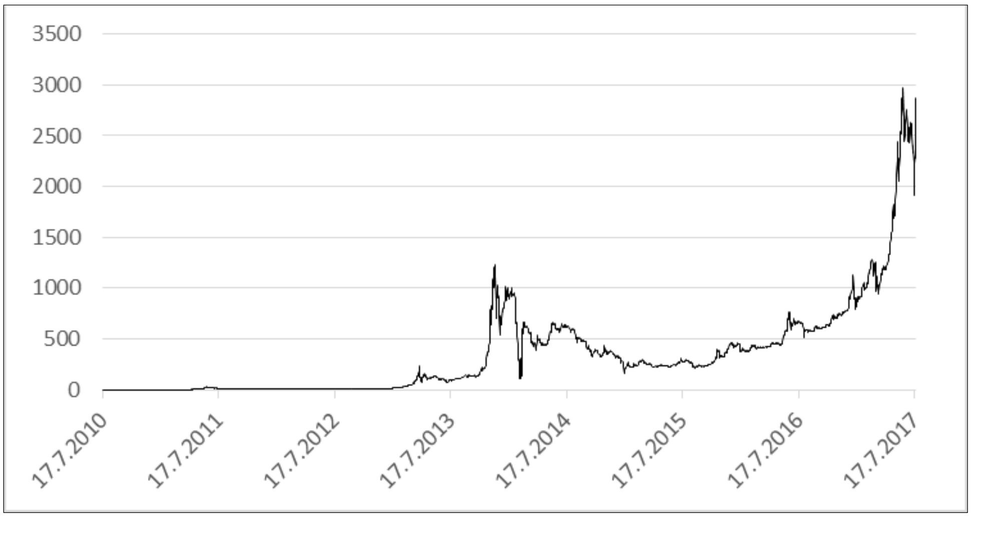


Figure 5.1: BTC/USD exchange rate

Source: Cryptocompare.com.

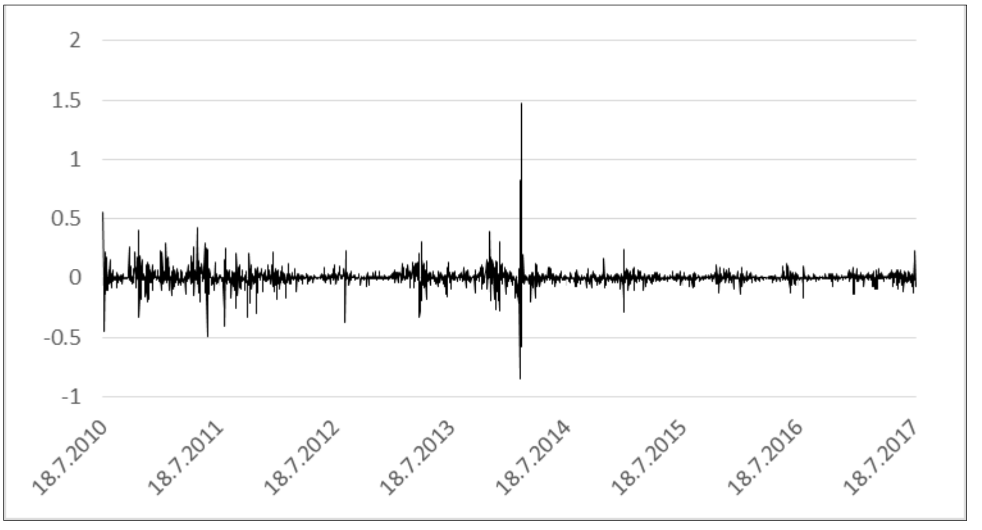


Figure 5.2: BTC/USD exchange rate returns

Source: Cryptocompare.com

In Figure 5.2 it can be seen that until April 2012 bitcoin returns were realized in a pattern which could be describes as one large volatility cluster with volatility decreasing for short time only. It could be expected that in the origins of bitcoin price formation the large part of volatility was caused by low liquidity.

During the second period Bitcoin started to get more attention and started to be used as a way of avoiding capital controls and economic downturns. This can be seen in the April 2013 price spike in Figure 5.1, when bitcoins' closing price reached 230 USD on 9.4.2013. This price spike is attributed to Cypriot financial crisis when threat of deposit taxes spread to other countries as Greece or Spain and stimulated the interest in Bitcoin ("Bitcoin hits record exchange values with Cyprus banking crisis," n.d.). The December 2013 price spike is attributed to faking trade volume at MtGox exchange which caused speculation bubble which reached 1 237 USD per bitcoin on 4.12.2013. The following price drop is partly attributed to the resolution made by The People's Bank of China to bar Chinese financial institutions from handling bitcoins ("Fake China Bitcoin Ban pushes BTC price below $600," 2014). In July 2014 the exchange rate began to follow U-shaped path which ended in spring 2017 when first price jumps appeared and eventually led to price spike reaching nearly 3000 USD per bitcoin. This price surge happened through the whole spectrum of cryptocurrencies.

5.1.2 Dash

In the first days after its release the Dash had to deal with "instamine" problem, meaning that 1.9 million of coins were mined due to the error in the protocol. This is probably the cause of high price jumps in the first quarter of 2014 as depicted in the Figure 5.3. The first speculation bubble in May 2014 was caused by the expectations of masternodes implementation on May 25 and by sudden developers' decision to decrease the total number of coins ever to be created to 22 million. In the beginning of 2017 the value of Dash began to rise in a bubble behavior manner reaching 119 USD per coin on March 18. According to information at Dash website ("Dash Price Rise, Explained — Dash," n.d.) this bubble is attributed to partnership between Dash and BlockPay which can result in increased usability of the coin in brick and mortar shops. Another reason is probably phenomena called "short squeeze" which is a situation when shorting traders react to unexpected rise in price in buying the asset even in loss to prevent higher losses. This drives the price further up (ibid.). As in case of Bitcoin, also Dash went through phase of sharp price increase in spring and summer 2017 causing increase in volatility.

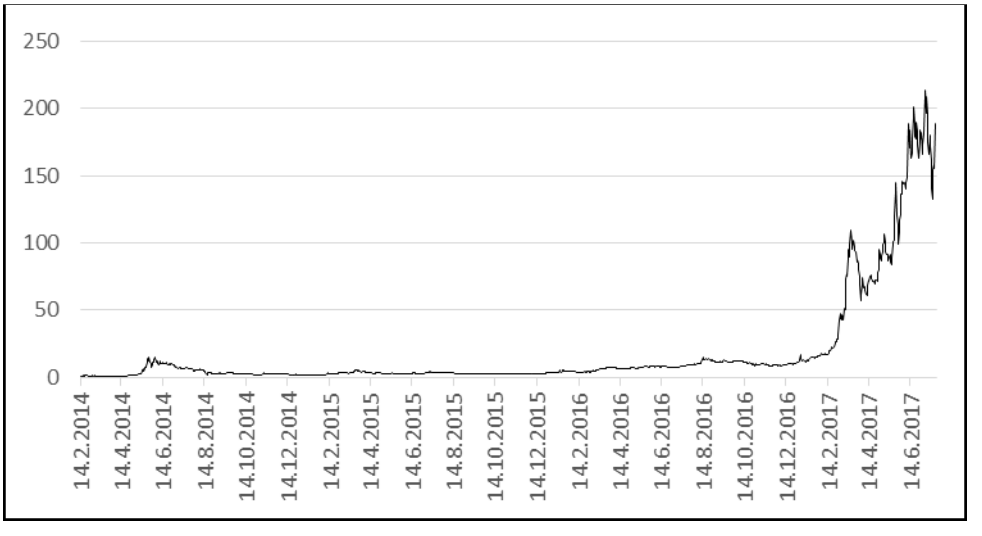


Figure 5.3: DASH/USD exchange rate

Source: Coinmarketcap.com

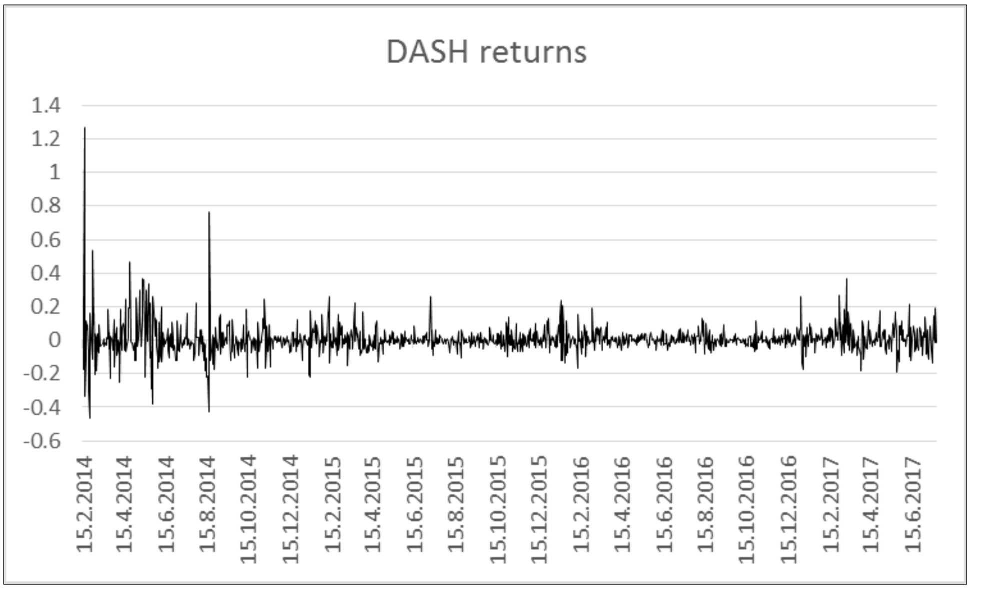


Figure 5.4: DASH/USD exchange rate returns

Source: Coinmarketcap.com

5.1.3 Litecoin

As one of the first currencies which emerged in period of less awareness about cryptocurrencies litecoins' price follow path more similar to that of bitcoins. There is a period of low interest in the currency followed by speculative bubble that spiked in December 2013, in the same time as Bitcoin's bubble. As in the case of Bitcoin the price of litecoins were decreasing until summer 2015 and began to climb up again afterwards, but unlike bitcoin which tends to reach new all-time heights during spring 2017 the pace of litecoin's price was lower. Again, also Litecoin went through sharp increase in price in spring and summer 2017 resulting in higher volatility of returns.

Figure 5.5: LTC/UDS exchange rate

Source: Coinmarketcap.com

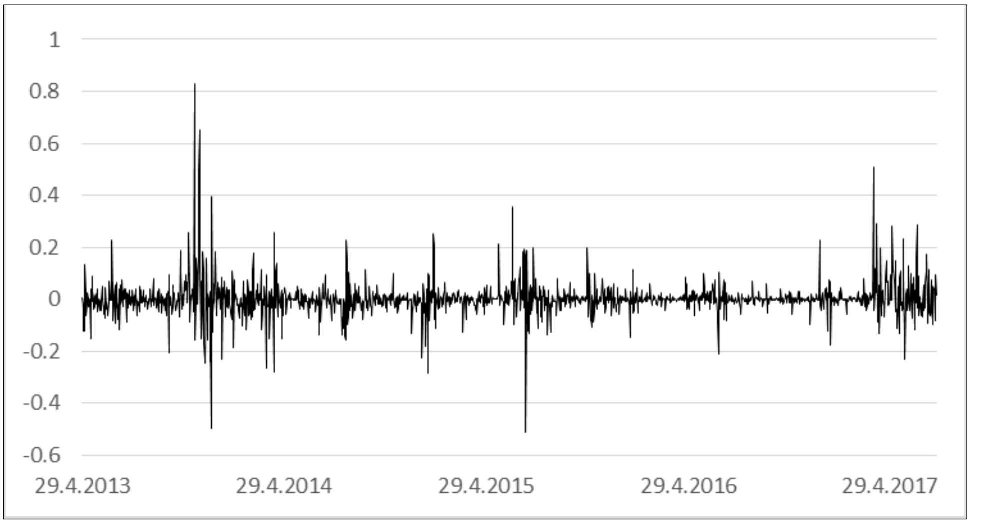


Figure 5.6: LTC/USD exchange rate returns

Source: Coinmarketcap.com

5.1.4 Monero

As can be seen in the chart the history of Monero price began with two spikes after its release (the two spikes seem to be very small when compared to the current development, but for the most of the Monero's existence they represented the highest values ever). After them two years of relatively low price followed resembling the history of bitcoin price before 2013. In the end of August and beginning of September 2016 the exchange rate went through the bubble reaching over 13 USD. This price movement was attributed to good cryptography maintained by experts and integration to darknet marketplaces as AlphaBay Market and Oasis Market, a move demanded by users who prefer privacy of transactions ("5 Major Reasons Why Monero Has Spiked," n.d.). The validity of this explanation is supported by positive price trend after the bubble crash. As can be seen in the spring 2017 few price surges appeared including the speculative bubble in June, however the price always returned to the trend level.

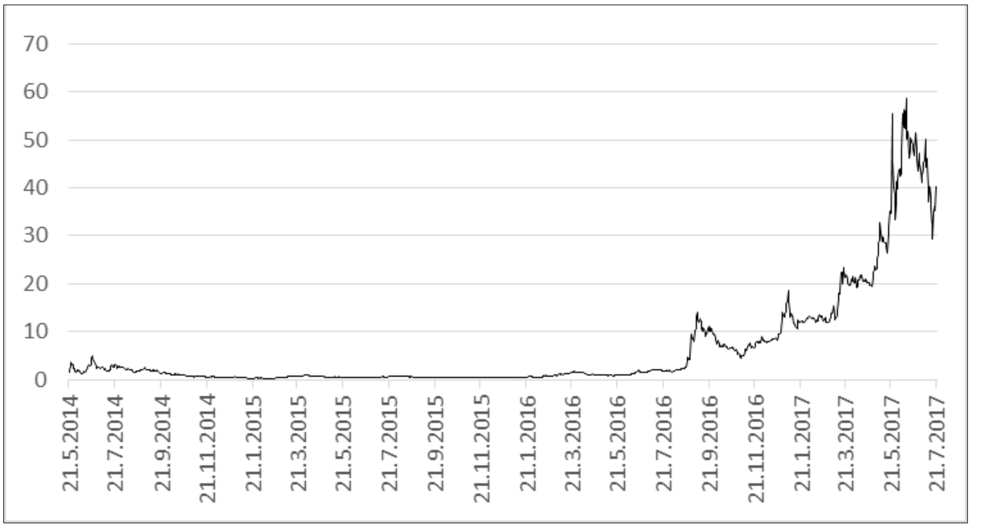


Figure 5.7: XMR/USD exchange rate

Source: Coinmarketcap.com

The graph of returns shows higher volatility in the first year after the introduction of the coin. The rest of the observed period shows slightly lower volatility with some remote values and volatility clusters in price surges periods.

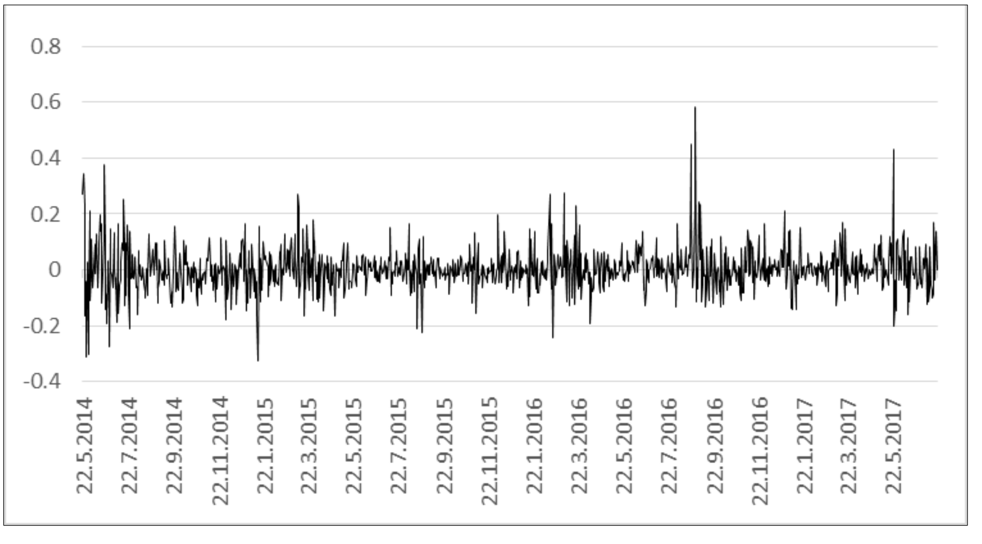


Figure 5.8: XMR/UDS exchange rate returns

Source: Coinmarketcap.com

5.1.5 Ripple

The figures of Ripple's price and returns show similar patterns as in case of previous cryptocurrencies. There were two price surges in the beginning of 2014 and first quarter of 2015 followed by the period of either stable or slowly decreasing price. As well as in previous cases, the returns show high volatility after the cryptocurrency's introduction eventually stabilizing to lower level with several remote values and with huge volatility increase during the price bubble in 2017.

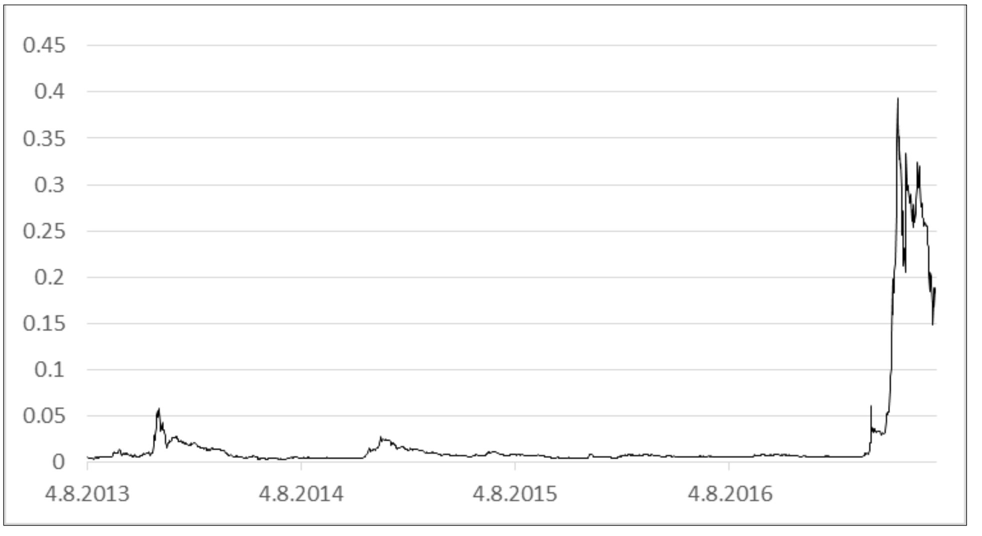


Figure 5.9: XRP/USD exchange rate

Source: Coinmarketcap.com

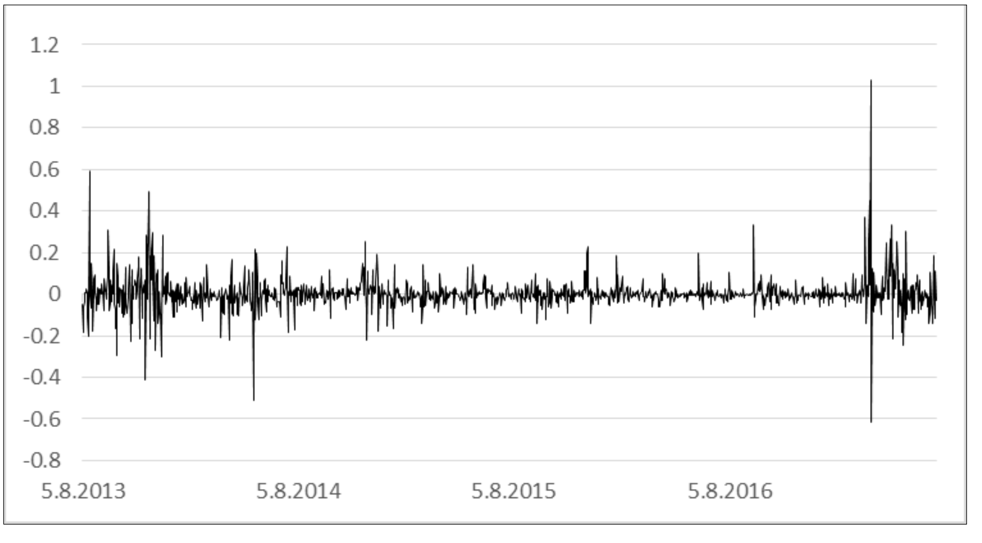


Figure 5.10: XRP/USD exchange rate returns

Source: Coinmarketcap.com

5.2. Exchange rates – fiat currencies

Exchange rates of fiat currencies which are most traded against cryptocurrencies are included in the analysis to allow multivariate models to be as precise as possible. According to cryptocompare.com the most traded fiat currency at cryptocurrencies' exchanges is dollar (USD), at the second place in terms of volume of traded cryptocurrencies is yuan (CNY) or euro (EUR), depending on particular coins.

Especially in case of Chinese yuan significant relationship between the two currencies can be expected. Bitcoin provides means to avoid strict capital controls imposed by government, therefore in periods of uncertainty or economic downturn Bitcoin is likely to be affected. (Alessandro, 2016) The exchange rates are denominated in pairs against pound sterling (GBP). The data were obtained from the interactive database of the Bank of England. ("Bank of England Statistical Interactive Database | Interest & Exchange Rates," n.d.) The data represent middle market prices taken around 16:00 GMT. ("Explanatory Notes - Spot Exchange Rates | Bank of England," n.d.) Unfortunately data taken at 24:00 GMT matching the exact time of cryptocurrencies' time series were not available. While the foreign exchange market runs 24/5 it is only because there is always one of the classical markets open. Unfortunately the closing hours of none of them matches the 24:00 GMT. The data of Bank of England were used because there are strong reasons given by overall capitalization of fiat currencies versus overall capitalization of cryptocurrencies that the causality goes in the fiat to cryptos direction. Therefore using the data taken before 24:00 GMT is not so problematic than the data taken after.

Another issue is that data of fiat currencies exclude observations from weekends and bank holidays. The observations corresponding to these missing values were therefore excluded from the cryptocurrencies' time series. The exchange rates were converted into daily returns by differencing their natural logarithms. This method was chosen to diminish the extreme values which are more often at cryptocurrencies' markets than at the classical ones.

6. Results

6.1. Univariate models

6.1.1 Mean equation specification process

All time series were tested for presence of unit root by Augmented Dickey-Fuller test and by KPSS test computed either with trend or level. The null hypothesis if ADF test is the presence of unit root in time series, the null hypothesis of KPSS test it stationarity of the series. Moreover the series were tested for presence of autocorrelation by Ljung-Box test testing the null hypothesis of no correlation between any of the observations. The results are depicted in the table 6.1.

Table 1: Results of diagnostic tests

Currency	CNY	EUR	USD	BTC
ADF test	-8.787	8.612	-8.985	-9.764
	(0.01*)	(0.01*)	(0.01*)	(0.01*)
KPSS with trend	0.045	0.076	0.056	0.036
	(0.1*)	(0.1*)	(0.1*)	(0.1*)
KPSS with level	0.053	0.257	0.059	0.718
	(0.1*)	(0.1*)	(0.1*)	(0.012)
Ljung-Box test	34.231	10.720	34.243	24.578
	(0.025)	(0.953)	0.0245)	(0.218)
Currency	DASH	LTC	XMR	XRP
ADF test	-8.821	-9.706	-8.800	-7.113
	(0.01*)	(0.01*)	(0.01*)	(0.01*)
KPSS with trend	0.041	0.077	0.038	0.254
	(0.1*)	(0.1*)	(0.1*)	(0.1*)
KPSS with level	0.554	0.459	0.633	0.495
	(0.029)	(0.052)	(0.02)	(0.043)
Ljung-Box test	23.164	31.337	29.906	36.219
	(0.281)	(0.051)	(0.071)	(0.015)

* the p-value is lower than depicted number in case of ADF test, higher in case of KPSS test

Source: author's computation

As can be seen in the table the time series of fiat currencies do not contain unit root. The augmented Dickey-Fuller test rejected the hypothesis of unit root at all levels of confidence and the hypothesis of stationarity of the series was not rejected by both

KPSS tests, also at all levels of confidence. While for euro time series the Ljung-Box test shows there is no autocorrelation between observations, the results for US dollar and yuan renminbi suggest the need to include ARMA model as mean equation in the models' specifications.

Regarding the cryptocurrencies, the results of both augmented Dickey-Fuller test and KPSS test with trend suggest there is no unit root in the time series. However, this is not in accordance with the results of KPSS test with level, which imply the opposite. The null hypothesis of stationarity is rejected at 5% level of confidence in case of all cryptocurrencies excluding Litecoin. For Litecoin, the null hypothesis is rejected at 10% level of confidence only. Given that ADF test suggest stationarity for Litecoin time series and the KPSS test rejects it at 10% confidence level only, Litecoin is the only cryptocurrency whose mean equation is not modeled using trend. According to the results of Ljung-Box test the null hypothesis of no autocorrelation is not rejected at all confidence levels for Bitcoin and Dash. For Litecoin and Monero the null hypothesis is rejected at 10% level and for Ripple also at 5% level. Nevertheless, given that the estimation of volatility and mean equations should be done jointly which could lead to different results of Ljung-Box test when applied on model's residuals, for all cryptocurrencies the need of using ARMA modeling is determined by estimation of several combinations of ARMA specifications with GARCH (1,1) variance equation as already stated above. The resulting significance of GARCH parameters from these estimations is also used for assessing whether the ARCH process is present in the series, which is, in the case of no ARCH process, then tested by ARCH-LM test on mean equation's residuals.

The Table 2: Results of ARMA(p,q)-GARCH(1,1) summarizes the results of finding the best ARMA specification.

Table 2: Results of ARMA(p,q)-GARCH(1,1)

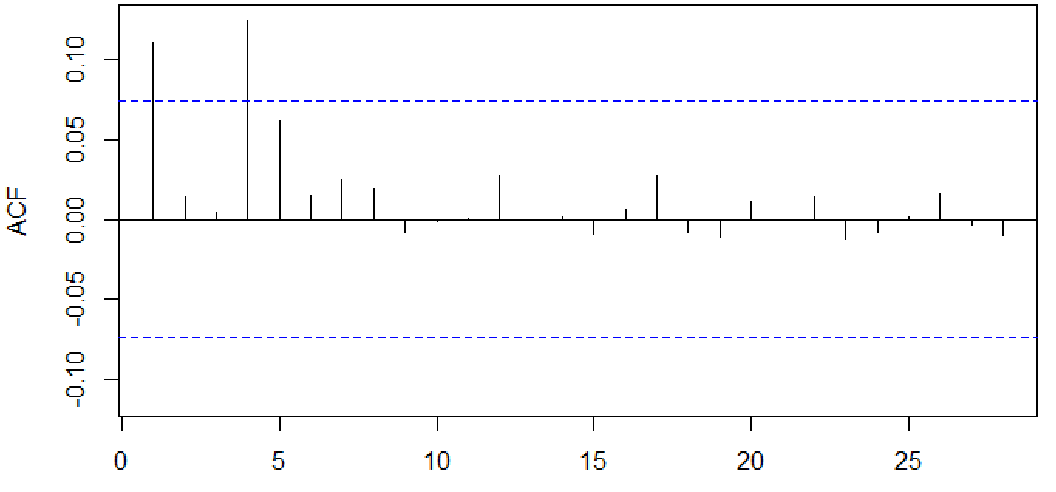
Currency	CNY	EUR	USD	BTC
Specification (p, I, q)	2, 2	0, 0	0, 0	2, 2
AR1	0.2330	N/A	N/A	0.7771
	(4.0e-06)***	N/A	N/A	(0.000)***
AR2	-0.8680	N/A	N/A	0.1968
	(0.000)***	N/A	N/A	(0.000)***
MA1	-0.1880	N/A	N/A	-0.7257
	(0.000)***	N/A	N/A	(0.000)***
MA2	0.9250	N/A	N/A	-0.2750

	(0.000)***	N/A	N/A	(0.000)***
ω	0.0000	0.0000	0.0000	0.0001
	(4.1e-05)***	(0.013)**	(0.455)	(7.9e-05)***
α	0.1414	0.0652	0.1441	0.2193
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
β	0.7865	0.8907	0.8180	0.7181
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
trend	N/A	N/A	N/A	0.0000
	N/A	N/A	N/A	(0.000)***
Ljung-Box test - z	[19] 10.401	[5] 0.9088	[5] 1.2282	[19] 10.76
	(0.403)	(0.880)	(0.806)	0.348)
ARCH-LM test - z	[3] 0.1594	[3] 0.236	[3] 0.1927	[3] 0.4608
	(0.69)	(0.627)	(0.660)	(0.497)

Currency	DASH	LTC	XMR	XRP
Specification (p, I, q)	0, 0	0, 0	1, 2	0, 0
AR1	N/A	N/A	-0.9232	N/A
	N/A	N/A	(0.000)***	N/A
AR2	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A
MA1	N/A	N/A	1.0064	N/A
	N/A	N/A	(0.000)***	N/A
MA2	N/A	N/A	0.0417	N/A
	N/A	N/A	(0.000)***	N/A
ω	0.0004	0.0003	0.0005	0.0008
	(0.002)***	(1.9e-05)***	(0.001)***	(0.000)***
α	0.3949	0.1272	0.2545	0.5698
	(0.000)***	(1.2e-05)***	(0.000)***	(0.000)***
β	0.6041	0.8209	0.7196	0.4292
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
trend	0.0000	N/A	0.0000	0.0000
	(0.071)*	N/A	(0.421)	(0.001)***
Ljung-Box test - z	[5] 1.4405	[5] 1.103	[14] 5.081	[5] 2.2844
	(0.755)	(0.836)	(0.888)	(0.553)
ARCH-LM test - z	[3] 0.1608	[3] 0.1677	[3] 0.4794	[3] 0.08284
	(0.688)	(0.682)	(4.88e-01)***	(0.774)

Source: author‘s computation

The autocorrelation in Chinese yuan time series was confirmed by significant parameters of ARMA(2,2) model. The test criterion of weighted Ljung-Box test on standardized residuals including 19 lags was 10.4011 with p-value 0,4031, thus the null hypothesis was not rejected at all levels of confidence. Regarding ARCH process, all GARCH parameters were found to be statistically significant. According to the results of ARCH-LM test on standardized residuals using 3 lags there is no remaining ARCH process in the series. To test whether the GARC specification had to been included in the model the residuals from simple ARMA(2,2) were tested by ARCH-LM test for the presence of ARCH process. The results did not reject the null hypothesis as well, however the ACF and PACF autocorrelograms of squared residuals depicted at figures bellow revealed autocorrelation at lags 1 and 4. Anyway, in the selection of GARCH specifications models with no ARCH process are treaded as well.



Source: author's computation

Figure 6.1: ACF – CNY ARMA(2,2) residuals

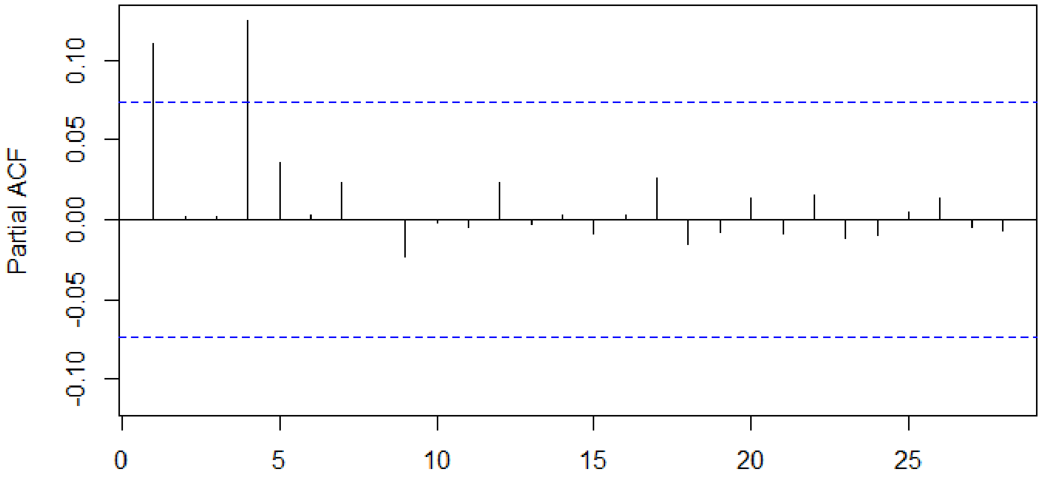


Figure 6.2: PACF - CNY ARMA(2,2) residuals

Source: author's computation

Regarding the euro time series the best mean equation model according to all information criteria computed (Akaike, Bayes, Shibata, Hannah-Quinn) was found to be ARMA(0,0) without constant, thus the mean is considered to be 0. The GARCH parameters were found to be statistically significant at all levels of confidence. According to weighted Ljung-Box test there is no remaining autocorrelation in standardized residuals (p-values 0.9088 for a test with 5 lags). The null hypothesis of ARCH-LM test with 3 lags was not rejected at all levels of confidence with p-value circa 0.6. When the returns were tested for presence of ARCH process the results are similar to yuan's results. The test did not reject null hypothesis of no ARCH process, but ACF and PACF autocorrelograms suggest there is a slightly significant autocorrelation in squared residuals, in this case in squared returns.

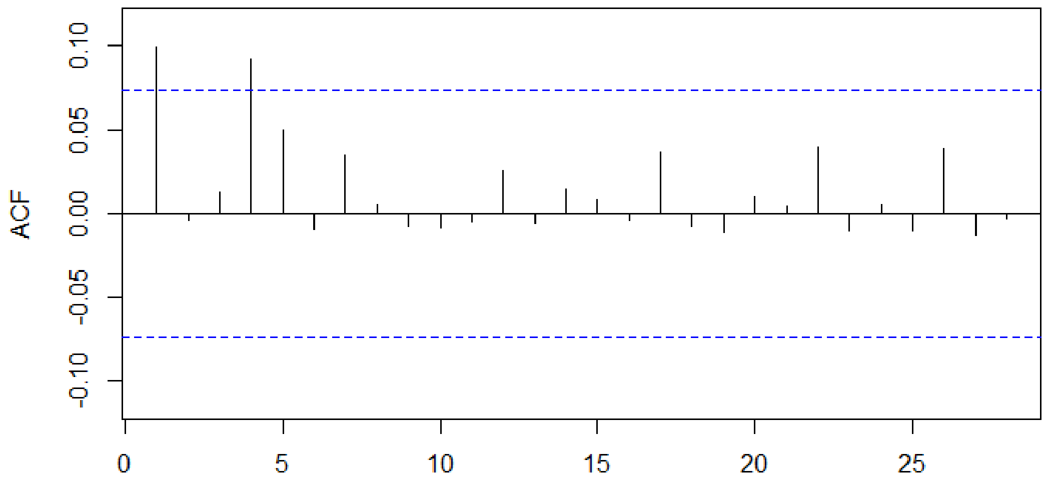


Figure 6.3: ACF – EUR squared returns

Source: author's computation

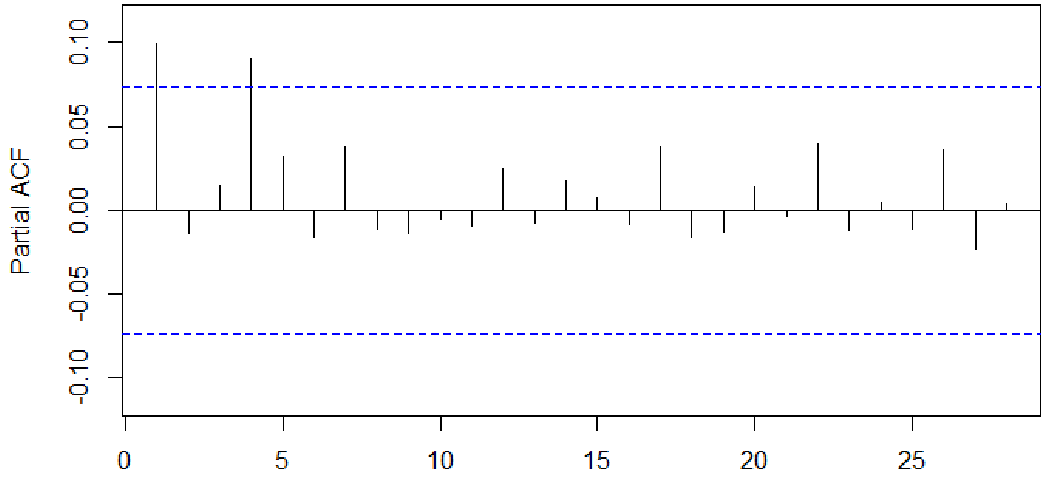


Figure 6.4: PACF – EUR squared returns

Source: author's computation

The results for US dollar are similar to euro. According to Bayes and Hannah-Quinn information criteria the ARMA(0,0) model was found to be the most corresponding to the data. The GARCH parameters were found to be significant at all levels of confidence except of the omega, the parameter representing the constant in the conditional variance model, whose difference from zero was not rejected. The result of weighted Ljung-Box test on standardized residuals shows there is no remaining autocorrelation. The same applies also for results of the ARCH-LM test. The ARCH-LM test on the returns did not reject the null hypothesis of no ARCH process (p-value 0.1007), but again the ACF and PACF autocorrelograms on squared returns show autocorrelation between squared returns.

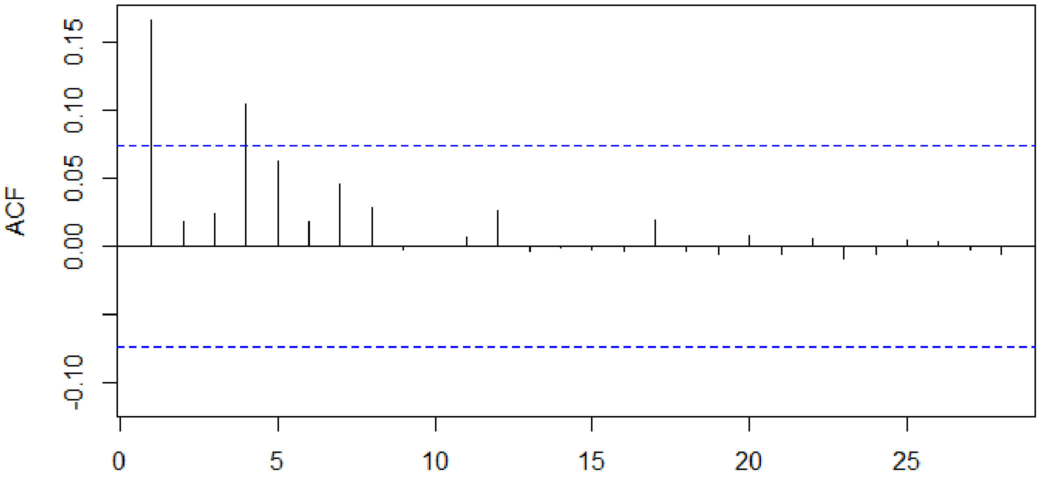


Figure 6.5: ACF – USD squared returns

Source: author's computation

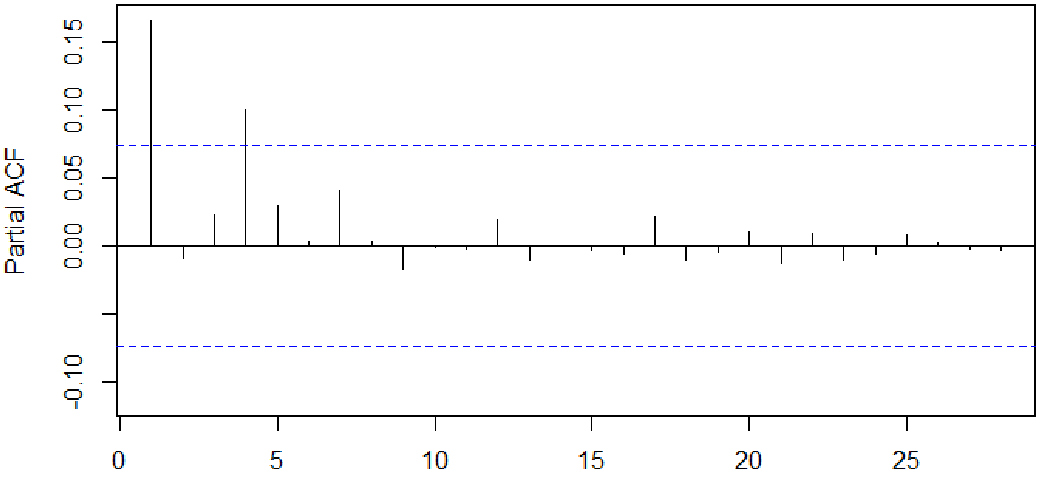


Figure 6.6: PACF – USD squared returns

Source: author's computation

The best mean equation specification of BTC according to information criteria was found to be ARMA(0,1). However, it could not be used because the MA parameter was not significantly different from zero. From the same reason or because of the rejection of no autocorrelation hypothesis in weighted Ljung-Box test several other models had to be rejected. The best model from all specifications which fulfilled the conditions of significant parameters and no autocorrelation was found to be ARMA(2,2). The adequacy of GARCH specification was confirmed by ARCH-LM test computed on the residuals from simple ARMA(2,2) model. The null hypothesis of no ARCH process was rejected at all levels of confidence (p-value 2.2e-16). ACF and PACF autocorrelograms confirmed the need of GARCH specification.

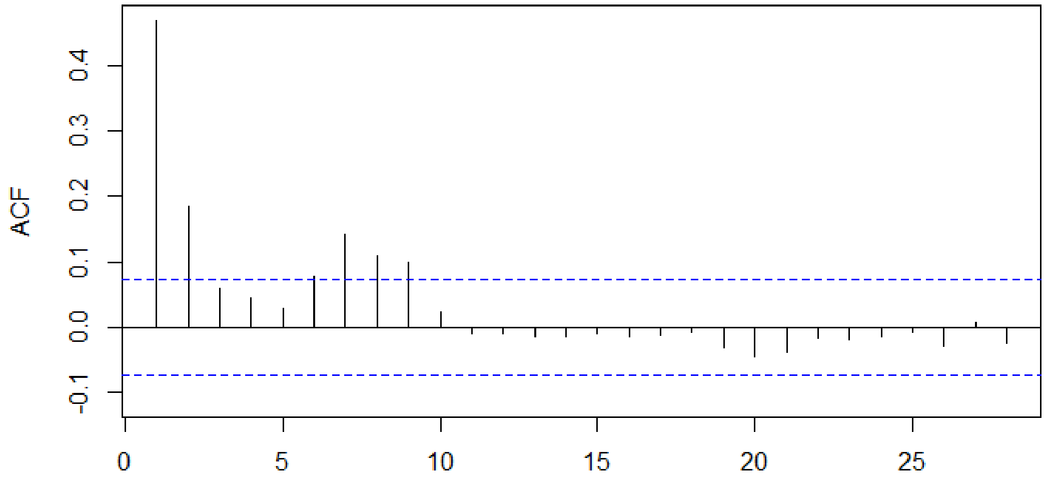


Figure 6.7: ACF - BTC ARMA(2,2) squared residuals

Source: author's computation

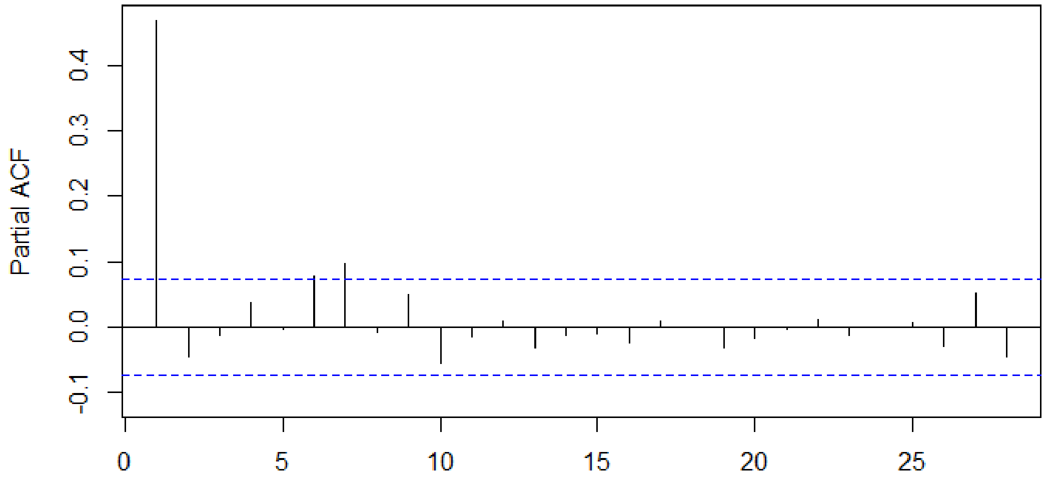


Figure 6.8: PACF - BTC ARMA(2,2) squared residuals

Source: author's computation

The best specification of mean equation for Dash's time series was found to be ARMA(0,0). The tests for presence of remaining autocorrelation among standardized residuals confirmed the adequacy of this specification. The weighted Ljung-Box test on standardized residuals did not reject null hypothesis at all levels of confidence. The same applies also for the ARCH-LM test on standardized residuals, implying that GARCH (1, 1) removed ARCH process from the time series. The time trend variable was found to be significant only at 10% level of confidence, however it is used in further estimations to avoid the unit root process suggested by the results of the KPSS tests. All GARCH parameters were found to be statistically significant at all levels of confidence. The adequacy of using GARCH specification was confirmed by ARCH-

LM test on returns which rejected the null hypothesis with p-value 2.747e-08. This was further confirmed by ACF and PACF autocorrelograms displayed at the pictures below.

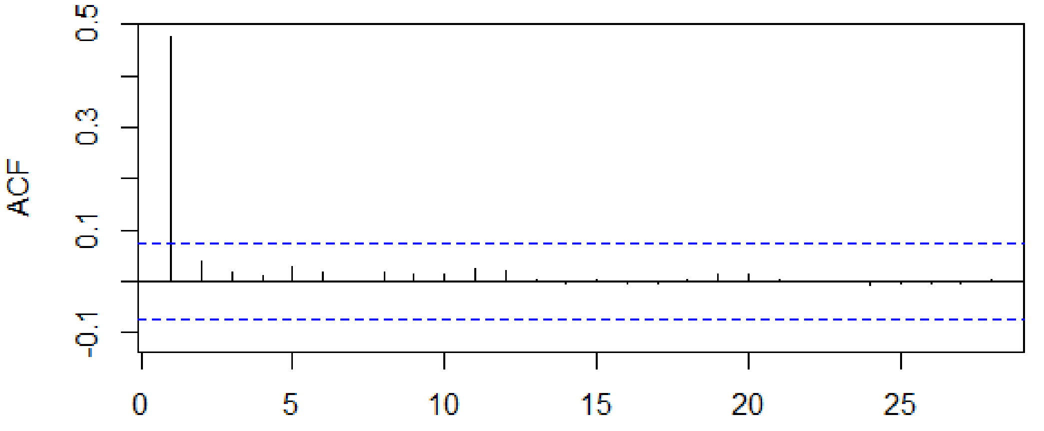


Figure 6.9: ACF – DASH squared returns

Source: author's computation

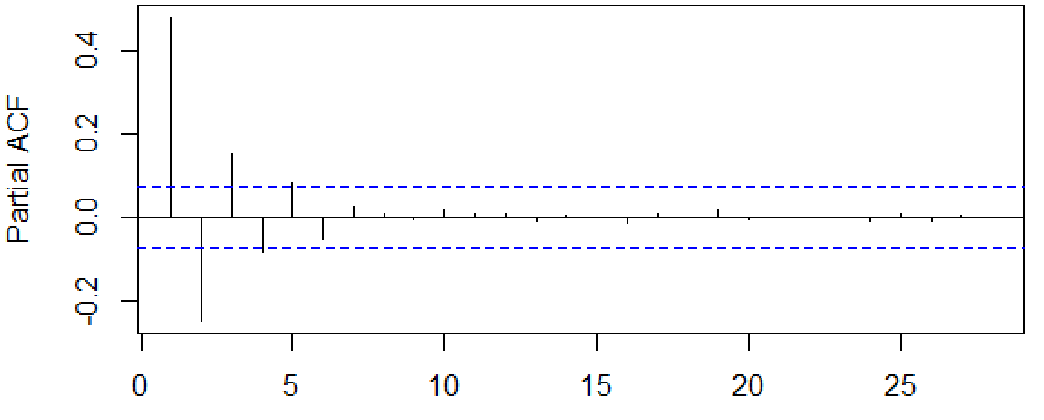


Figure 6.10: PACF – DASH squared returns

Source: author's computation

Litecoin time series are best specified by ARMA(0,0) as well. The time trend parameter suggested by KPSS tests was found to be nonsignificant, therefore, as the level KPSS test rejected the null hypothesis at 10% level of confidence only, the parameter is not used in further estimation. The result of weighted Ljung-Box test show there is no remaining autocorrelation among standardized residuals and the results ARCH-LM test show that there is no remaining ARCH process. All GARCH parameters were found to be significant at all levels of confidence and adequacy of GARCH specification was confirmed by ARCH-LM test on the Litecoin's returns (p-value 0.000151) and by autocorrelograms of squared returns.

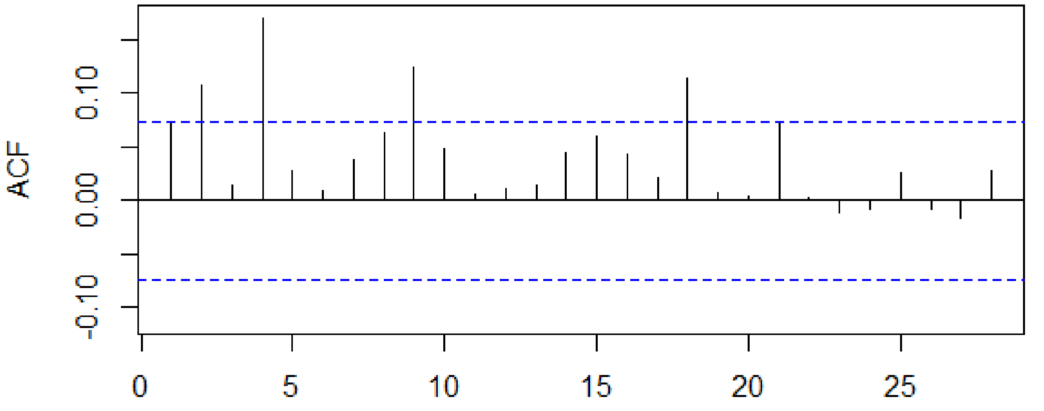


Figure 6.11: ACF – LTC squared returns

Source: author’s computation

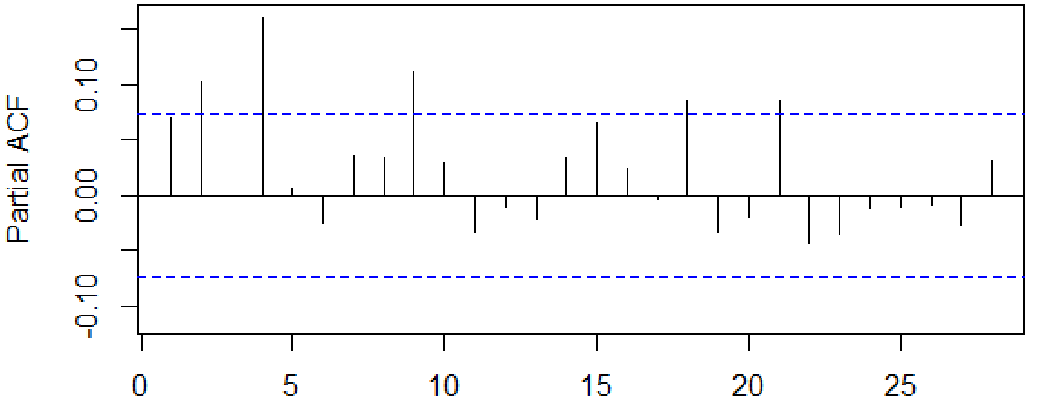


Figure 6.12: PACF – LTC squared returns

Source: author’s computation

Ripple time series can be added among series without an ARMA process. The negative time trend parameter was found to be statistically significant at all levels of confidence. According to weighted Ljung-Box tests and ARCH-LM test there is neither remaining autocorrelation nor ARCH process among standardized residuals. All GARCH parameters are statistically significant and the need of GARCH specification was also confirmed by ARCH-LM test on model’s residuals (p-value 3.32E-11) and by both autocorrelograms.

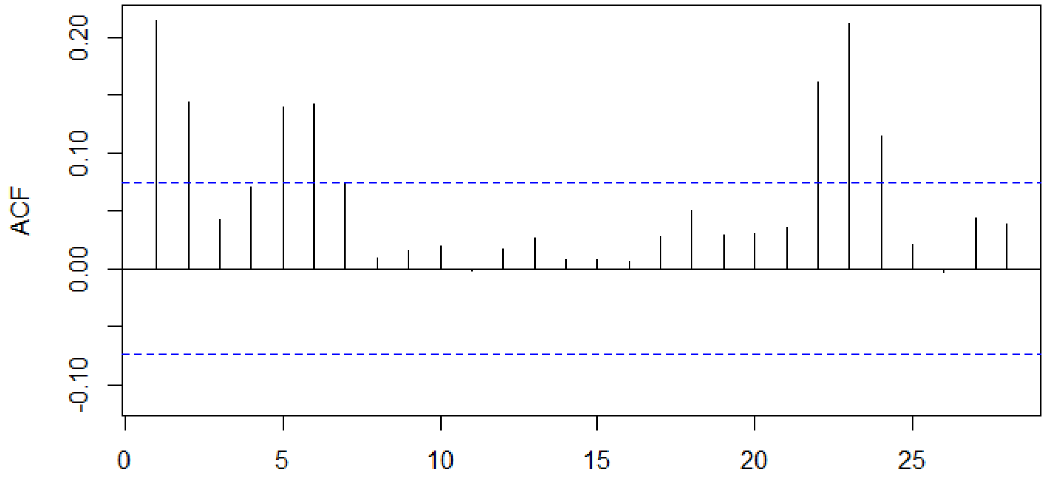


Figure 6.13: ACF – XRP squared returns

Source: author's computation

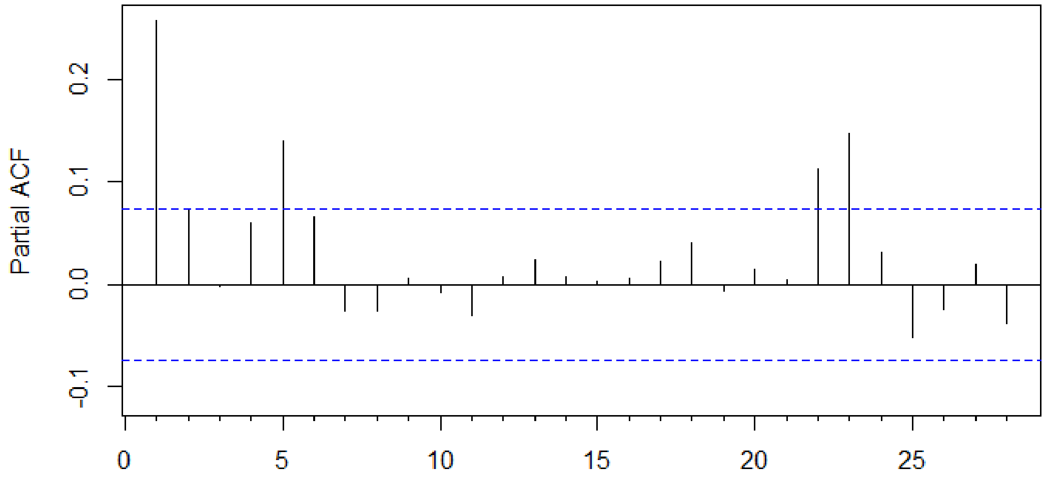


Figure 6.14: PACF – XRP squared returns

Source: author's computation

Finally, Monero time series was found to be best described by ARMA(1,2) specification. The time trend parameter was found to be nonsignificant, nevertheless it is kept in further estimation as KPSS tests' results suggested. According to weighted Ljung-Box test on standardized residuals the specification removed autocorrelation, what does not apply for the ARCH process which is according to the results of ARCH-LM test still present in standardized residuals. Both autocorrelograms of squared standardized residuals suggest it is because of strong autocorrelation at fifth lag. This problem is treated in the next step where the proper GARCH specification is specified.

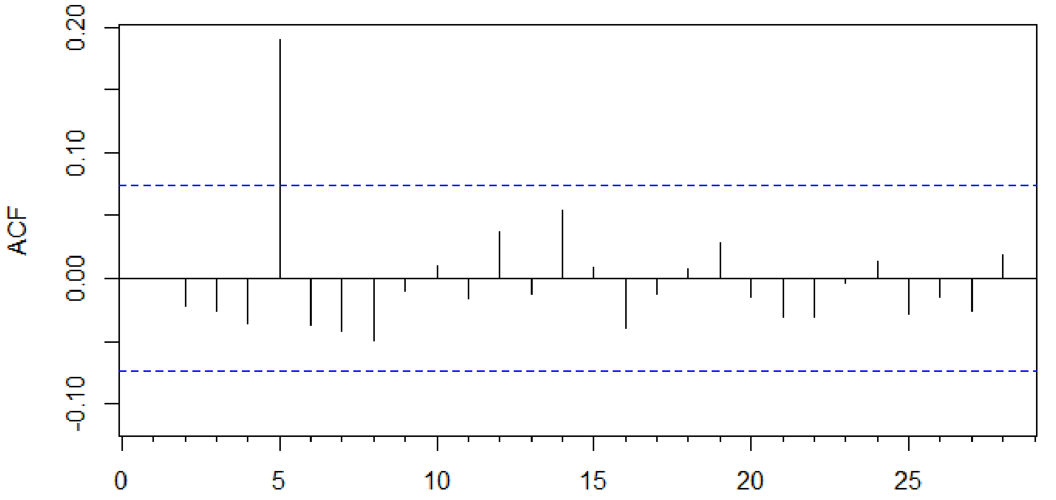


Figure 6.15: ACF – XMR ARMA(1,2)-GARCH(1,1) squared standardized residuals

Source: author's computation

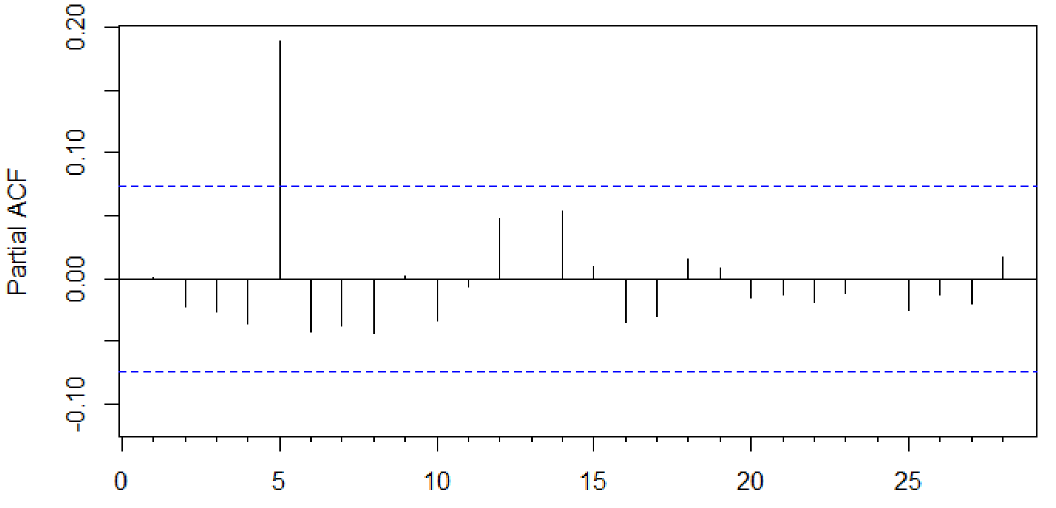


Figure 6.16: PACF - XMR ARMA(1,2)-GARCH(1,1) squared standardized residuals

Source: author's computation

6.1.2 Conditional volatility equation specification process

The next step of univariate models' specification was to find appropriate volatility model by its estimation using already found mean specification. As in the case of finding mean specification the best model was chosen by comparing information criteria, checking significance of parameters and the results of weighted Ljung-Box tests and ARCH-LM tests. The characteristics of the chosen models are depicted at the table.

Table 3: Results of ARMA(p,q)-__GARCH(p,q)

	CNY	EUR	USD	BTC	DASH
ARMA (p,q)	2, 2	0, 0	0, 0	2, 2	0, 0
GARCH spec.	gjrGARCH(1,1)	GARCH(1,1)	gjrGARCH(1,1)	GARCH(1,1)	csGARCH(0,1)
AR1	0.234151 (0.000004)***	N/A	N/A	0.777071 (0.0e+00)***	N/A
AR2	-0.877377 (0.000000)***	N/A	N/A	0.196833 (0.0e+00)***	N/A
MA1	-0.190752 (0.000000)***	N/A	N/A	-0.725715 (0.0e+00)***	N/A
MA2	0.928805 (0.000000)***	N/A	N/A	-0.275001 (0.0e+00)***	N/A
ω	0.000004 (0.000000)***	0.000002 (0.013498)**	0.000003 (0.000058)***	0.000127 (7.9e-05)***	0.00030 (2e-06)***
α1	0.069268 (0.000155)***	0.065223 (0.000000)***	0.066833 (0.000420)***	0.219306 (0.0e+00)***	N/A
α2	N/A	N/A	N/A	N/A	N/A
β	0.784295 (0.000000)***	0.890685 (0.000000)***	0.817368 (0.000000)***	0.718062 (0.0e+00)***	0.86926 (0e+00)***
γ	0.110126 (0.008601)***	N/A	0.127866 (0.001786)***	N/A	N/A
δ	N/A	N/A	N/A	N/A	N/A
η11	N/A	N/A	N/A	N/A	0.99911 (0e+00)***
η21	N/A	N/A	N/A	N/A	0.33906 (0e+00)***
trend	N/A	N/A	N/A	0.000019 (0.0e+00)***	N/A
ARCH-M	N/A	N/A	N/A	-0.116517 (0.0e+00)***	N/A
Ljung-Box test - z	[19] 9.93458 (0.4792)	[5] 0.9088 (0.8800)	[5] 1.0916 (0.8386)	[19] 10.76 (0.34798)	[5] 2.2932 (0.5509)
ARCH-LM test - z	[3] 0.05528 (0.81412)	[3] 0.236 (0.6271)	[3] 0.05768 (0.8102)	[3] 0.4608 (0.4973)	[2] 0.00349 (0.9529)
Unconditional variance	4.21E-05	4.61E-05	5.49E-05	0.002022689	0.337102
Persistence	0.908626	0.9559085	0.9481341	0.9373677	0.9991110
Transitory persistence	N/A	N/A	N/A	N/A	0.8692621

	DASH - shortened	LTC	XMR	XRP	XRP - shortened
ARIMA (p, I, q)	0, 0	0, 0	1, 1	0, 0	0, 0
GARCH spec.	GARCH(1,1)	csGARCH(0,1)	GARCH(5,0)	csGARCH(1,1)	apARCH(1,1)
AR1	N/A	N/A	0.996308 (0.000000)***	N/A	N/A
AR2	N/A	N/A	N/A	N/A	N/A

MA1	N/A	N/A	-0.995725 (0.000000)***	N/A	N/A
MA2	N/A	N/A	N/A	N/A	N/A
ω	0.000257 (0.001261)***	0.00030 (0.009186)***	0.003215 (0.000000)***	0.000329 (0e+00)***	0.050689 (0.037653)**
α1	0.281549 (0.000000)***	N/A	0.380997 (0.000001)***	0.526611 (0e+00)***	0.472403 (0.000000)***
α2	N/A	N/A	α5 0.264916 (0.000004)***	N/A	N/A
β	0.704913 (0.000000)***	0.88289 (0.000000)***	N/A	0.440898 (0e+00)***	0.358331 (0.000000)***
γ	N/A	N/A	N/A	N/A	-0.531374 (0.000000)***
δ	N/A	N/A	N/A	N/A	0.684729 (0.000072)***
η11	N/A	0.95746 (0.000000)***	N/A	0.999148 (0e+00)***	N/A
η21	N/A	0.14174 (0.000097)***	N/A	0.320812 (0e+00)***	N/A
trend	N/A	N/A	0.000003 (0.312789)	-0.000015 (3e-06)***	0.000000 (0.924989)
ARCH-M	N/A	N/A	N/A	N/A	N/A
Ljung-Box test - z	[5] 1.9558 (0.6289)	[5] 1.1927 (0.8147)	[14] 9.820 (1.347e-01)***	[5] 2.626 (0.4796)	[5] 0.800260 (0.9030)
ARCH-LM test - z	[3] 0.8738 (0.3499)	[2] 0.0204 (0.8864)	[7] 0.4780 (0.4893)	[3] 0.02288 (0.8798)	[3] 0.001474 (0.9694)
Unconditional variance	0.01899591	0.007063666	0.009078277	0.3859852	0.007101712
Persistence	0.9864617	0.9574640	0.6459124	0.9991476	0.7242418
Transitory persistence	N/A	0.8828954	N/A	0.9675092	N/A

Source: author's computation

The best model for Chinese yuan was found to be ARMA(2,2) – gjrGARCH(1,1). All ARMA and GARCH parameters are statistically significant at all levels of confidence. The series was cleansed from autocorrelation process in residuals, which is supported by the results of the weighted Ljung-Box test on standardized residuals. ARCH-LM test did not reject the null hypothesis of no remaining ARCH process, confirming the adequacy of the specification. The absence of remaining ARCH process was also confirmed by ACF and PACF autocorrelograms of squared standardized residuals depicted at pictures below. The series is without autocorrelations with a slight exception at lag 5. The persistence of the conditional volatility is 0.908626.

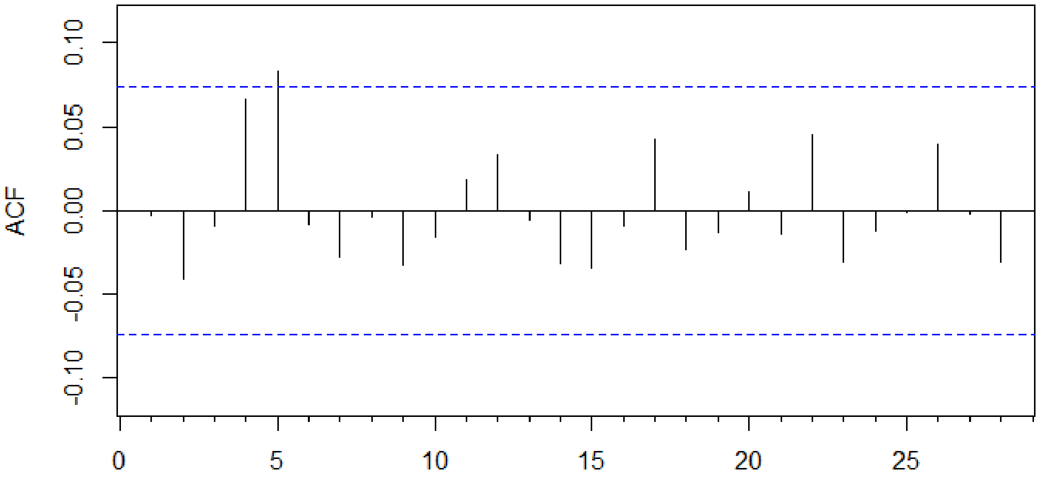


Figure 6.17: ACF – CNY ARMA(2,2)-gjrGARCH(1,1) squared standardized residuals

Source: author's computation

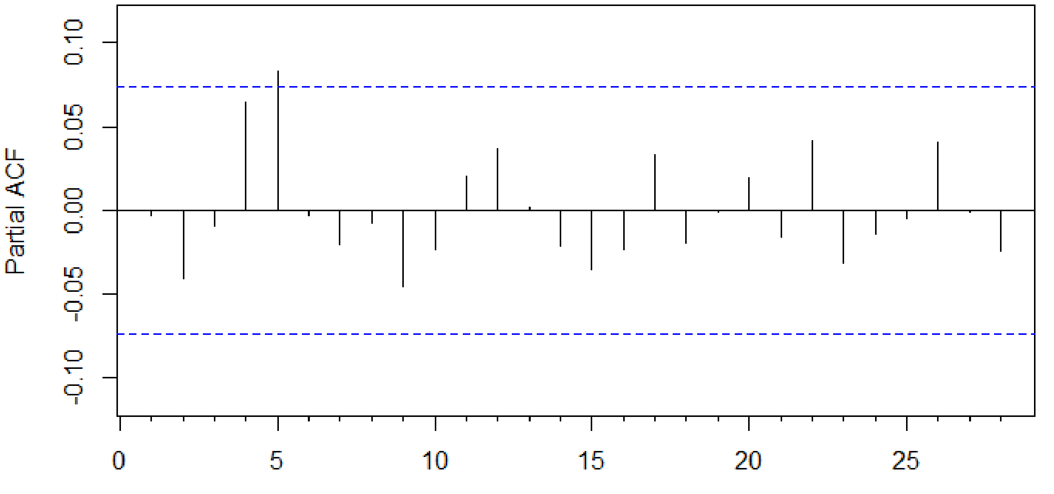


Figure 6.18: PACF – CNY ARMA(2,2)-gjrGARCH(1,1) squared standardized residuals

Source: author's computation

The picture below shows the estimated conditional variance. It can be seen that the model captured the effect of price jumps in June 2016.

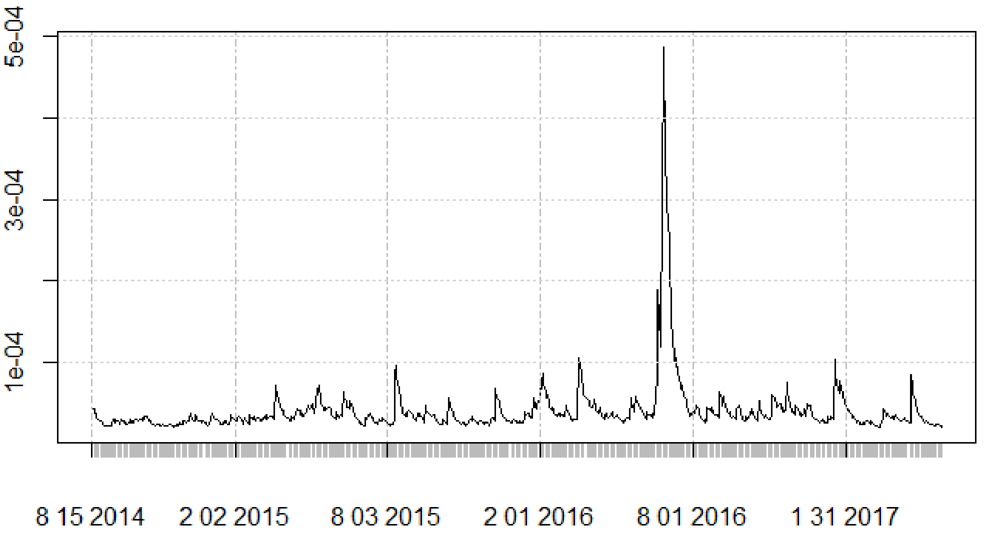


Figure 6.19: CNY conditional variance

Source: author's computation

Regarding euro returns, the best fitting model was found to be simple GARCH(1,1) without ARMA specification. All parameters are statistically significant at all levels of confidence while both tests suggest there is neither remaining autocorrelation process among standardized residuals nor remaining ARCH process. The null hypotheses were not rejected at all levels of confidence. As in the case of yuan the ACF and PACF autocorrelograms show no ARCH process with almost insignificant exception of lag 4. The persistence of conditional volatility is 0.9559085.

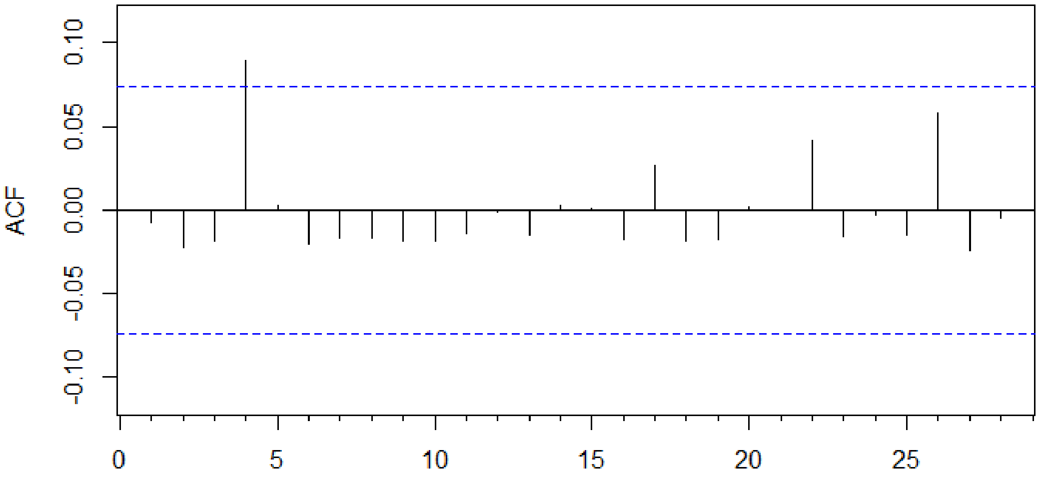


Figure 6.20: ACF – EUR GARCH(1,1) squared standardized residuals

Source: author's computation

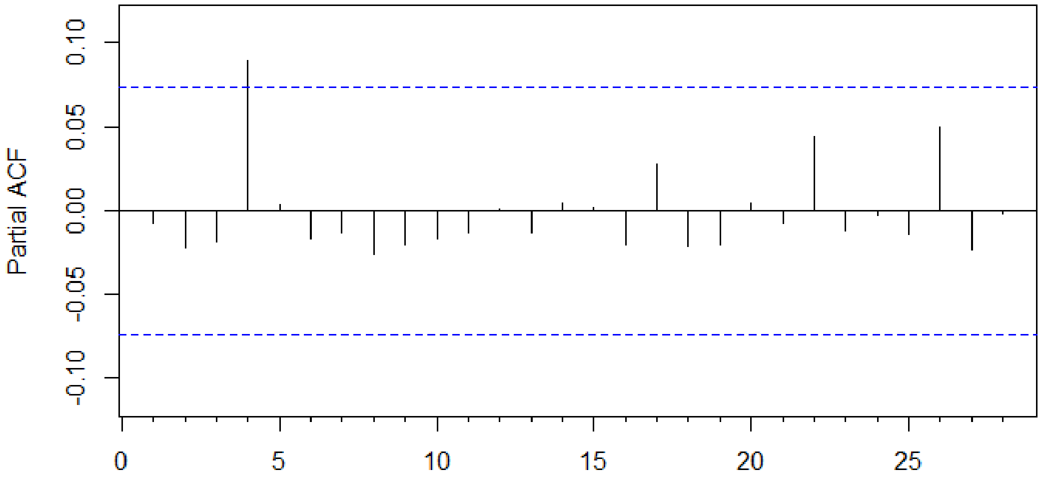


Figure 6.21: PACF – EUR GARCH(1,1) squared standardized residuals

Source: author's computation

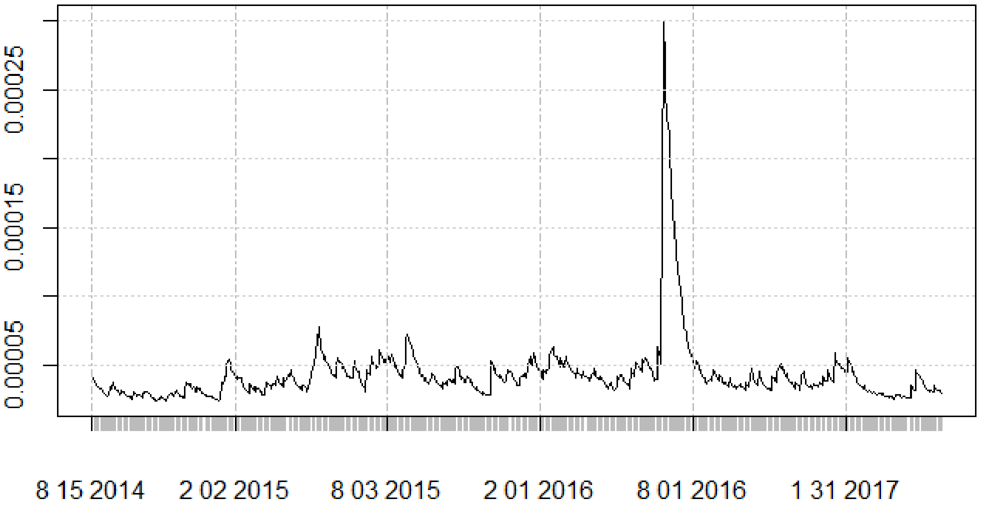


Figure 6.22: EUR conditional variance

Source: author's computation

For USD returns the best model showed to be gjrGARCH(1,1). The adequacy of this model was again confirmed by statistically significant parameters and results of weighted Ljung-Box test and ARCH-LM test whose hypotheses of no remaining autocorrelation and no remaining ARCH process were not rejected at all levels of confidence. Persistence of the conditional volatility is 0.9481341. The ACF and PACF correlograms of squared standardized residuals confirm there is no remaining ARCH process for any of the lags.

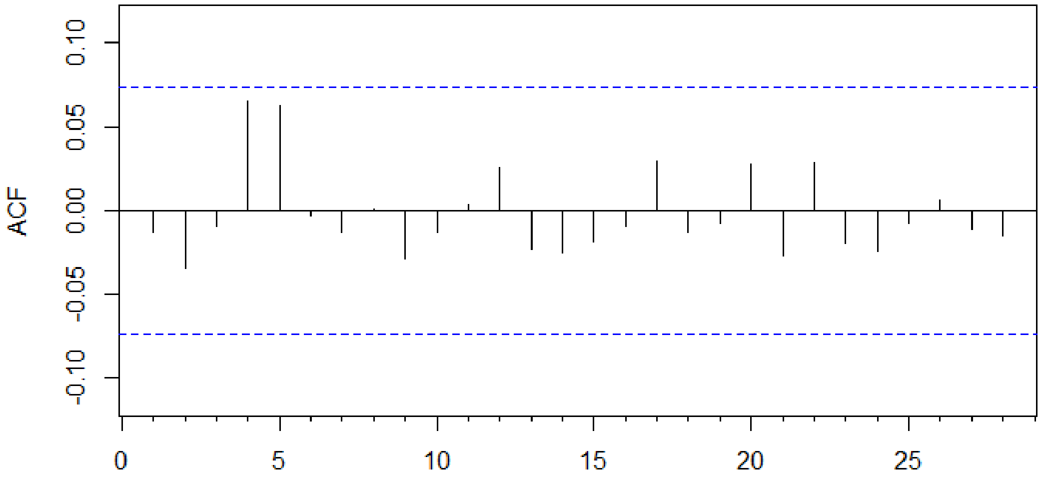


Figure 6.23: ACF – USD gjrGARCH(1,1) squared standardized residuals

Source: author's computation

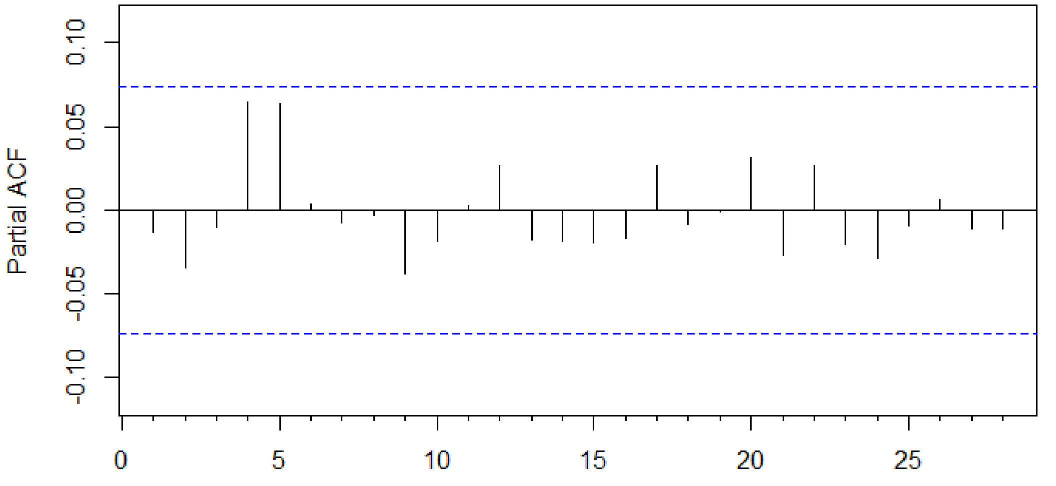


Figure 6.24: PACF – USD gjrGARCH(1,1) squared standardized residuals

Source: author's computation

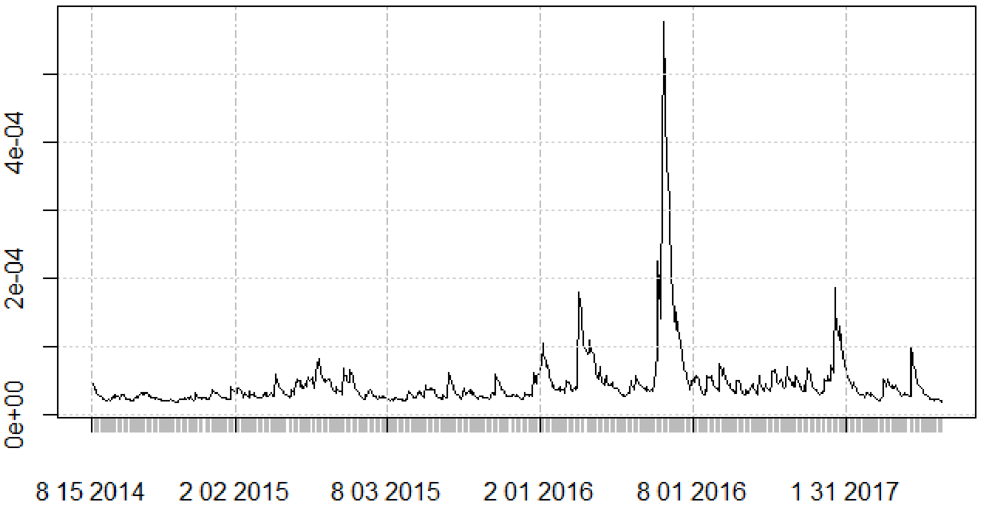


Figure 6.25: USD conditional variance

Source: author's computation

The chosen volatility model for Bitcoin is GARCH-M(1,1) with ARMA(2,2) including time trend mean specification. The time trend parameter is positive which is not surprising, given that the price of bitcoins was steadily growing since May 2015. The value of ARCH in mean parameter was found to be negative which is in accordance to the basic theory of money. Lower volatility makes the asset to be more attractive as a medium of exchange. According to the result of the weighted Ljung-Box test on standardized residuals with 19 lags the null hypothesis of no remaining autocorrelation was not rejected at all levels of confidence. According to the results of the ARCH-LM test the presence of remaining ARCH process was not confirmed, which is supported by autocorrelograms of squared standardized residuals depicted below, where only lag 9 shows slight significance. The persistence of the conditional volatility is 0.9373677.

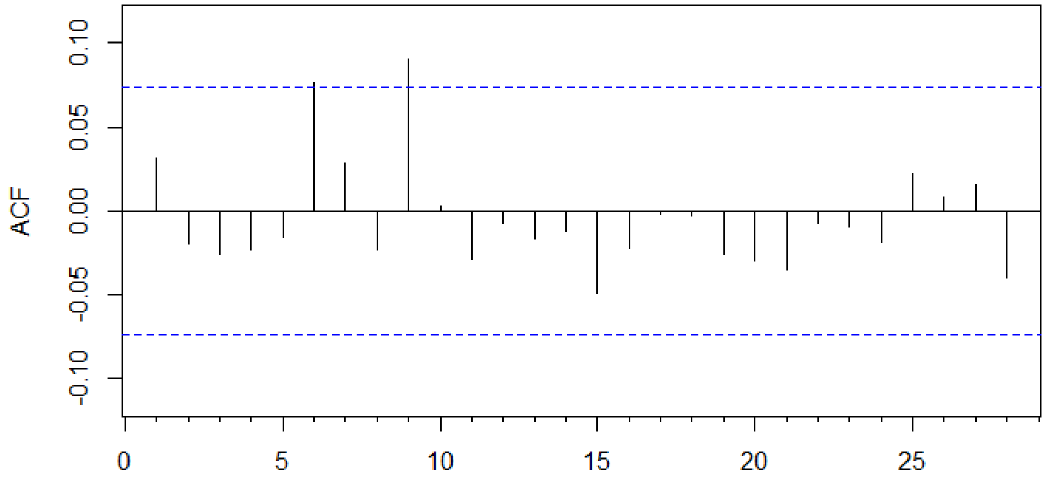


Figure 6.26: ACF – BTC ARMA(2,2)-GARCH(1,1) squared standardized residuals

Source: author's computation

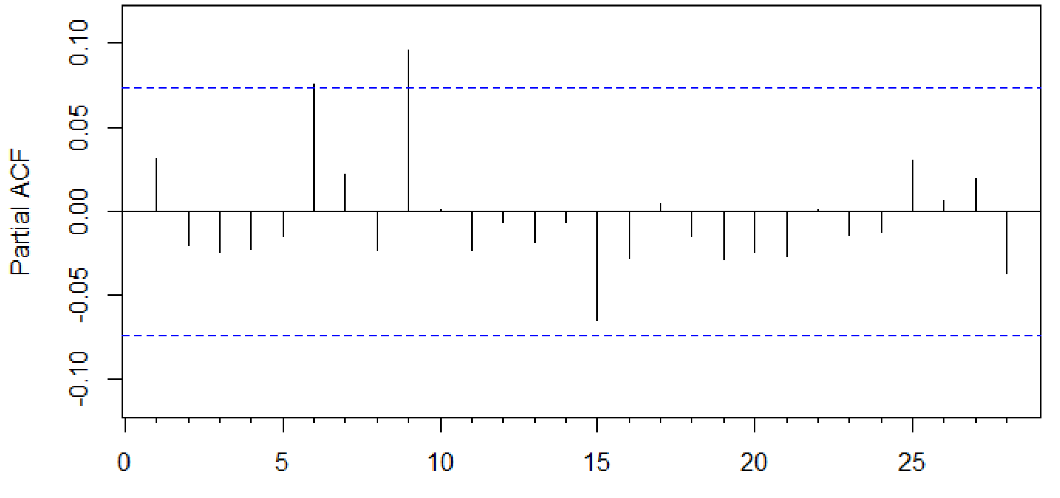


Figure 6.27: PACF – BTC ARMA(2,2)-GARCH(1,1) squared standardized residuals

Source: author's computation

The figure of variance depicted below shows that the specification captured the increased volatility of the end of 2013 and the beginning of 2014.

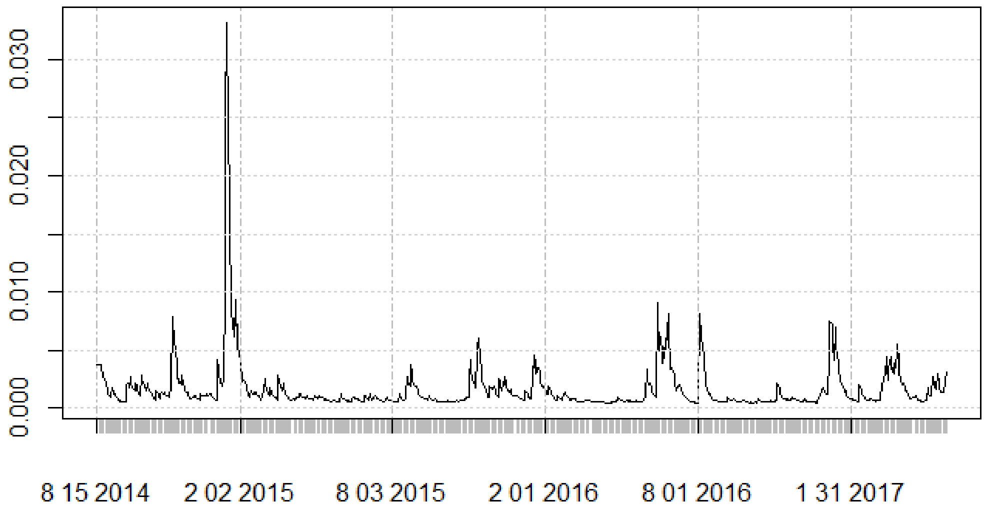


Figure 6.28: BTC conditional variance

Source: author's computation

For DASH returns, the best volatility model is cGARCH(0,1). The weighted Ljung-Box test on standardized residuals did not reject the null hypothesis of no autocorrealation among residuals at any level of confidence. The same applies for ARCH-LM test regarding the remaining ARCH process. This was also confirmed by ACF and PACF autocorrelograms. The permanent persistence of volatility is 0.9991110 and the transitory persistence is 0.8692621.

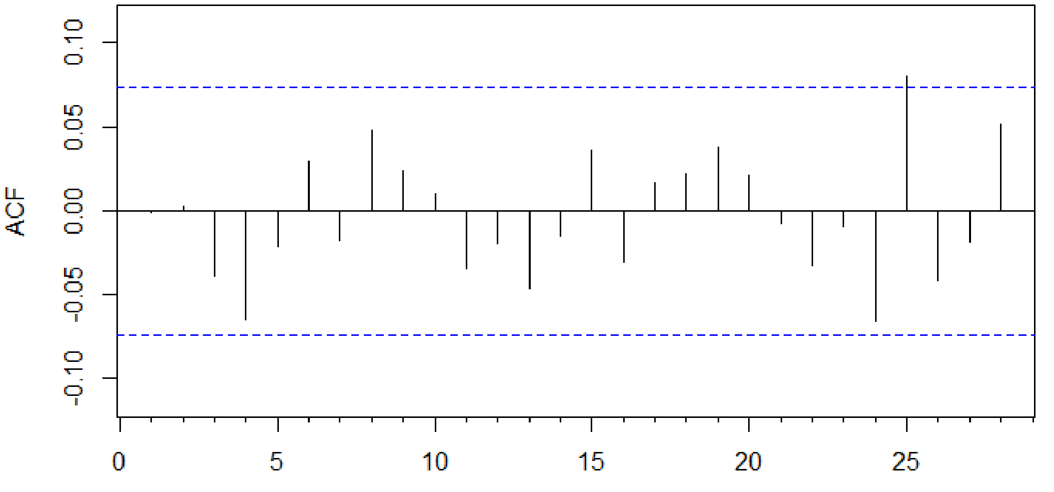


Figure 6.29: PACF – DASH cGARCH(0,1) squared standardized residuals

Source: author's computation

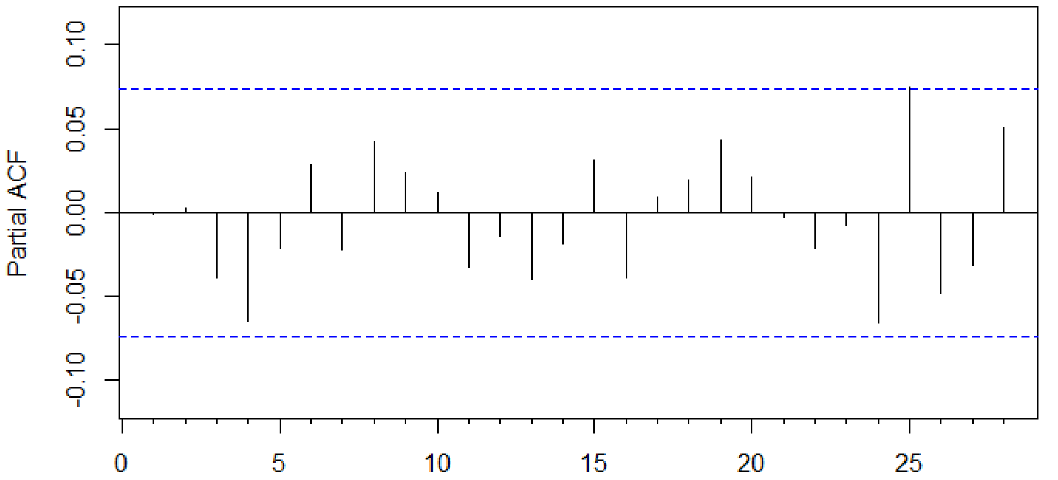


Figure 6.30: PACF – DASH cGARCH(0,1) squared standardized residuals

Source: author's computation

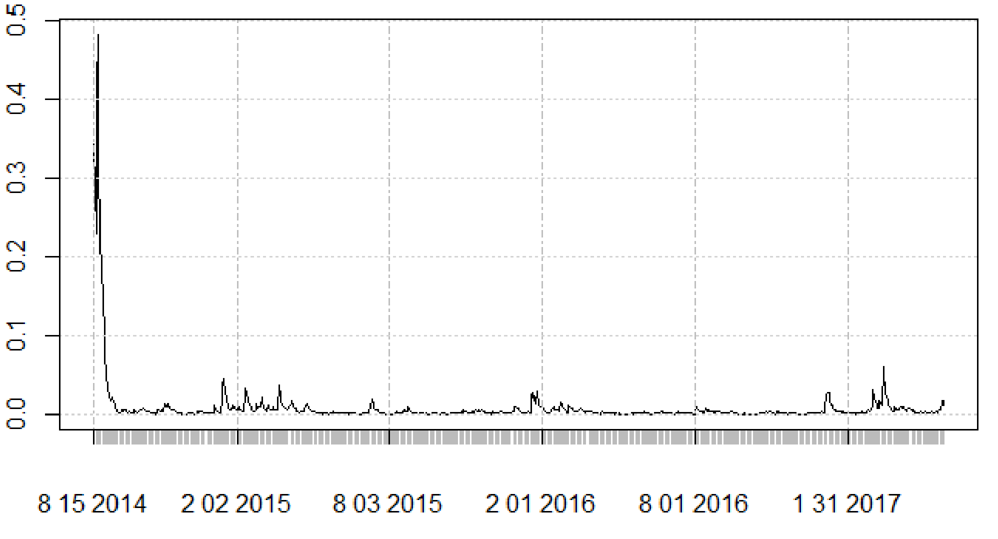


Figure 6.31: DASH conditional variance

Source: author's computation

The figure of the conditional variance shows high volatility in the beginning of the series. This volatility is so high compared to the rest of the sample it is probable that these remote values in return series might have affected the whole estimation, making the model weak in terms of accuracy of predictions during the rest of the sample. This is also supported by the value of unconditional variance which is 0.337, while the unconditional variances of other series are of much lower scale. The estimation process was therefore performed also for the sample beginning by the 30st observation. The best specification for this sample was found to be IGARCH(1,1) however, because for the purposes of this work the unconditional variance which does not exist for integrated

GARCH is needed, this specification is omitted. The second best specification was simple GARCH(1,1). All parameters were found to be significant at all levels of confidence and results of both weighted Ljung-Box test and ARCH-LM test are in accordance with hypotheses of no autocorrelation and no ARCH process in standardized residuals. The persistence is circa 0.98 and the unconditional variance has much more reasonable value of 0.019.

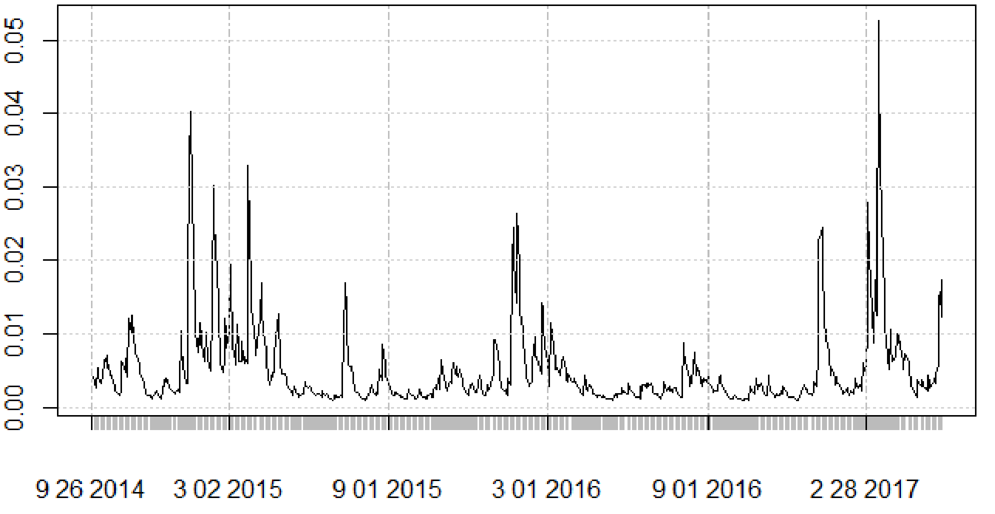


Figure 6.32: DASH conditional variance – restricted sample

Source: author's computation

For Litecoin's returns the best specification was found to be cGARCH(0,1). The result of weighted Ljung-Box tests suggests no remaining autocorrelation among standardized. The null hypothesis of ARCH-LM test was not rejected at any level of condfidence, suggesting the ARCH process was successfully treated. The permanent persistence of volatility is 0.957464 and the transitory persistence is 0.8828954.

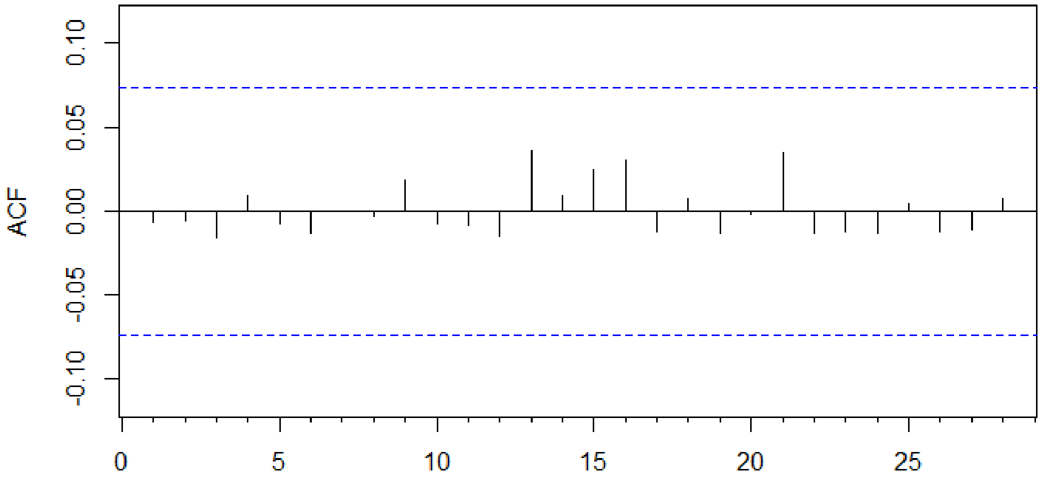


Figure 6.33: ACF – LTC cGARCH(0,1) squared standardized residuals

Source: author's computation

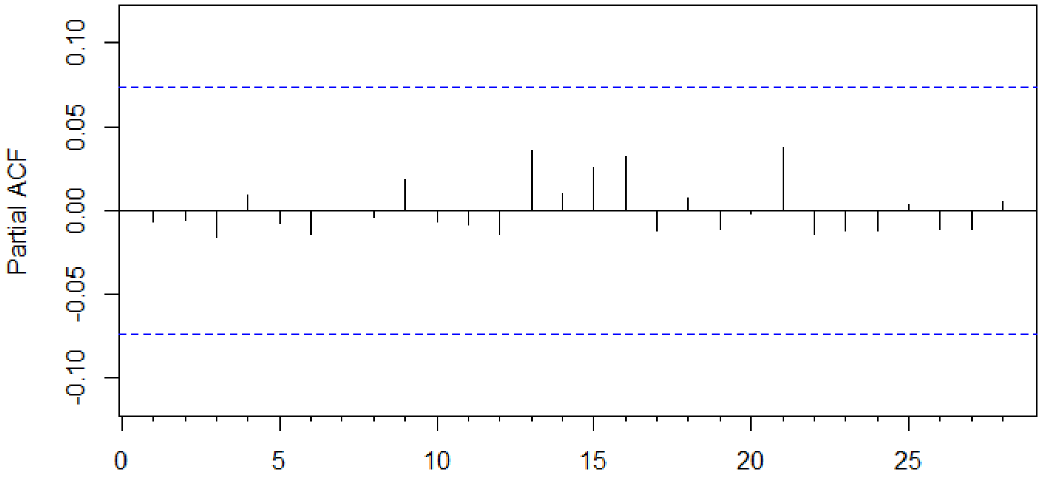


Figure 6.34: PACF – LTC cGARCH(0,1) squared standardized residuals

Source: author's computation

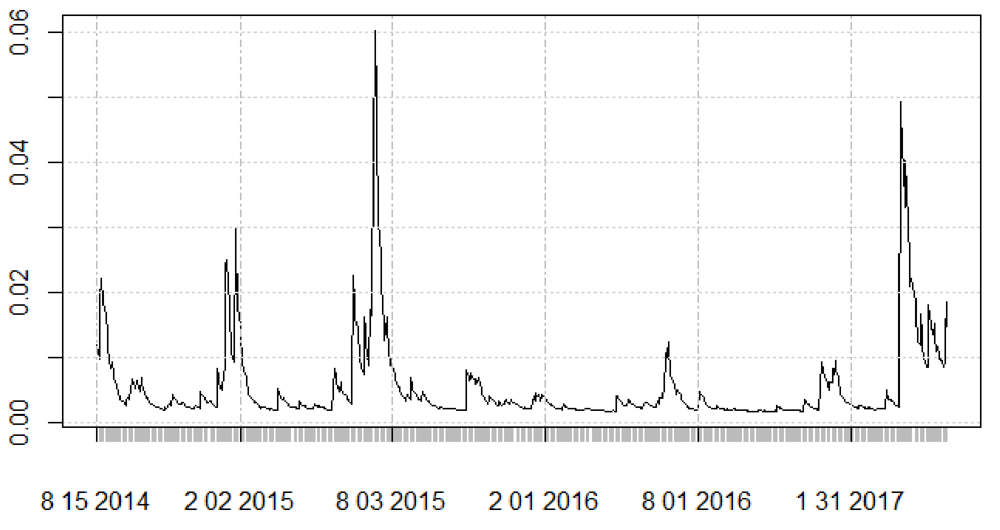


Figure 6.35: LTC conditional variance

Source: author's computation

The estimation of the correct specification for Monero's returns had to be done in different way than in the case of other currencies. While the highest order of GARCH model considered for other currencies was 2 both for alpha and beta, in case of Monero none of these models was able to remove ARCH process from the series. The ACF and PACF correlograms of squared returns suggested there was a strong autocorrelation at lag 5. So the models for Monero were estimated using various GARCH specifications with 5 being the order of alpha and letting the order of beta vary from 0 to 2. The final model had to be cleansed from insignificant parameters by fixing their value to be 0. The final model is simple GARCH(5,0) – ARMA(1,1). All alphas except the first and fifth were set to be equal to 0. The trend parameter was found to be insignificant at all levels of confidence. The results of the weighted Ljung-Box test on standardized residuals suggests the autocorrelation was not successfully removed from the series. However, the ARCH-LM test suggest that there is no remaining ARCH process. The persistence of the volatility is 0.6459124.

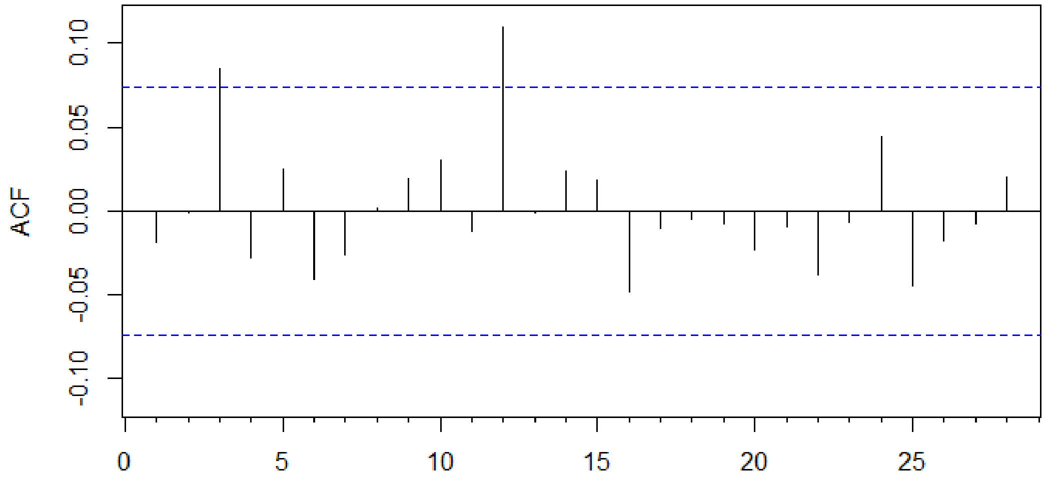


Figure 6.36: ACF – XMR ARMA(1,1)-GARCH(5,0) squared standardized residuals

Source: author's computation

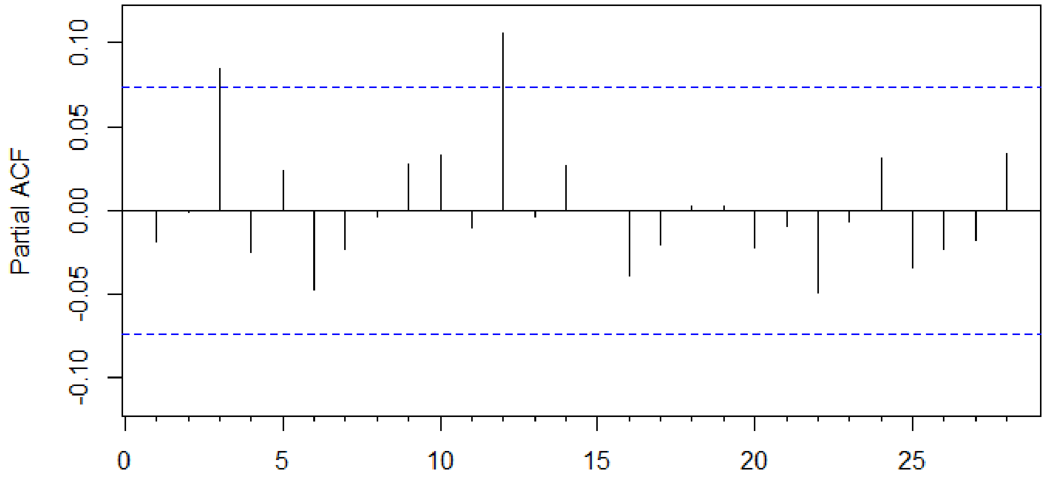


Figure 6.37: PACF – XMR ARMA(1,1)-GARCH(5,0) squared standardized residuals

Source: author's computation

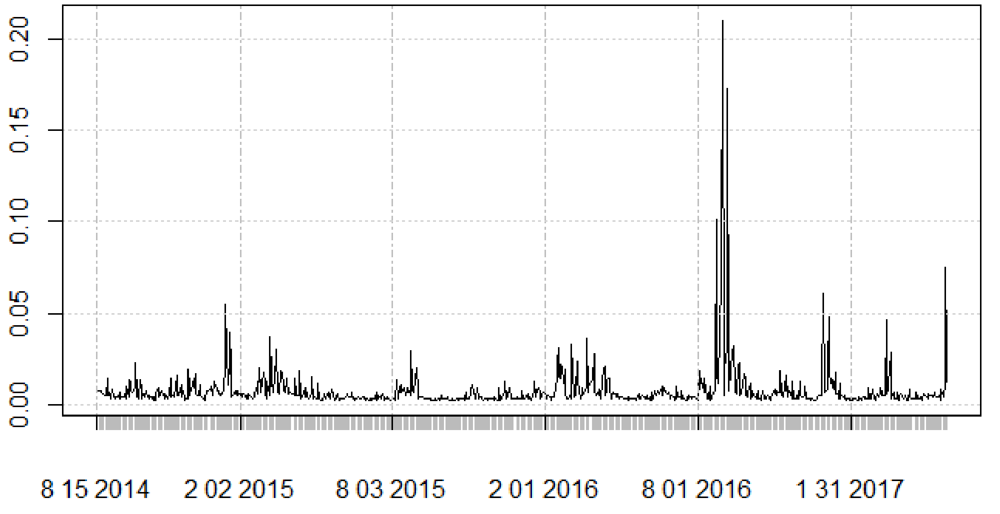


Figure 6.38: XMR conditional variance

Source: author's computation

Finally regarding the Ripple series, the chosen model is cGARCH(1,1) without ARMA process and with trend as exogenous variable. The parameter of time trend was found to be negative and significant at all levels of confidence. The result of the weighted Ljung-Box test suggests there is no remaining autocorrelation and the same applies for the result of ARCH-LM test when considering remaining ARCH process.

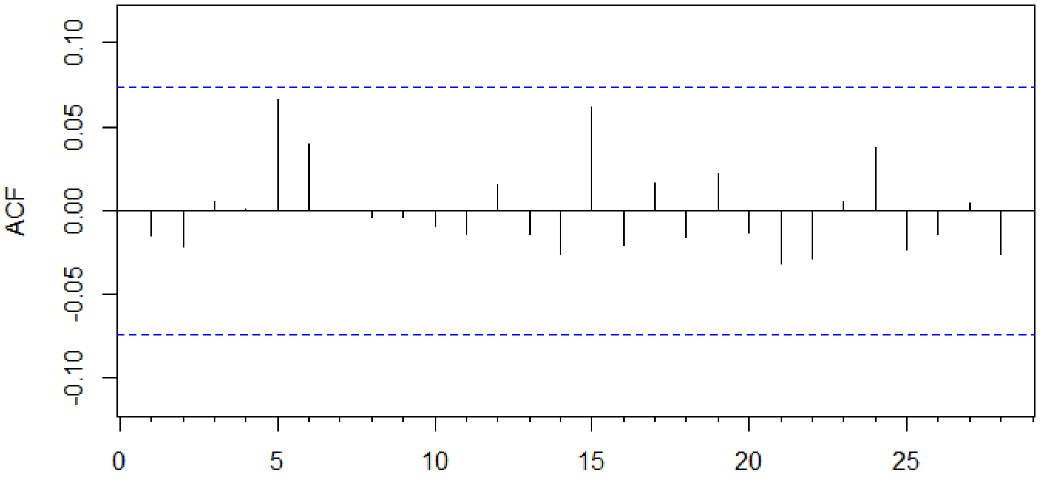


Figure 6.39: ACF – XRP cGARCH(1,1) squared standardized residuals

Source: author's computation

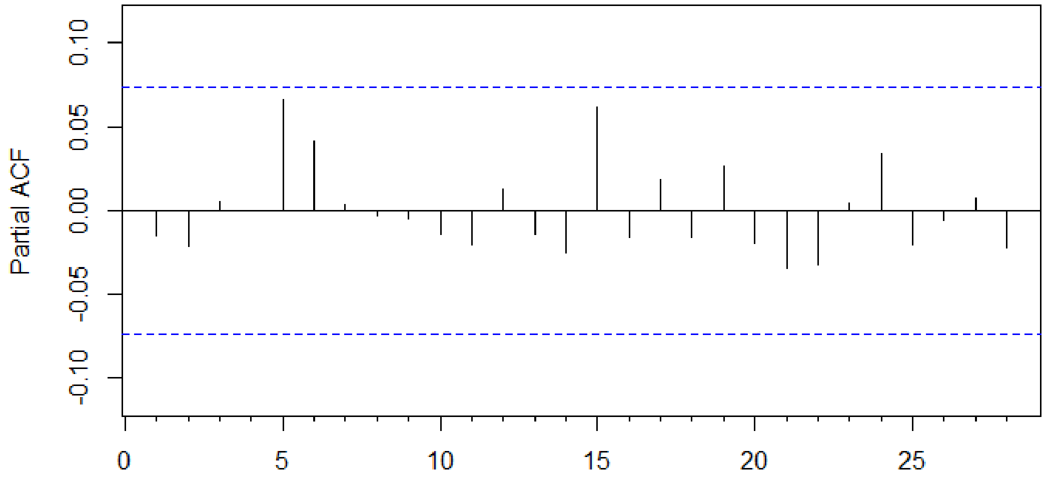


Figure 6.40: PACF – XRP cGARCH(1,1) squared standardized residuals

Source: author's computation

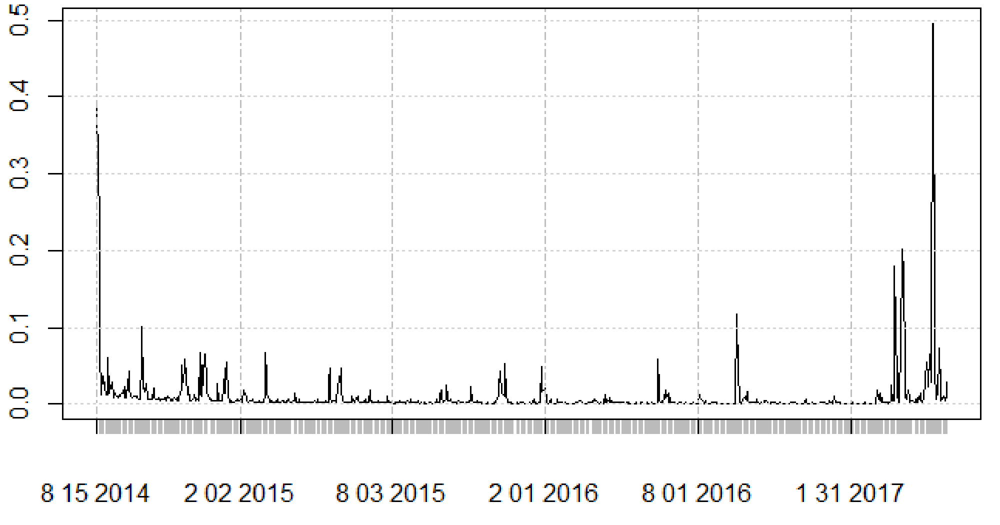


Figure 6.41: XRP conditional variance

Source: author's computation

As in the case of the first specification of Dash the unconditional variance of XRP series is strangely high – 0.39. Therefore the estimation was performed again on the reduced sample excluding first 14 and last 28 observations. The model chosen in this sample is apARCH(1,1). The specification fulfills the conditions of significant parameters (except of the trend parameter) and no remaining autocorrelation and ARCH process. The unconditional variance is 0.007 which resembles other cryptocurrencies much more.

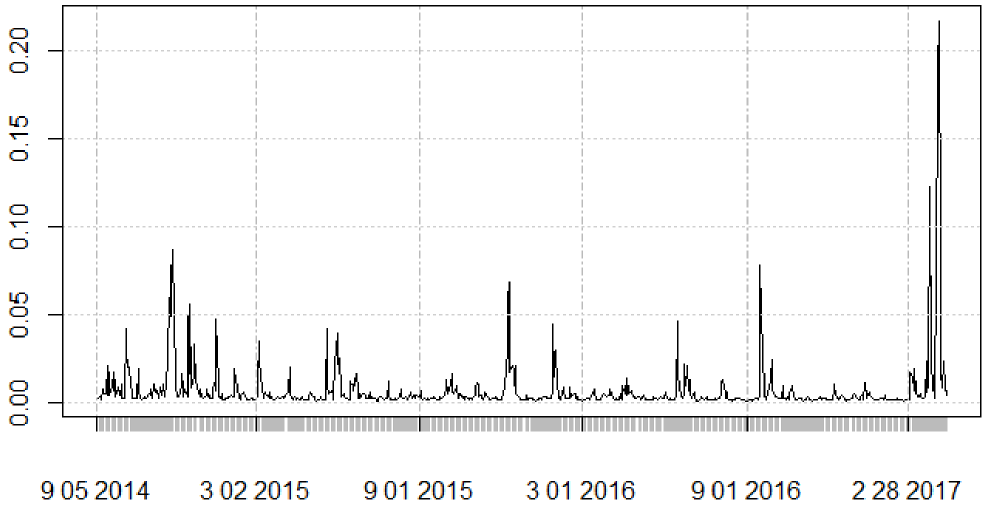


Figure 6.42: XRP conditional variance – restricted sample

Source: author's computation

What is important to stress out is the scale of parameter ω in the volatility equations of these currencies. This parameter seems to be much lower for fiat currencies. For yuan the value is 0.000004, for euro 0.000002 and for US dollar it is 0.000003 while for bitcoin it is 0.000127, for DASH and Litecoin 0.00030, for Monero 0.003215 and for Ripple 0.000329. The omega parameter is a constant in volatility equation. This means that while the rest of the volatility is considered to be created by incoming news and developments the value of the constant can be understood as a level of volatility given by the liquidity of the market and overall maturity. In this sense it is clear that omega is higher for quite recently developed cryptocurrencies than for long used fiat currencies. The same logic applies when considering the cryptocurrencies only. Bitcoin is the oldest of them and the most capitalized which reflects in the omega parameter which is lower by half than the omegas of the rest of cryptocurrencies. The same logic applies in the case of unconditional variance. It is in much lower scale for fiat currencies than for cryptocurrencies and lower for Bitcoin than for the rest of cryptocurrencies. In case of Dash, the unconditional variance is even higher by scale than the one of Bitcoin.

Another result which is worth noticing is that except of Chinese yuan, US dollar and Ripple no other currency's volatility reacts to shocks asymmetrically. Only for these three the chosen model contains the gamma parameter, denoting different reaction to negative shocks. While for both fiat currencies the parameter is positive, meaning higher volatility following a negative shock, the gamma parameter of the Ripple specification is negative, suggesting the opposite relationship. This might be caused by the safe haven property (Bourri, Azzi and Haubo Dyhrberg, 2016).

Regarding other cryptocurrencies the results are in contradiction with previous studies which found either positive or negative gamma for bitcoin's exchange rate returns. The positive gamma was attributed to immaturity of the market (Bouoiyour & Selmi, 2016), while negative gamma was reasoned by the safe haven property of Bitcoin network (Bourri, Azzi and Haubo Dyhrberg, 2016).

Regarding the maturity of the currencies the results are ambiguous. While the omega parameters and unconditional variance are in accordance with expectations and suggest lower maturity of younger cryptocurrencies, the methodology of using the gamma parameter as a sign of immaturity seems to be questioned by the results which imply that the presence of a leverage effect is more typical for mature market of fiat currencies.

6.2. GARCH-BEKK results

This part of the thesis analyzed the correlation between the currencies. The correlation coefficient is estimated using the results of multivariate volatility models, specifically the BEKK model. The BEKK model estimates the conditional covariance matrix which is then used to compute the correlation coefficient. The methodology is as follows. At first the combinations of Bitcoin series with individual fiat currencies series are used as input for BEKK. The fiat currency whose correlation with Bitcoin, either positive or negative, is strongest is then taken as the most important in analyzing the results of the trivariate BEKK models comprised of Bitcoin series with combinations of one individual fiat currency and one individual alternative cryptocurrency. The estimated correlation coefficients are depicted at the figures below.

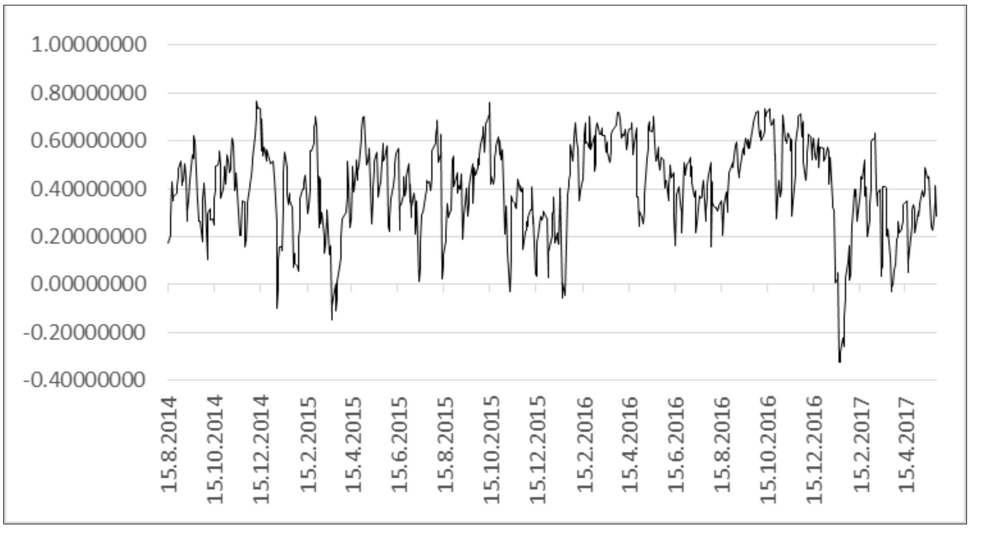


Figure 6.43: CNY-BTC correlation coefficient

Source: author’s computation

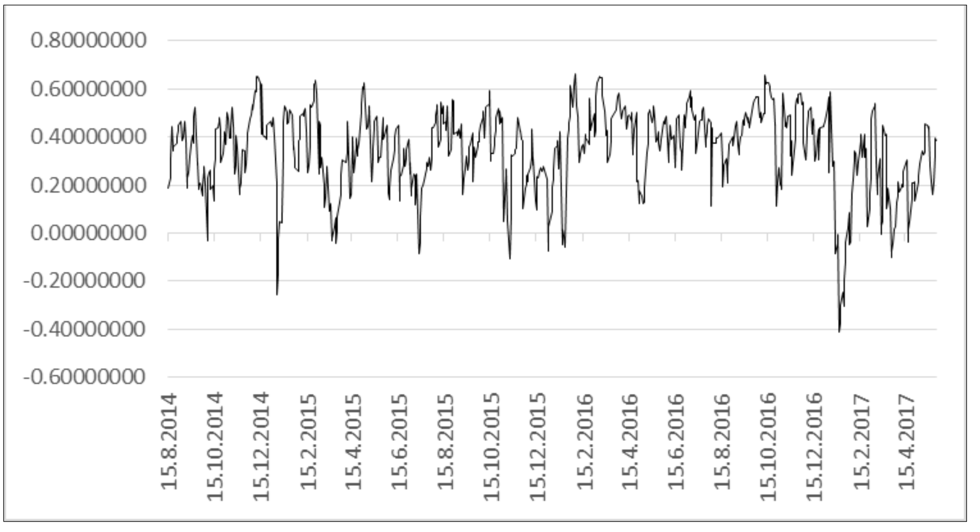


Figure 6.44: USD-BTC correlation coefficient

Source: author’s computation

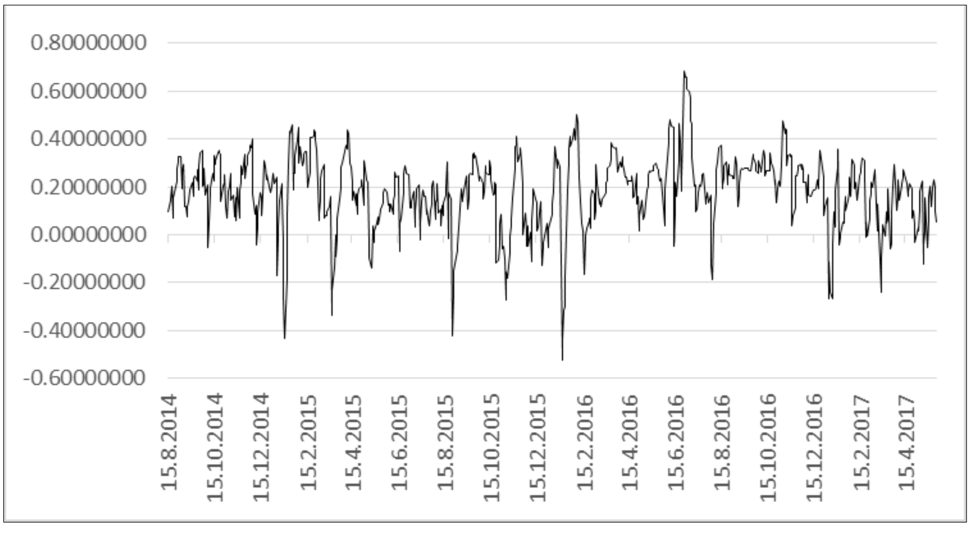


Figure 6.45: EUR-BTC correlation coefficient

Source: author’s computation

As the figures suggest the lowest correlation is between Bitcoin and euro. The fiat currency with the strongest correlation with Bitcoin is Chinese yuan renminbi with average correlation coefficient of 0.4, being slightly higher than the 0.35 between Bitcoin and US dollar. The models including yuan are therefore considered as the ones with the highest informational value in the following analysis. The figures plotted below therefore comes from the models including yuan and when the results are reported in the table, the results of yuan models are in bold.

6.2.1 Dash

The estimated covariance and correlation coefficients of the time series are depicted at the figures below.

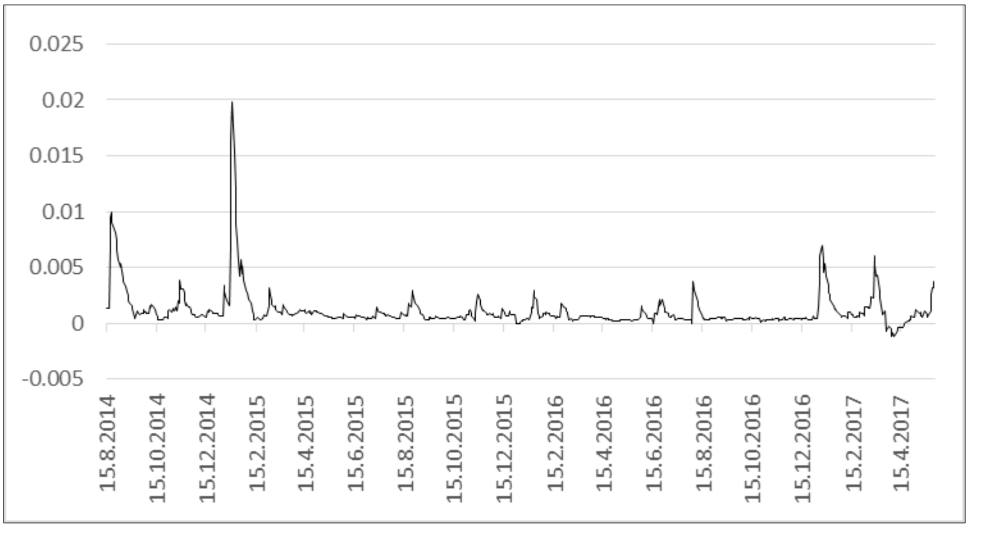


Figure 6.46: BTC-DASH covariance

Source: author's computation

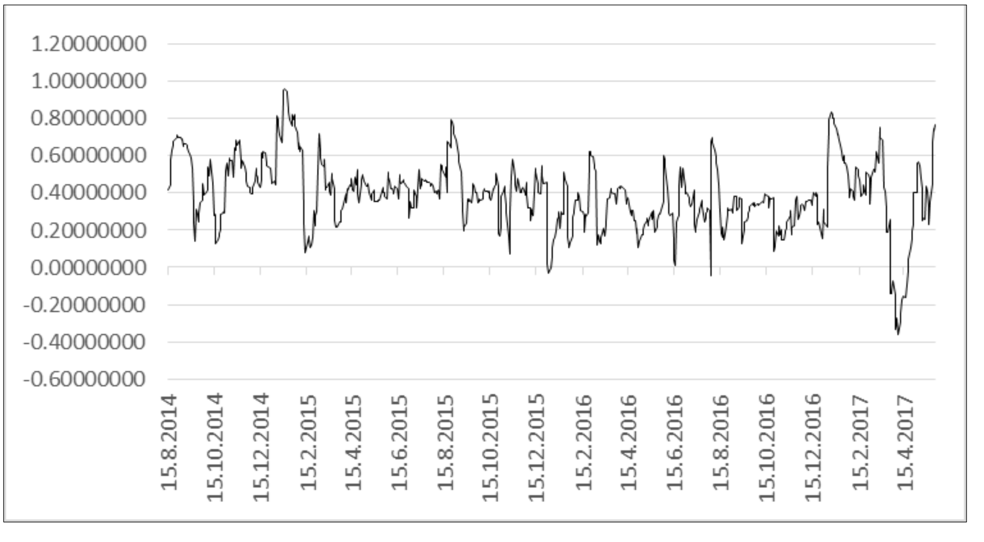


Figure 6.47: BTC-DASH correlation coefficient

Source: author's computation

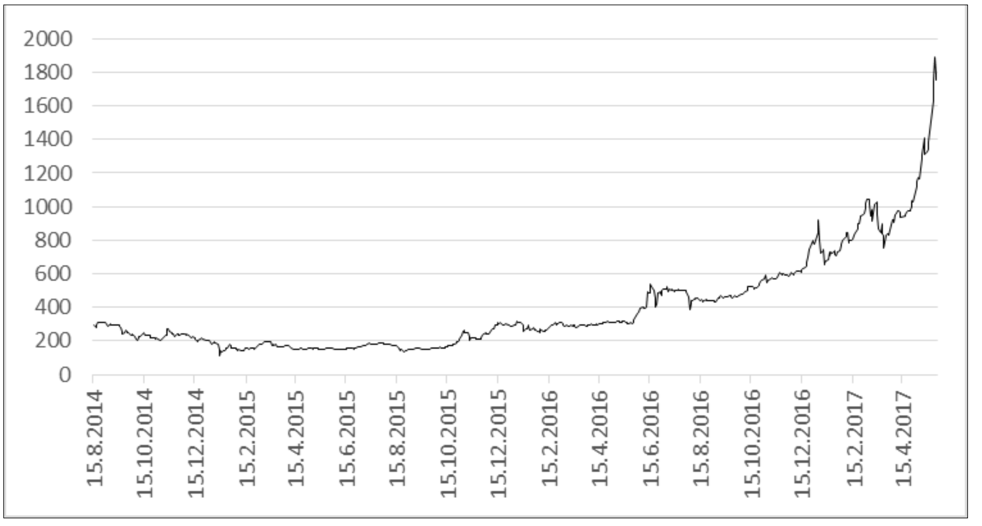


Figure 6.48: BTC/GBP exchange rate

Source: author's computation

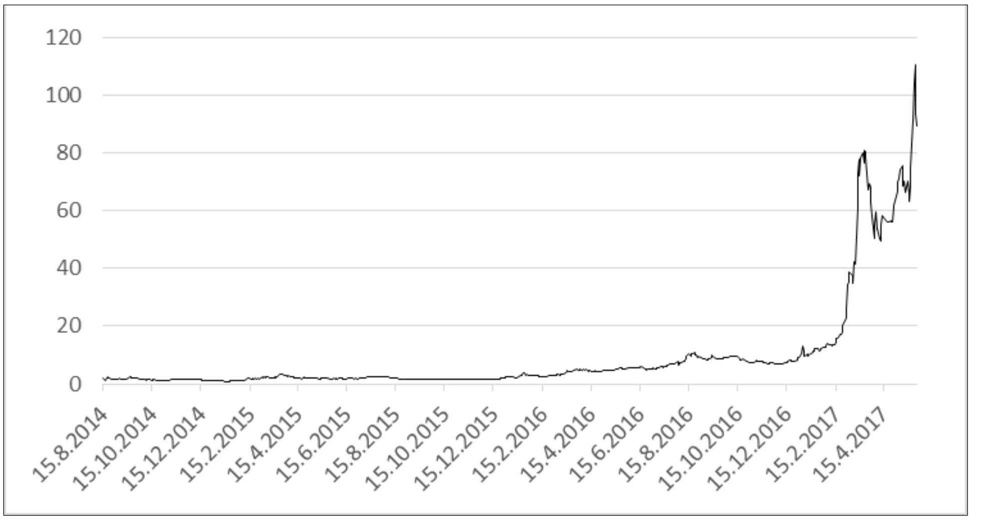


Figure 6.49: DASH/GBP exchange rate

Source: author's computation

It is worth notice that the covariance between bitcoin and dash has almost never been negative. The only exception is in the end of March and first half of April 2017 which is the start of the price surge which reached almost 3000 USD for bitcoin. The same pattern is visible at the figure depicting the correlation coefficient between BTC and DASH. The correlation is positive during almost all analyzed period with negative trend until October 2016. In the spring 2017 there is strong drop into negative numbers followed by its return to normal values. This behavior is in contradiction with the expectations. The correlation coefficient is relatively high and positive during calm phases and goes negative during turmoil phase.

The charts of correlation coefficient and prices restricted to year 2017 allows better insight to the development of the coefficient. The price of both currencies went through grow phase prior the correlation drop. For Dash the price spike was much higher and that is also the reason why the recovery was longer than in case of Bitcoin. So when the price of bitcoins started to grow again in a speculative bubble, the price of dash remained in after-bubble crash uncertainty.

Figure 6.50: BTC-DASH correlation coefficient (2017)

Source: author's computation

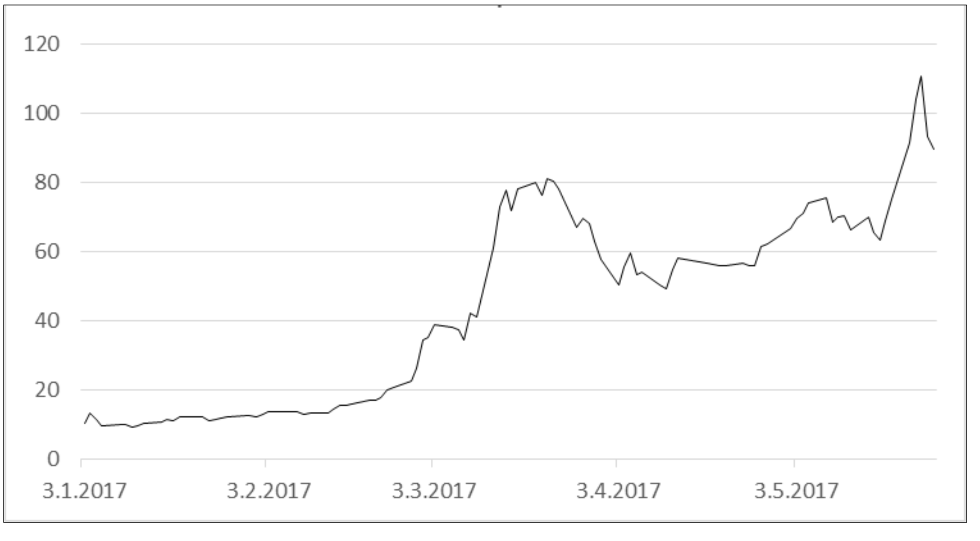


Figure 6.51: DASH/GBP exchange rate (2017)

Source: author's computation

Figure 6.52: BTC/GBP exchange rate (2017)

Source: author's computation

Based on the bitcoin price development three subsamples containing price spikes were chosen. The first one is from 26.5.2016 to 2.8.2016, the second one is from 22.12.2016 to 12.1.2017 and the last one is since 24.3.2017 to 26.5.2017. The table below show the average values of the correlation coefficient for these periods and the periods between them. The periods of price spikes are denoted with asterisk.

Table 4: DASH – BTC subsamples

		I	II*	III	IV*	V	VI*	Whole sample
CNY	**Average**	**0.4208**	**0.3238**	**0.3177**	**0.5183**	**0.5218**	**0.1734**	**0.3929**
	Min	**-0.0317**	**-0.0437**	**0.0860**	**0.1539**	**0.3170**	**-0.3606**	**-0.3606**
	Max	**0.9595**	**0.6050**	**0.7018**	**0.8362**	**0.7753**	**0.7652**	**0.9595**
	St.dev	**0.1701**	**0.1305**	**0.1172**	**0.2856**	**0.1244**	**0.3245**	**0.1912**
USD	**Average**	0.3978	0.3810	0.2420	0.5512	0.5264	0.1539	0.3710
	Min	-0.1658	-0.1368	-0.1296	0.0807	0.2367	-0.5129	-0.5129
	Max	0.9800	0.7833	0.8273	0.8976	0.8306	0.8419	0.9800
	St.dev	0.2237	0.2073	0.1688	0.3360	0.1666	0.4142	0.2475
EUR	**Average**	0.4186	0.4292	0.2897	0.5792	0.5352	0.2268	0.4001
	Min	0.0191	0.0549	0.0409	0.1980	0.3049	-0.3263	-0.3263
	Max	0.9704	0.7547	0.8120	0.8788	0.8123	0.8046	0.9704
	St.dev	0.1838	0.1717	0.1415	0.2792	0.1395	0.3346	0.2040

Source: author's computation

The average correlation coefficient in the first price spike period does not seem to be significantlyy different from the average of whole period. This is supported by the fact that in case of model including chinese yuan the avereage coefficient is lower than the whole sample average, while in case of US dollar and euro models it is higher.

In case of the second chosen period the average coefficient is higher than whole sample average in all cases, but the difference is low and the average is very similar to the on of following period. The only significant difference is in the last period as was already discussed above.

6.2.2 Litecoin

The following figures depict covariance, correlation coefficients between the two cryptocurrencies and their prices.

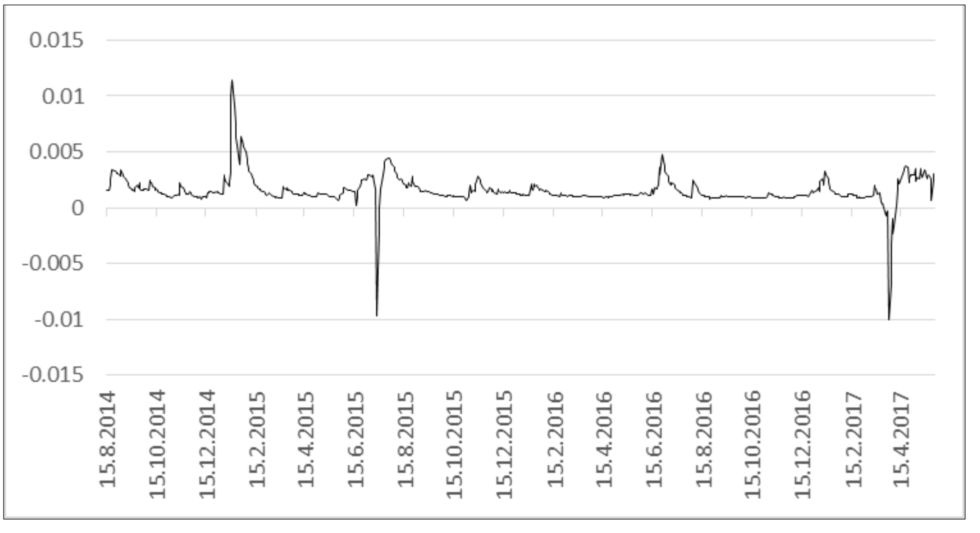


Figure 6.53: BTC-LTC covariance

Source: author's computation

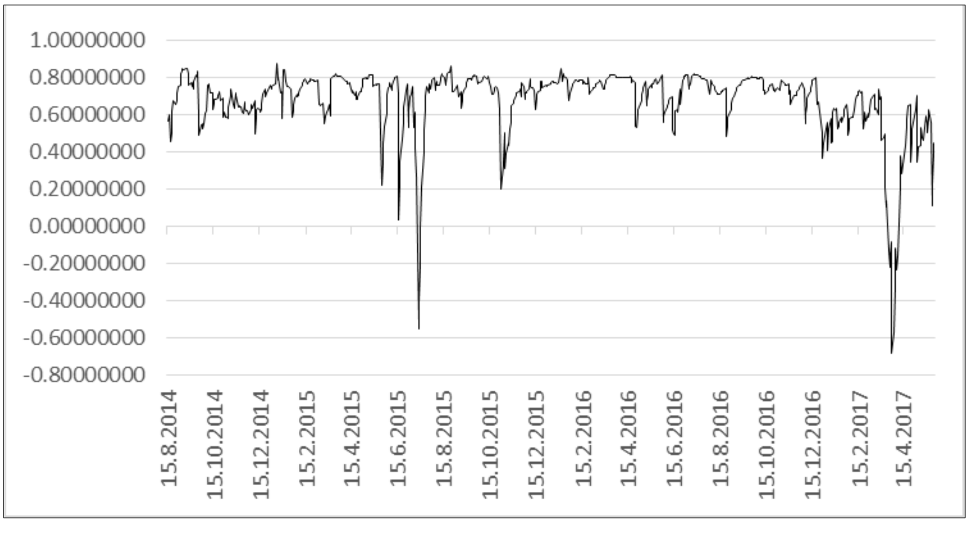


Figure 6.54: BTC-LTC correlation coefficient

Source: author's computation

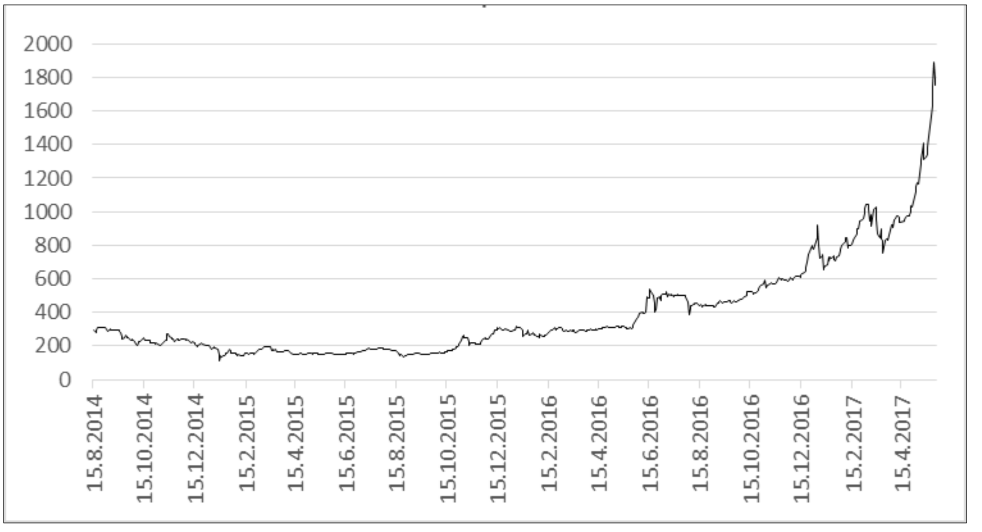


Figure 6.55: BTC/GBP exchange rate

Source: author's computation

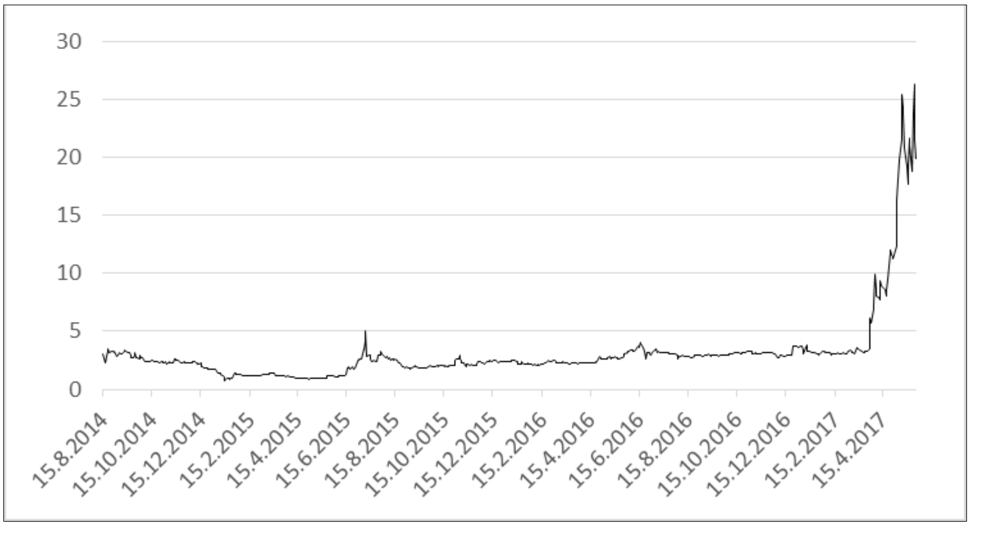


Figure 6.56: LTC/GBP exchange rate

Source: author's computation

The figures of correlation coefficient show similar pattern as in case of Dash. The correlation is positive and relatively strong during most of the analyzed period dropping to negative and moderate in two occasions only. The second period is depicted at following figures. In the period prices of both currencies begun a climb towards price bubble. While the price of bitcoin began to increase by 10 % on 27.3.2017 the price of Litecoin decreased by 14 % and continued falling until 4.4.2017. This few cases of high scale returns on both sides but with mismatching signs caused the deep drop in correlation.

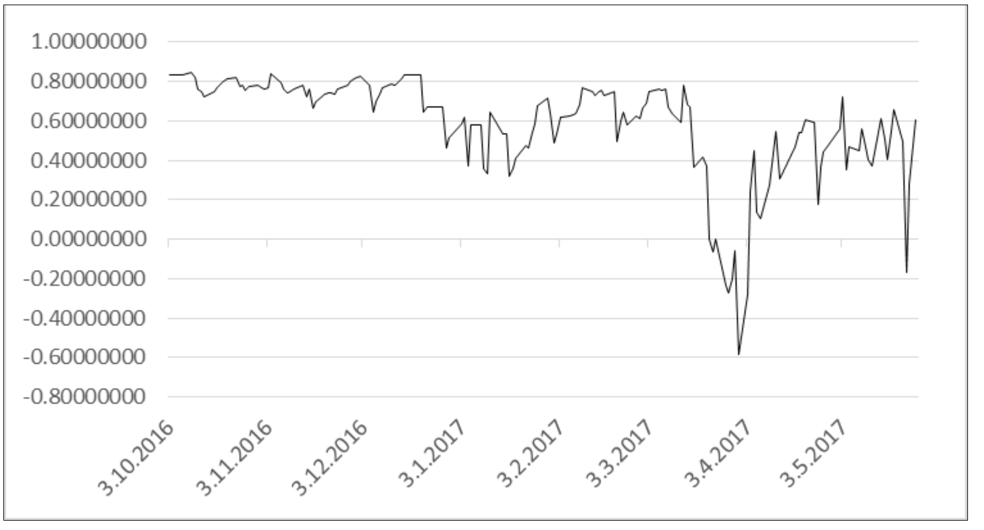


Figure 6.57: BTC-LTC correlation coefficient (October 2016 – May 2017)

Source: author's computation

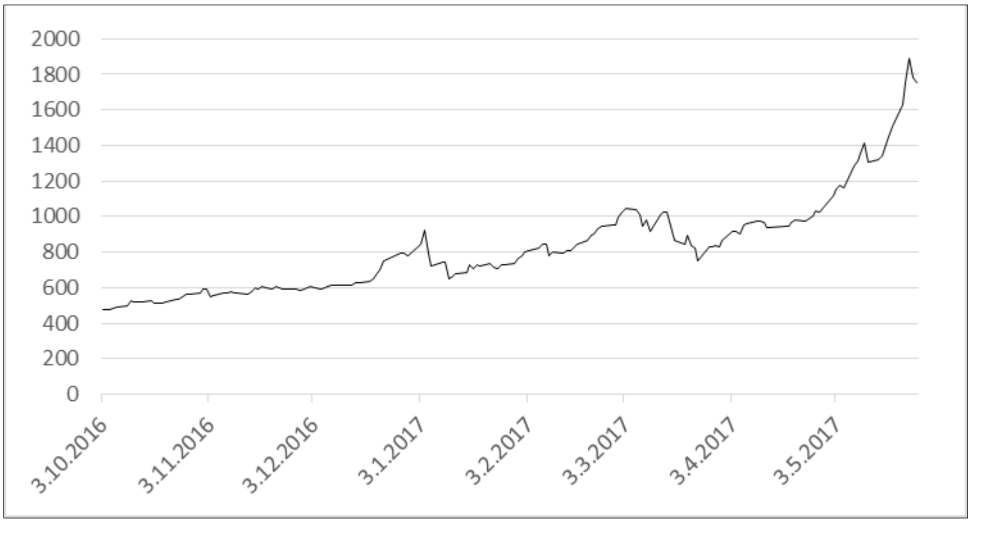


Figure 6.58: BTC/GBP exchange rate (October 2016 – May 2017)

Source: author's computation

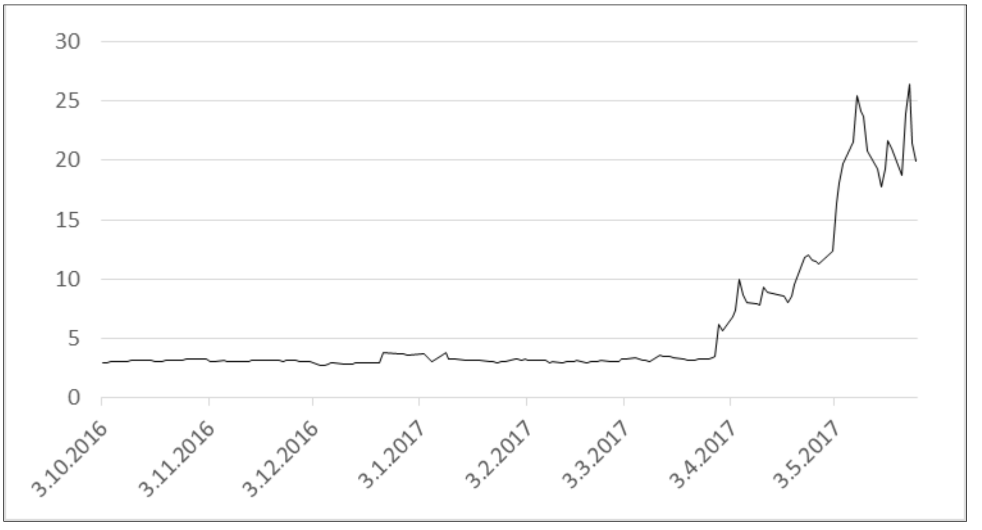


Figure 6.59: LTC/GBP exchange rate (October 2016 – May 2017)

Source: author's computation

The previous period of negative correlation is in more detail depicted at the figures below. Here it can be clearly seen that the negative correlation was caused by mismatch in returns is the period of Litecoin's price spike. This is in accordance with expectations that development in price of alternative cryptocurrencies does not influence Bitcoin.

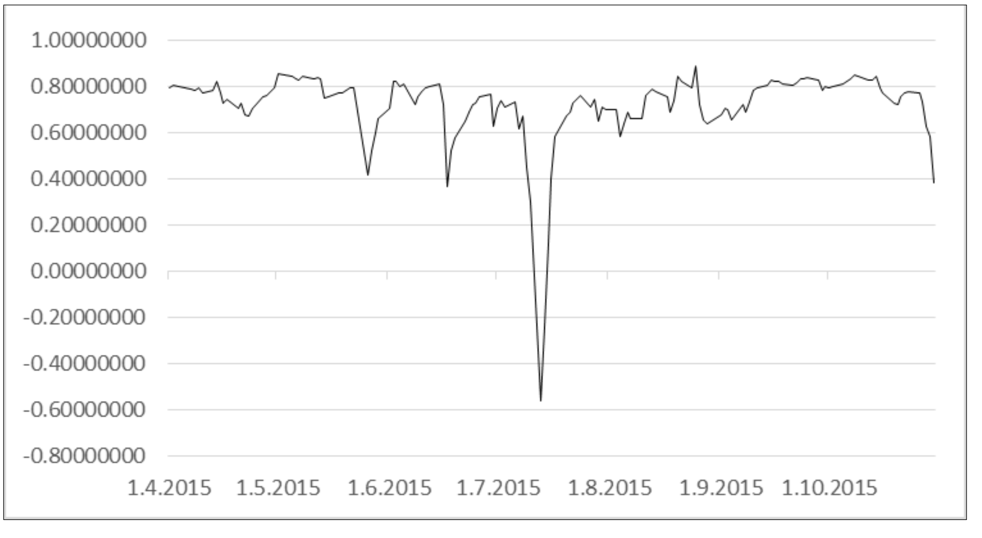


Figure 6.60: BTC-LTC correlation coefficient (April 2015 – October 2015)

Source: author's computation

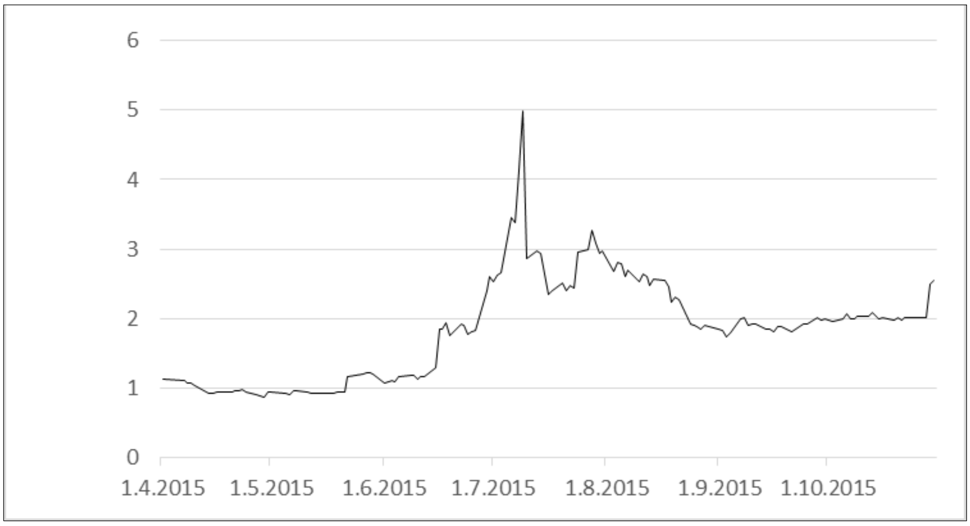


Figure 6.61: LTC/GBP exchange rate (April 2015 – October 2015)

Source: author's computation

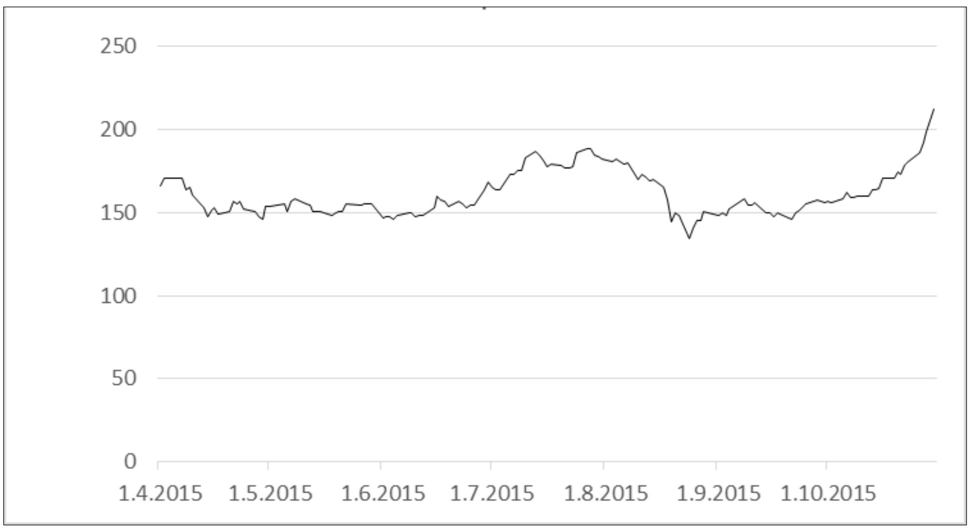


Figure 6.62: BTC/GBP exchange rate (April 2015 – October 2015)

Source: author's computation

The correlation is analyzed in periods of price increases in Bitcoin price. The periods are the same as in case of Dash enriched by the only case of Litecoin's price surge when there was no surge in Bitcoin's price is the case analyzed above – 1.6.2015 to 1.9.2015. Thus, the sample is divided into 8 subsamples. The first period, tagged with double asterisk in the table is the price surge of Dash in 2015. The coefficient is lower than whole sample average in all three models. The average coefficient in the second chosen period (in the table tagged as period IV) is higher than the whole sample average, however the difference is very small and the value is almost the same as averages of previous and following periods. The average coefficient of period VI is lower in comparison with both whole sample average and with averages of period number V and period number VII. The same applies for coefficient of the last period, which is the period of two huge correlation drops, once into the whole sample minimum of -0.68.

Table 5: LTC – BTC subsamples

		I	II**	III	IV*	Whole sample
CNY	**Average**	**0.7036**	**0.6173**	**0.7341**	**0.7264**	**0.6732**
	Min	**0.2212**	**-0.5548**	**0.1986**	**0.4883**	**-0.6802**
	Max	**0.8766**	**0.8623**	**0.8436**	**0.8187**	**0.8766**
	St.dev	**0.0978**	**0.2899**	**0.0964**	**0.0948**	**0.1871**
USD	**Average**	0.7016	0.6583	0.7553	0.7106	0.686919
	Min	0.2452	-0.5578	0.3222	0.2241	-0.58433
	Max	0.9348	0.8895	0.8926	0.8596	0.934776
	St.dev	0.1194	0.2296	0.0946	0.1367	0.181222
EUR	**Average**	0.6984	0.6162	0.7323	0.7078	0.670591
	Min	0.3974	-0.5084	0.3554	0.4266	-0.57599
	Max	0.9074	0.8667	0.8429	0.8221	0.907435
	St.dev	0.0851	0.2520	0.0824	0.0971	0.1717

		V	VI*	VII	VIII*	Whole sample
CNY	**Average**	**0.7376**	**0.5180**	**0.6082**	**0.2777**	**0.6732**
	Min	**0.4789**	**0.3677**	**0.2035**	**-0.6802**	**-0.6802**
	Max	**0.8025**	**0.6693**	**0.7375**	**0.7028**	**0.8766**
	St.dev	**0.0577**	**0.0946**	**0.0931**	**0.3483**	**0.1871**
USD	**Average**	0.7647	0.5404	0.6007	0.312989	0.686919
	Min	0.4810	0.3319	-0.0026	-0.58433	-0.58433
	Max	0.8431	0.6723	0.7809	0.720502	0.934776
	St.dev	0.0797	0.1223	0.1514	0.30496	0.181222
EUR	**Average**	0.7381	0.5469	0.6082	0.279655	0.670591
	Min	0.5284	0.3994	0.1931	-0.57599	-0.57599
	Max	0.7998	0.6643	0.7594	0.641284	0.907435
	St.dev	0.0512	0.0884	0.1019	0.3012	0.1717

Source: author's computation

6.2.3 Monero

Following charts depict estimated covariances and correlation coefficients of Bitcoin – Monero pair.

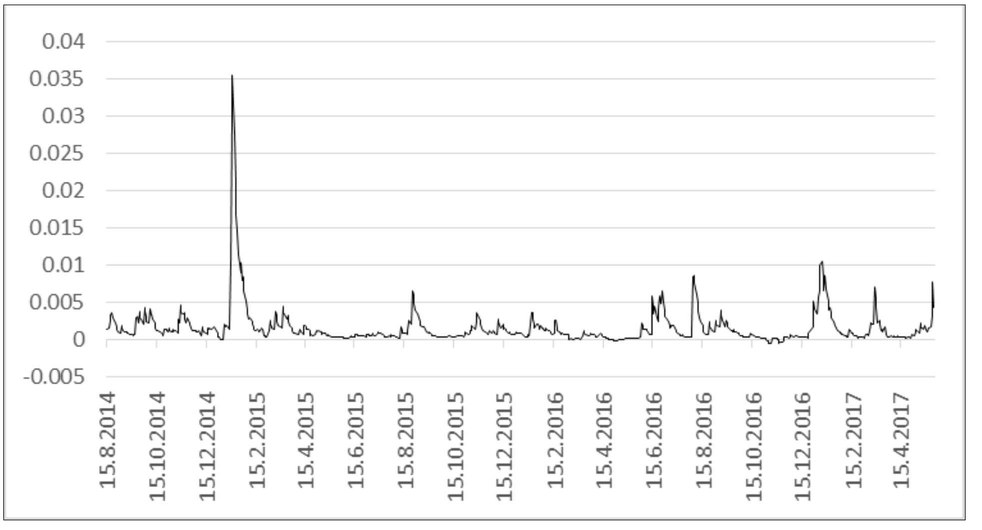


Figure 6.63: BTC-XMR covariance

Source: author's computation

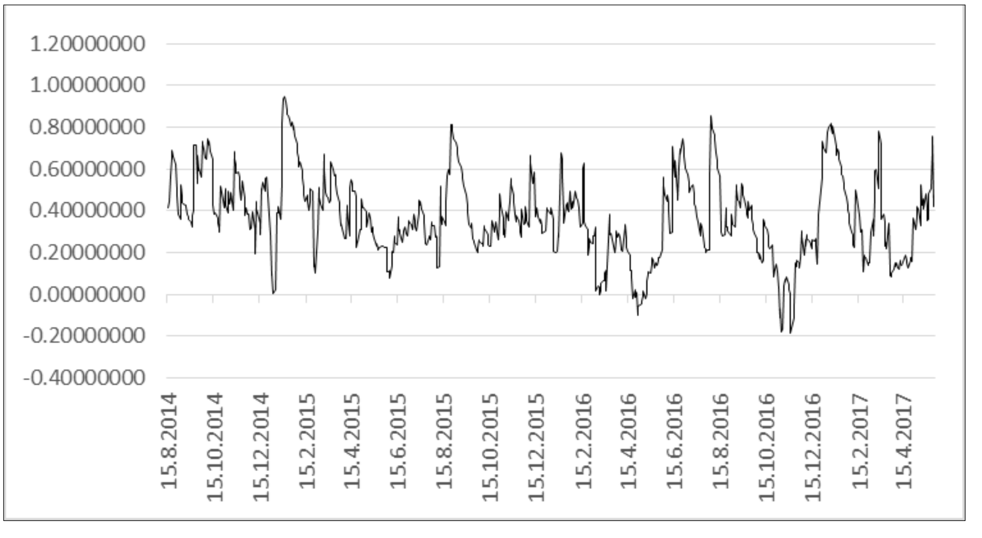


Figure 6.64: BTC-XMR correlation coefficient

Source: author's computation

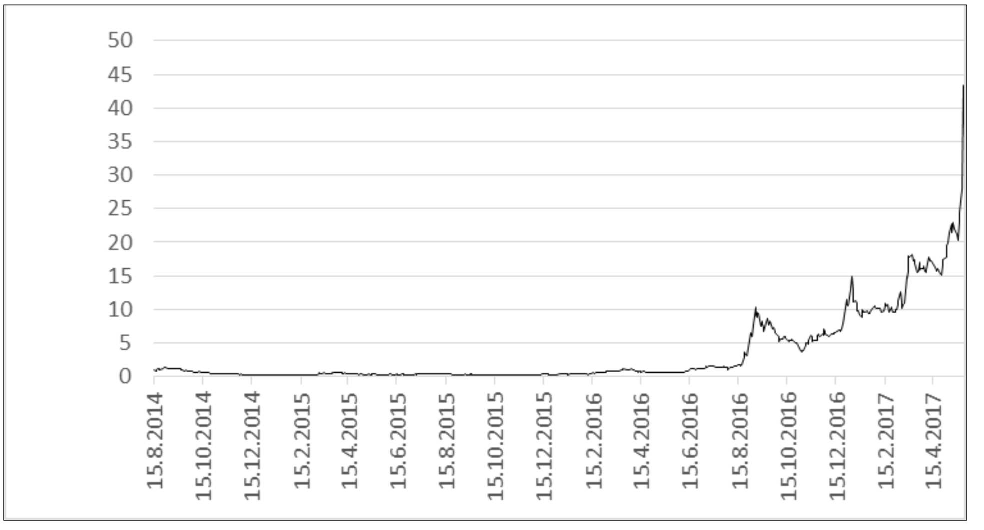


Figure 6.65: XMR/GBP exchange rate

Source: author's computation

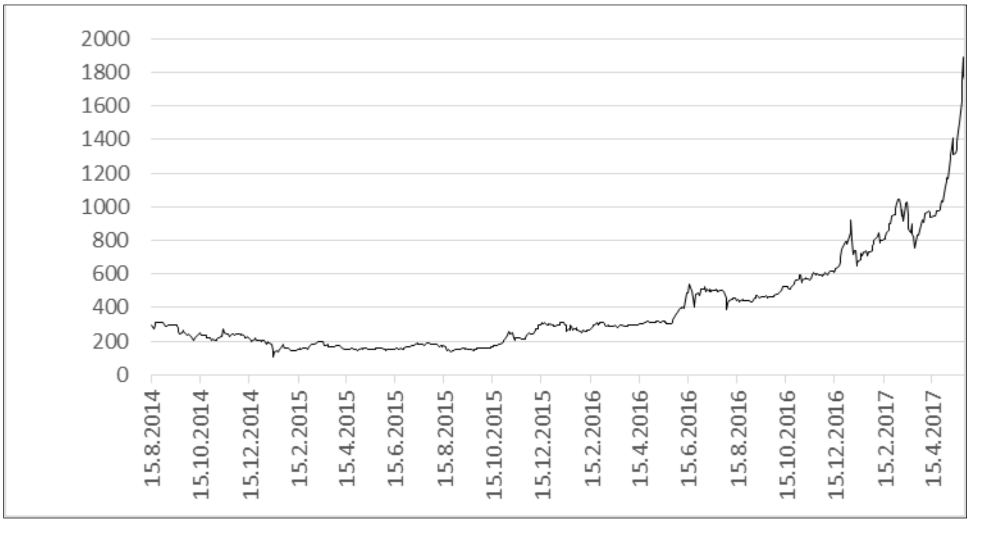


Figure 6.66: BTC/GBP exchange rate

Source: author's computation

According to the figures depicting correlation coefficient the Monero seems to differ from so far analyzed cryptocurrencies. Unlike Dash and Litecoin, Monero's conditional correlation is generally lower with spikes going to both directions. The price chart of Monero reveals price surge beginning in the half of August 2016 and returning back to trend level in the beginning of November 2016. The period added will therefore be 15.8.2016 to 4.11.2016. As before, the period which belongs to Monero price surge is tagged with double asterisk.

Table 6: XMR – BTC subsamples

		I	II*	III	IV**	Whole sample
CNY	**Average**	**0.3821**	**0.4495**	**0.7423**	**0.2909**	**0.3738**
	Min	**-0.0967**	**0.1730**	**0.6056**	**-0.1805**	**-0.1856**
	Max	**0.9453**	**0.7427**	**0.8578**	**0.5677**	**0.9453**
	St.dev	**0.1877**	**0.1648**	**0.0937**	**0.1544**	**0.1996**
USD	**Average**	0.3578	0.4034	0.7037	0.2794	0.348729
	Min	-0.0894	0.1918	0.5580	-0.2324	-0.23237
	Max	0.9378	0.6850	0.8359	0.5524	0.937754
	St.dev	0.1767	0.1383	0.1045	0.1562	0.188164
EUR	**Average**	0.3447	0.3808	0.5868	0.2366	0.336211
	Min	0.1050	0.2849	0.4593	-0.0071	-0.00705
	Max	0.8737	0.5833	0.7109	0.4354	0.873714
	St.dev	0.1060	0.0819	0.0952	0.0846	0.1162
		V	**VI***	**VII**	**VIII***	**Whole sample**
CNY	**Average**	**0.1316**	**0.6728**	**0.4239**	**0.2890**	**0.3738**
	Min	**-0.1856**	**0.1435**	**0.1099**	**0.0837**	**-0.1856**
	Max	**0.3021**	**0.8185**	**0.7797**	**0.7587**	**0.9453**
	St.dev	**0.1430**	**0.1998**	**0.1911**	**0.1692**	**0.1996**
USD	**Average**	0.1425	0.6451	0.3839	0.253058	0.348729
	Min	-0.1990	0.1315	0.0826	-0.02263	-0.23237
	Max	0.2991	0.8049	0.7538	0.71473	0.937754
	St.dev	0.1482	0.2000	0.1885	0.160094	0.188164
EUR	**Average**	0.2244	0.5240	0.3787	0.270352	0.336211
	Min	0.0672	0.3026	0.2106	0.105966	-0.00705
	Max	0.3349	0.6793	0.6297	0.499663	0.873714
	St.dev	0.0797	0.1250	0.0987	0.1001	0.1162

Source: author's computation

Regarding Bitcoin price surges the results are ambiguous again. While in the first two of them the average correlation coefficient is higher than the whole sample average in the case of the price huge price surge in the spring 2017 the coefficient is lower. This is in accordance with previous findings where the coefficient for this period was lower too.

6.2.4 Ripple

The following figures depict the price development during analyzed period and the estimated correlation and covariance between XRP and BTC.

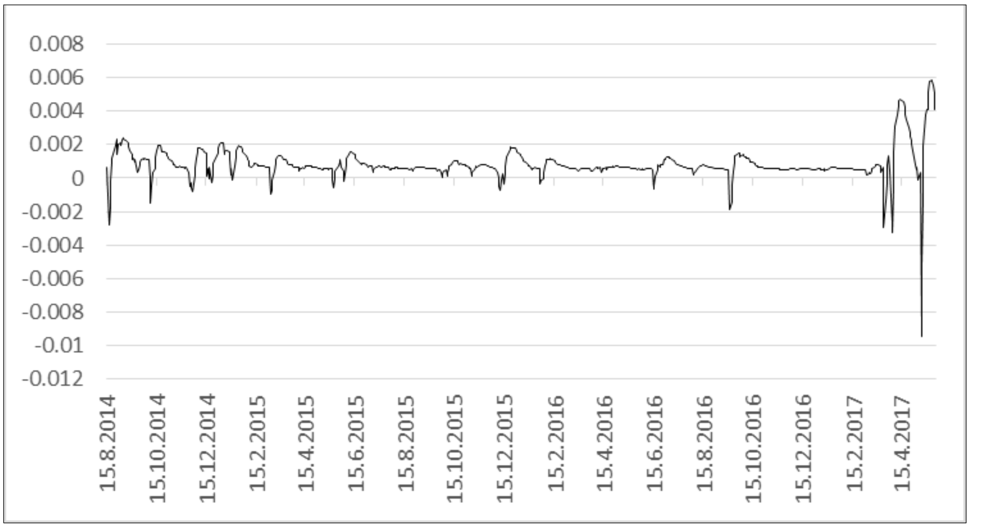


Figure 6.67: BTC-XRP covariance

Source: author's computation

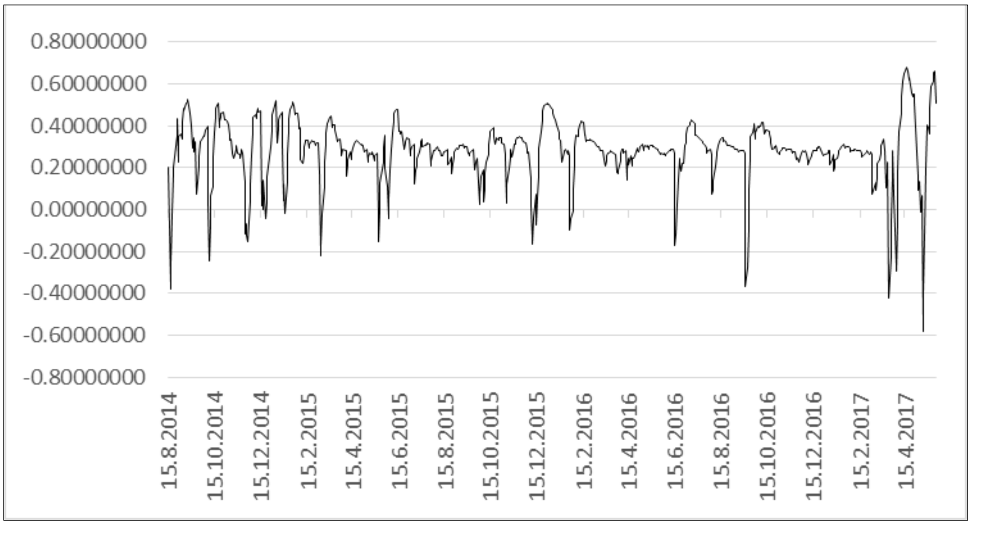


Figure 6.68: BTC-XRP correlation coefficient

Source: author's computation

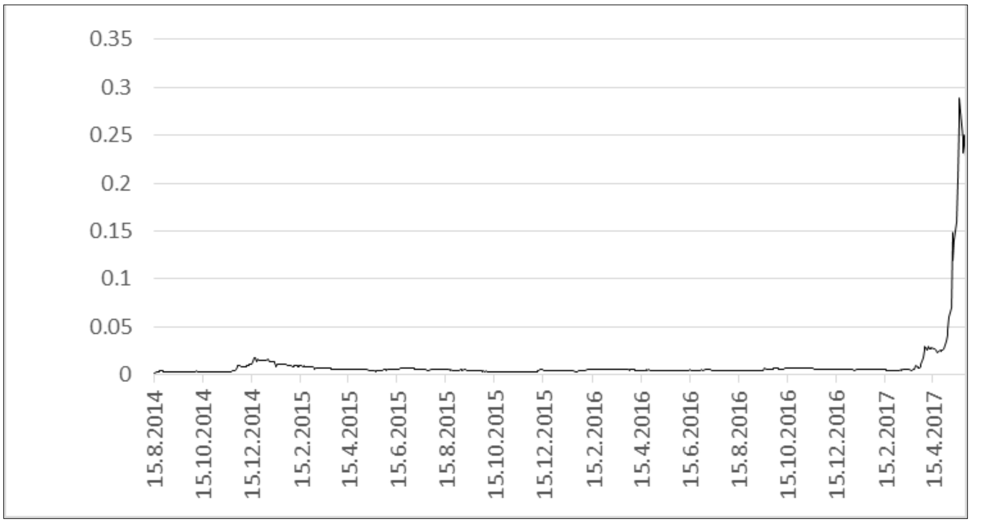


Figure 6.69: XRP/GBP exchange rate

Source: author's computation

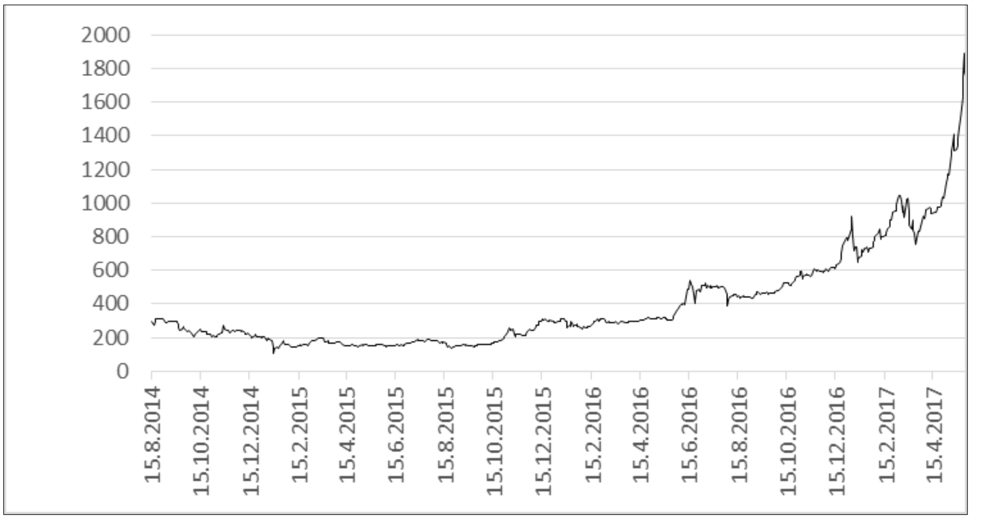


Figure 6.70: BTC/GBP exchange rate

Source: author's computation

The estimated conditional correlation seems to be very different in case of model with Chinese yuan than in case of the other two. As in case of Monero the spikes go in both directions and are very frequent. There is no price spike visible at the chart of Ripple price but that might be caused by the huge price surge in 2017. The chart below depicts the price cleansed from 2017 observations. It is visible that there was price surge from the mid of November 2014, spiking in the end of December and falling back to trend in the middle of April 2015. This period is added among the bitcoin's price surges in the table below.

Table 7: XRP –BTC subsamples

		I	II**	III	IV*	Whole sample
CNY	**Average**	**0.3010**	**0.2806**	**0.2736**	**0.2801**	**0.2772**
	Min	**-0.3783**	**-0.2228**	**-0.1630**	**-0.1723**	**-0.5827**
	Max	**0.5254**	**0.5191**	**0.5096**	**0.4269**	**0.6777**
	St.dev	**0.1881**	**0.1683**	**0.1074**	**0.1161**	**0.1498**
USD	**Average**	0.1303	0.0943	0.1880	0.0760	0.151311
	Min	-0.5217	-0.3925	-0.2781	-0.2991	-0.52168
	Max	0.5084	0.8697	0.6902	0.3227	0.904413
	St.dev	0.1933	0.2678	0.1709	0.1208	0.198851
EUR	**Average**	0.1383	0.1440	0.1938	0.1314	0.16605
	Min	-0.4508	-0.3832	-0.2464	-0.2653	-0.48169
	Max	0.5496	0.8838	0.7350	0.3992	0.920083
	St.dev	0.1966	0.2829	0.1743	0.1145	0.2052

		V	VI*	VII	VIII*	Whole sample
CNY	**Average**	**0.2780**	**0.2547**	**0.2570**	**0.2813**	**0.2772**
	Min	**-0.3686**	**0.1811**	**0.0749**	**-0.5827**	**-0.5827**
	Max	**0.4180**	**0.3002**	**0.3363**	**0.6777**	**0.6777**
	St.dev	**0.1120**	**0.0365**	**0.0611**	**0.3489**	**0.1498**
USD	**Average**	0.1710	0.0769	0.1006	0.198165	0.151311
	Min	-0.0355	-0.1847	-0.1222	-0.27924	-0.52168
	Max	0.7794	0.4347	0.4266	0.904413	0.904413
	St.dev	0.1554	0.1401	0.1294	0.319042	0.198851
EUR	**Average**	0.1761	0.0658	0.1587	0.134029	0.16605
	Min	-0.2200	-0.2389	-0.0139	-0.48169	-0.48169
	Max	0.7600	0.3951	0.4545	0.920083	0.920083
	St.dev	0.1691	0.1469	0.1056	0.3604	0.2052

Source: author's computation

Again, the average coefficient provide ambiguous information. In specification with yuan, the correlation coefficients are almost the same in all periods. In case of specification with US dollar, the coefficients in periods of surges are lower than whole sample average, except of the average coefficient of the last period. This is in complete contradiction with results for other alternative cryptocurrencies, whose correlation dropped for all of them in the last period.

The results of the section with multivariate models are in total contradiction with the expectations. The correlation between Bitcoin and alternative cryptocurrencies is positive and in the case of Litecoin even strong. While it was expected that in the periods without common bubble behavior, when it could be assumed the prices are not driven by market mood but rather by fundamentals, the increase in price caused by better fundamentals should mean the advantage against others and thus decrease in the price of others, the results show the opposite. The positive correlation might be caused by joint perception of cryptocurrencies. The improvement in fundamentals of one cryptocurrency might be perceived as a possibility for this improvement to happen in other cryptocurrencies, causing the co-movement of the prices.

With the exception of Ripple, the behavior during the last phase, the period of high price surge across all analyzed cryptocurrencies, contradicts the expectations that during the boom phases the correlation is stronger. This is attributed to the fact that during the boom phase the returns are relatively high, therefore the mismatch between the directions of two high returns of two cryptocurrencies might cause huge drop in estimated correlation coefficient. It cannot be therefore argued that the correlation is low or even negative in this period. Much more reasonable conclusion would be that in general price surge phases the correlation should not be estimated by the same model used during calmer periods.

7. Conclusion

The thesis analyzed the cryptocurrencies in context of their evolution to become money with focus on their volatility. The aim of the thesis was to find whether the cryptocurrencies are competing between themselves or rather behave as one market competing against other media of exchange. This was tested by identifying and estimating factors which could be interpreted as signs of either independent or common perception of various digital coins.

While the results of univariate models found different levels of maturity of the currencies, implying the independent perception, the results of the correlation estimation are contradictory, implying positive and in some cases even strong correlation. These results can be therefore interpreted that the results of univariate models might have been caused by different factors than perception, for example by the different level of liquidity. In further research it could be beneficial to include a variable capturing the effect of liquidity.

Regarding the hypothesis of stronger correlation during the boom phases the results suggest its invalidity. The sample ends by period of large price surge when the correlation coefficients dropped in case of all altcoins except one – Ripple. This result is probably caused by the fact that during the period of large price movements a discrepancy in the direction of price movements can significantly decrease the estimated correlation.

Cryptocurrencies are on a rise and offer a variety of attractive economic topics. Given that most of the literature was so far focused at Bitcoin, which is losing its market share to altcoins as Ethereum or Ripple, the further research could focus at alternative currencies. As some of them were not intended to serve as a medium of exchange only but were designed to offer “real” value functions as data storage or processing applications (for example the before mentioned Ethereum) the further research could analyze the link between the usage of the network and the value of its coin. Given that the environment of cryptocurrencies changes very fast, many of the interesting studies mentioned above, as the analysis of the demand for bitcoins, would deserve an actualization.

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Appendix A: The results of estimations

Univariate models

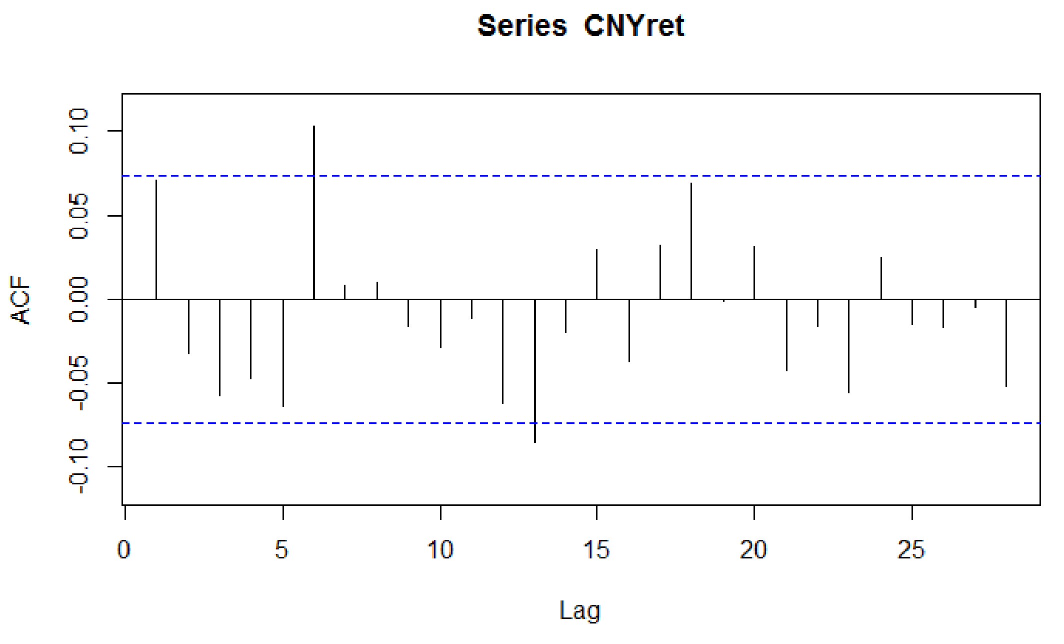
Diagnostics of the series

Results of diagnostic tests

Currency	CNY	EUR	USD	BTC
ADF test	-8.787	8.612	-8.985	-9.764
	(0.01*)	(0.01*)	(0.01*)	(0.01*)
KPSS with trend	0.045	0.076	0.056	0.036
	(0.1*)	(0.1*)	(0.1*)	(0.1*)
KPSS with level	0.053	0.257	0.059	0.718
	(0.1*)	(0.1*)	(0.1*)	(0.012)
Ljung-Box test	34.231	10.720	34.243	24.578
	(0.025)	(0.953)	0.0245)	(0.218)
Currency	**DASH**	**LTC**	**XMR**	**XRP**
ADF test	-8.821	-9.706	-8.800	-7.113
	(0.01*)	(0.01*)	(0.01*)	(0.01*)
KPSS with trend	0.041	0.077	0.038	0.254
	(0.1*)	(0.1*)	(0.1*)	(0.1*)
KPSS with level	0.554	0.459	0.633	0.495
	(0.029)	(0.052)	(0.02)	(0.043)
Ljung-Box test	23.164	31.337	29.906	36.219
	(0.281)	(0.051)	(0.071)	(0.015)

* the p-value is lower than depicted number in case of ADF test, higher in case of KPSS test

Source: author's computation



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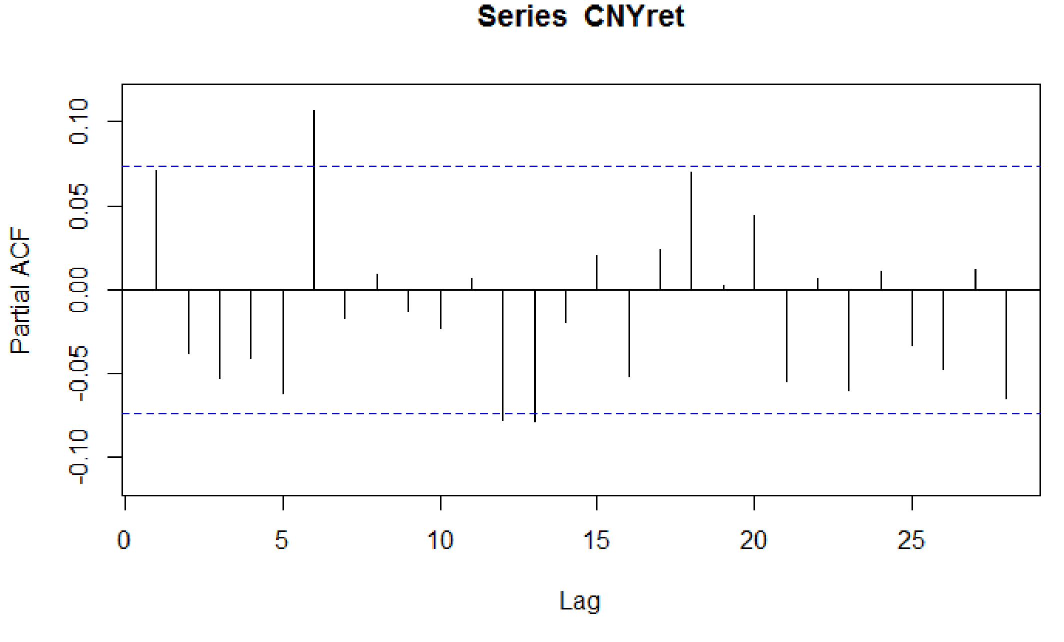

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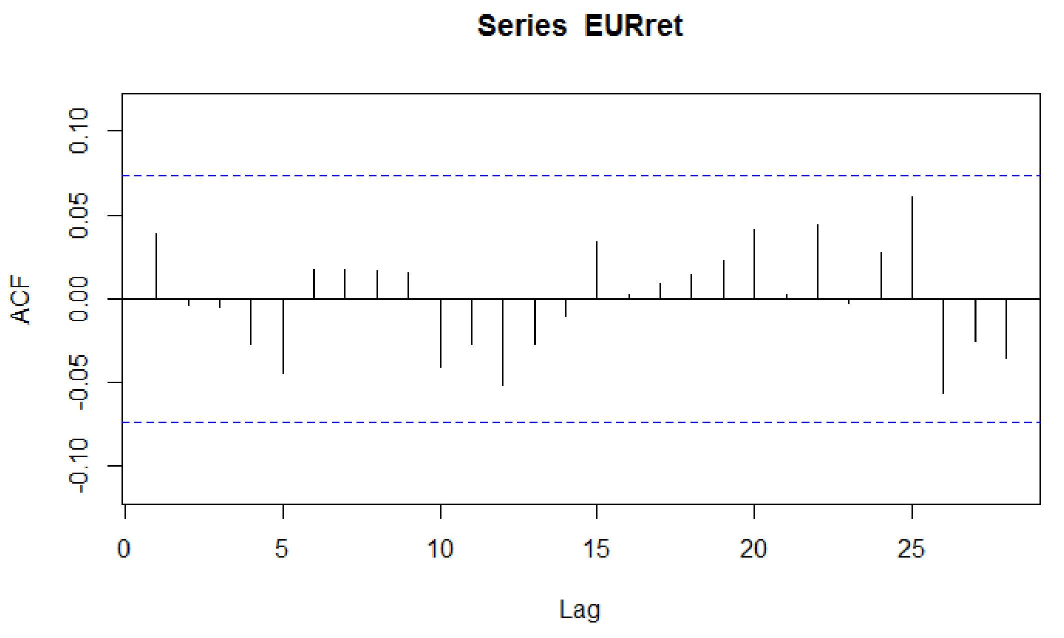

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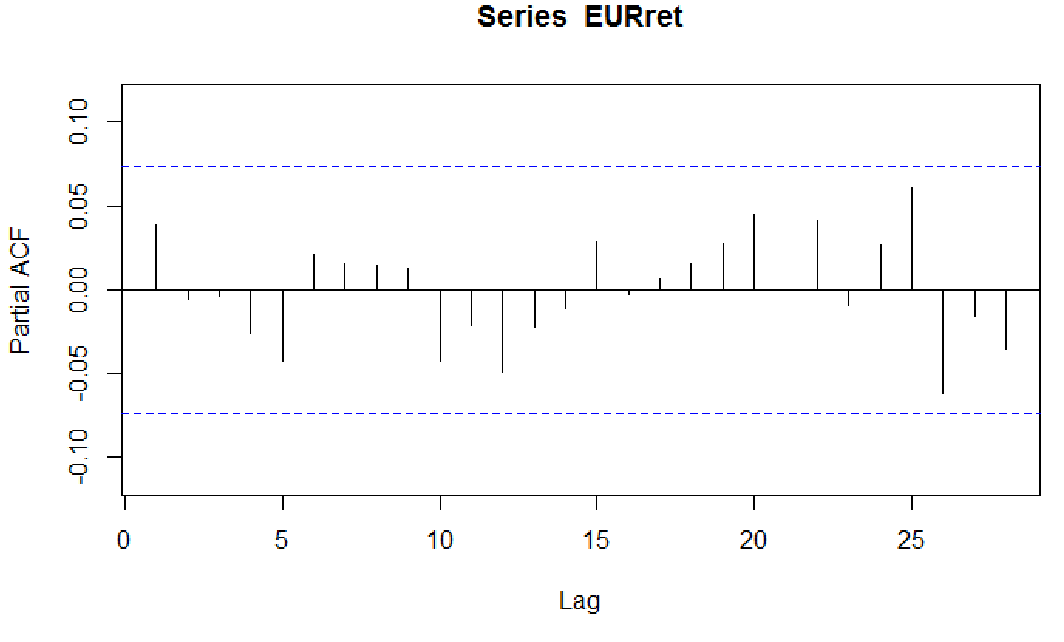

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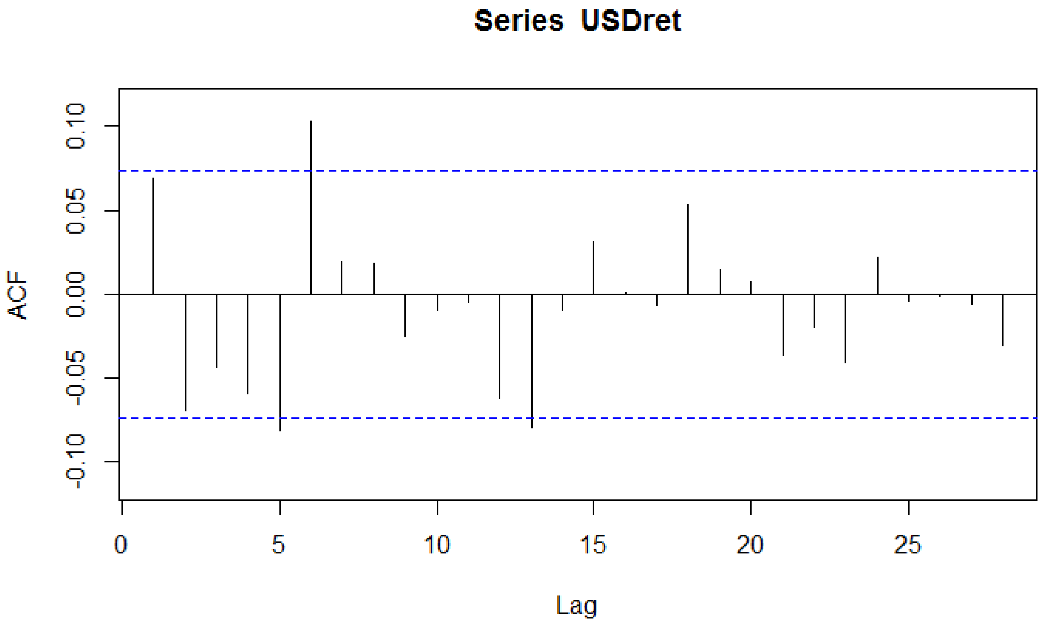

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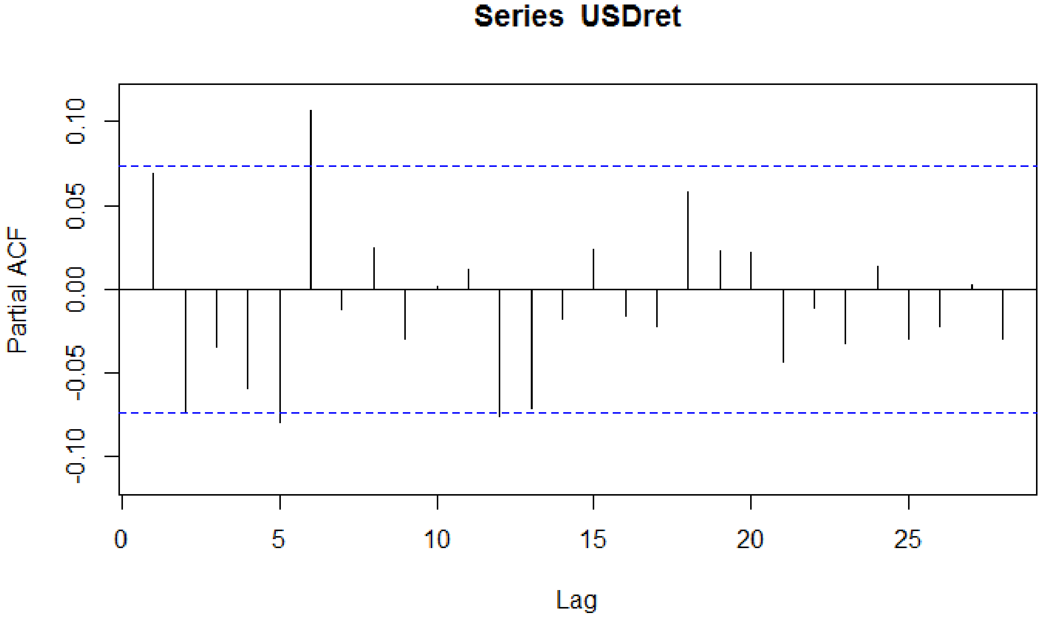

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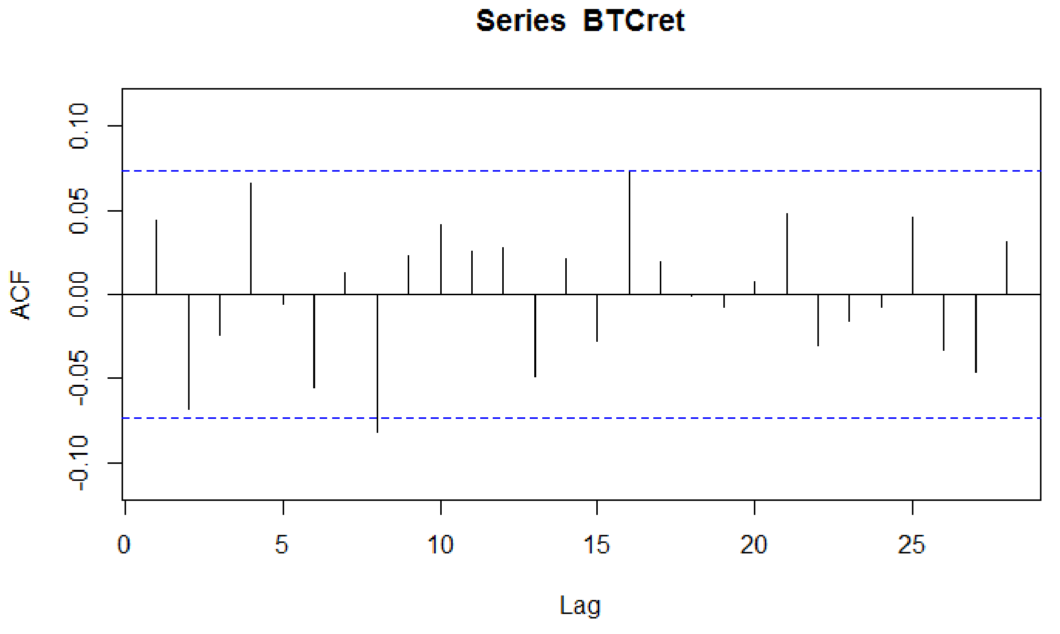

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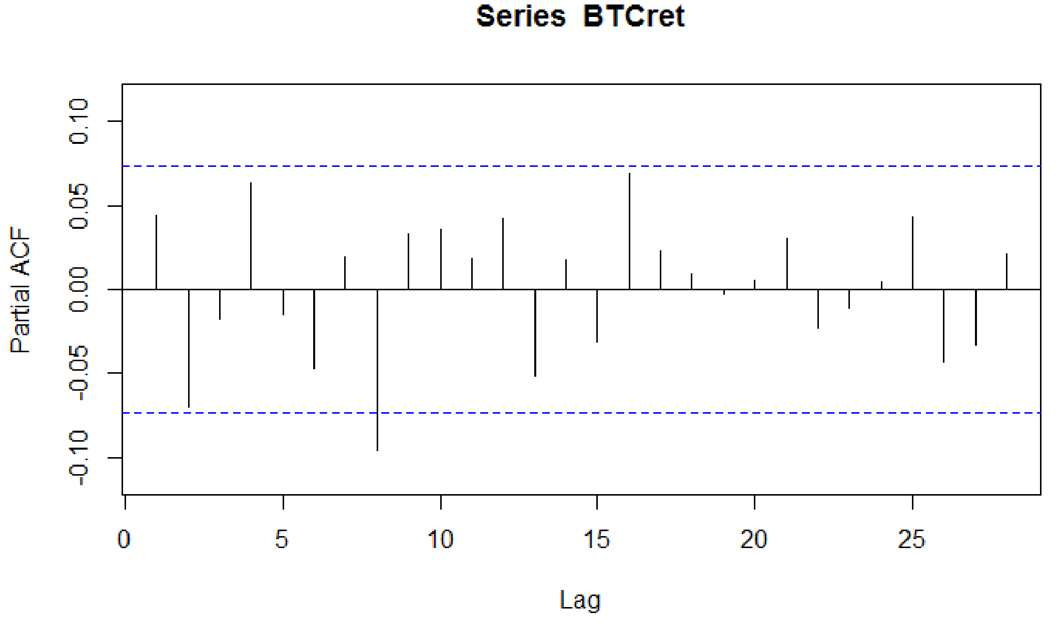

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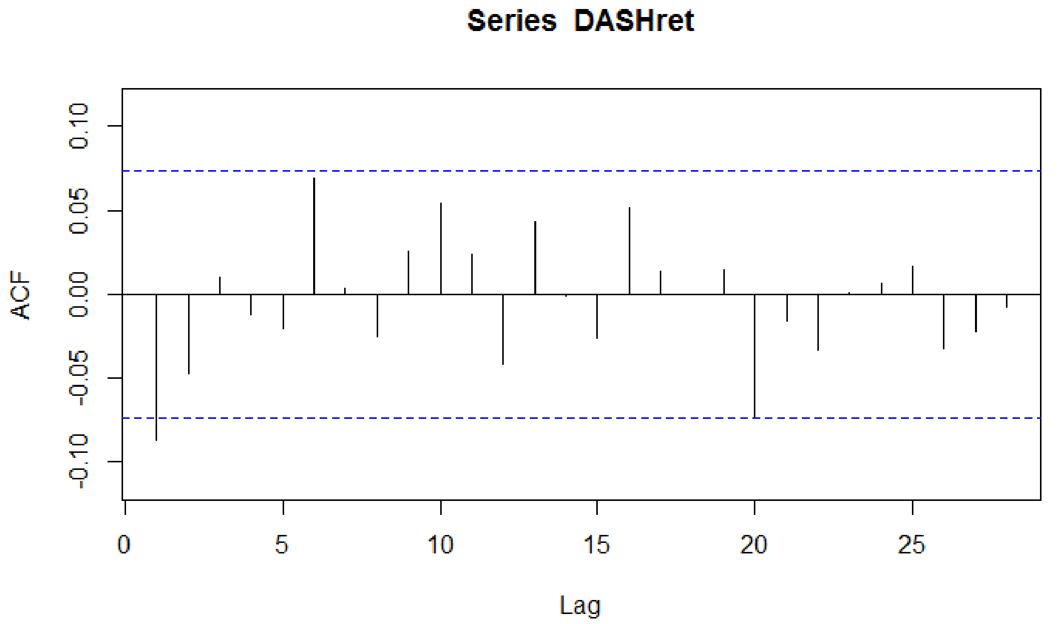

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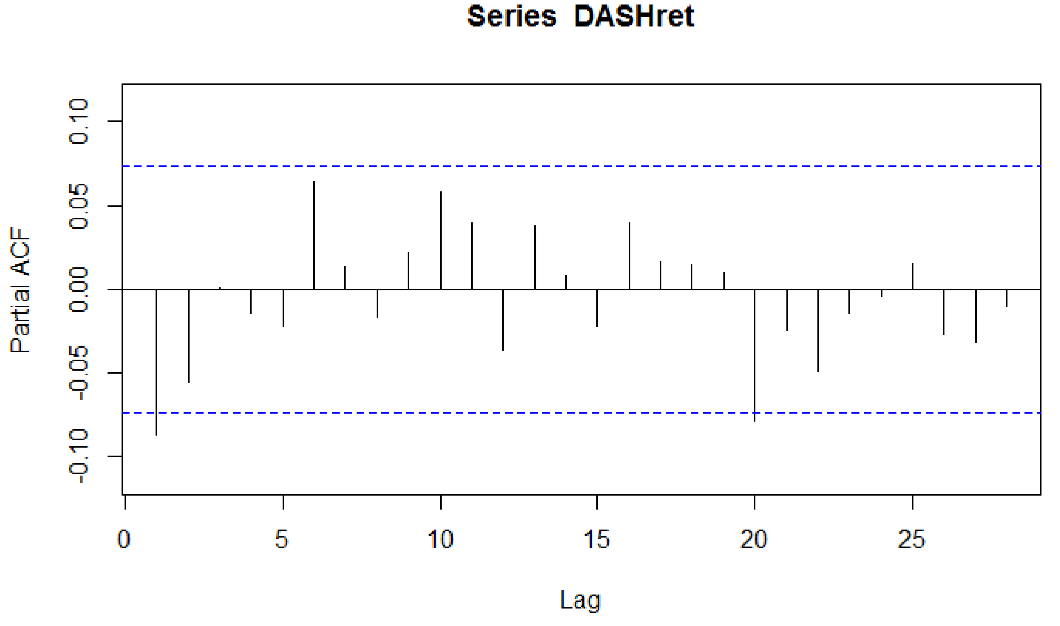

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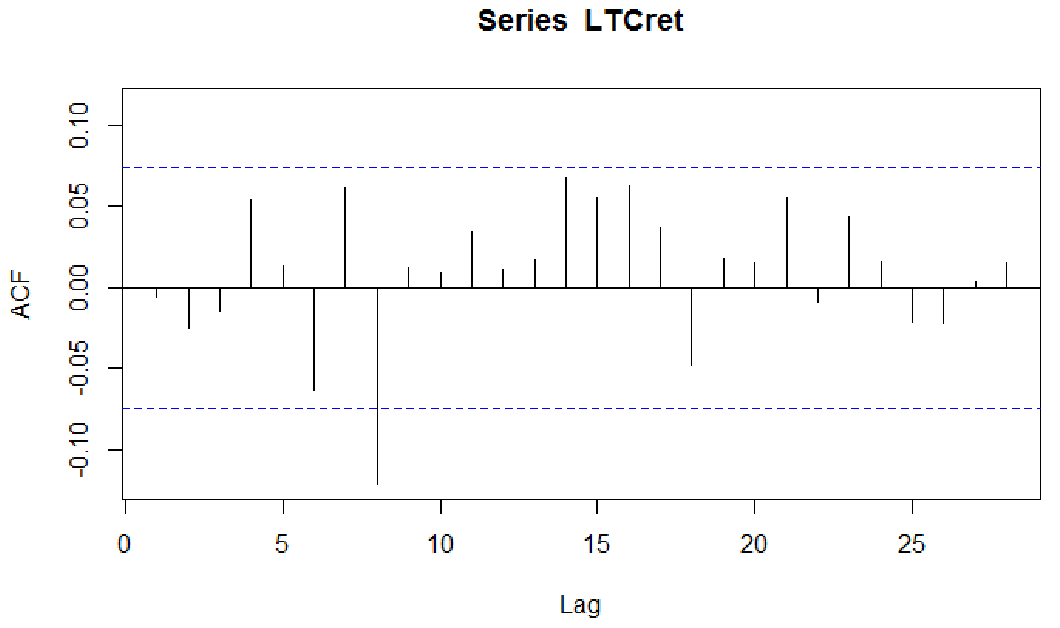

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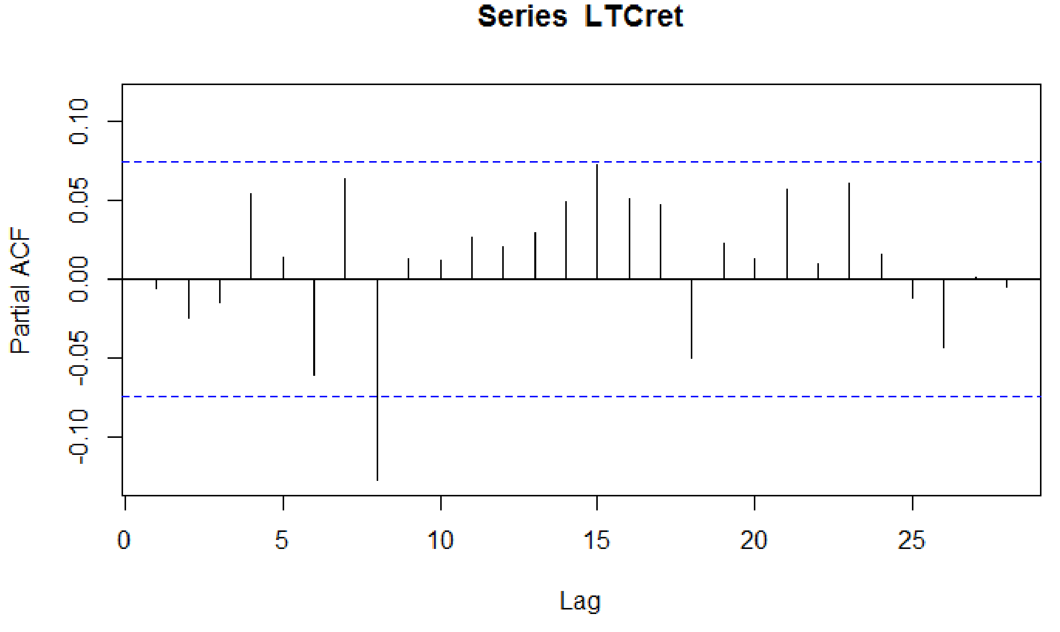

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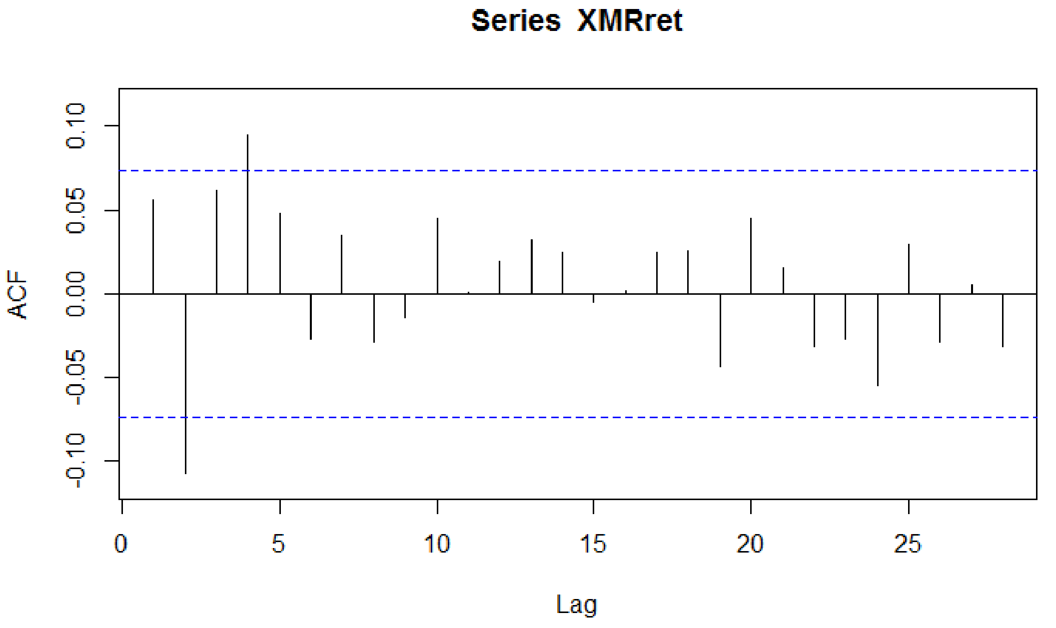

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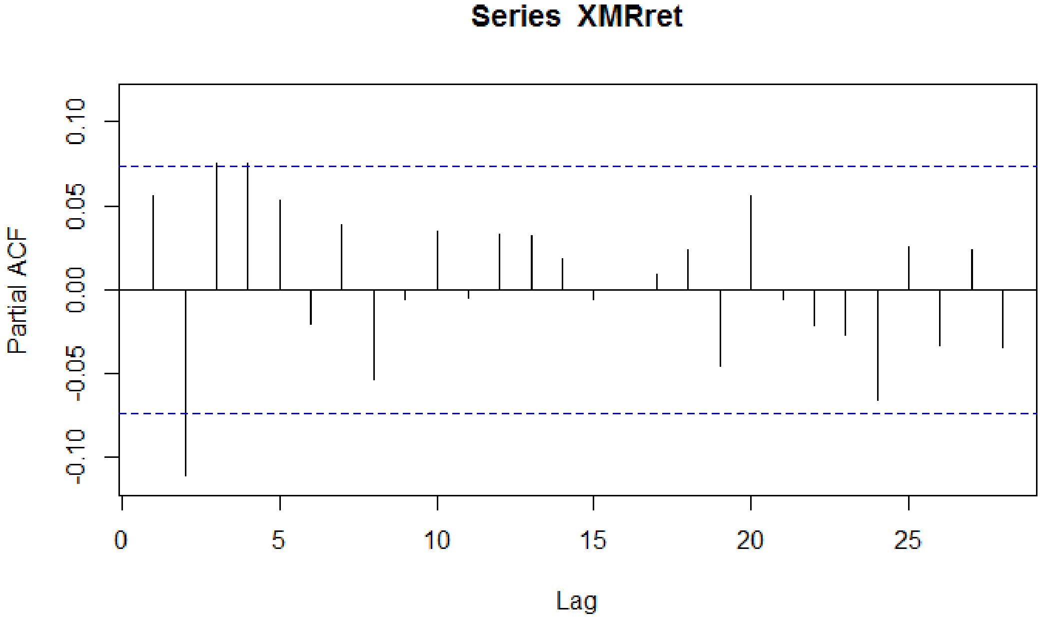

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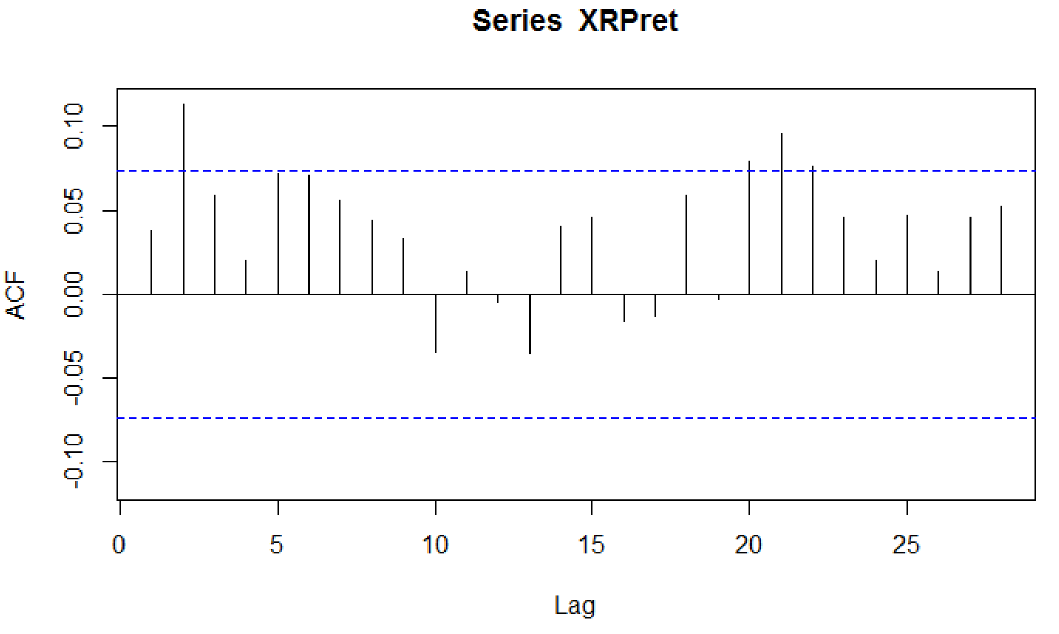

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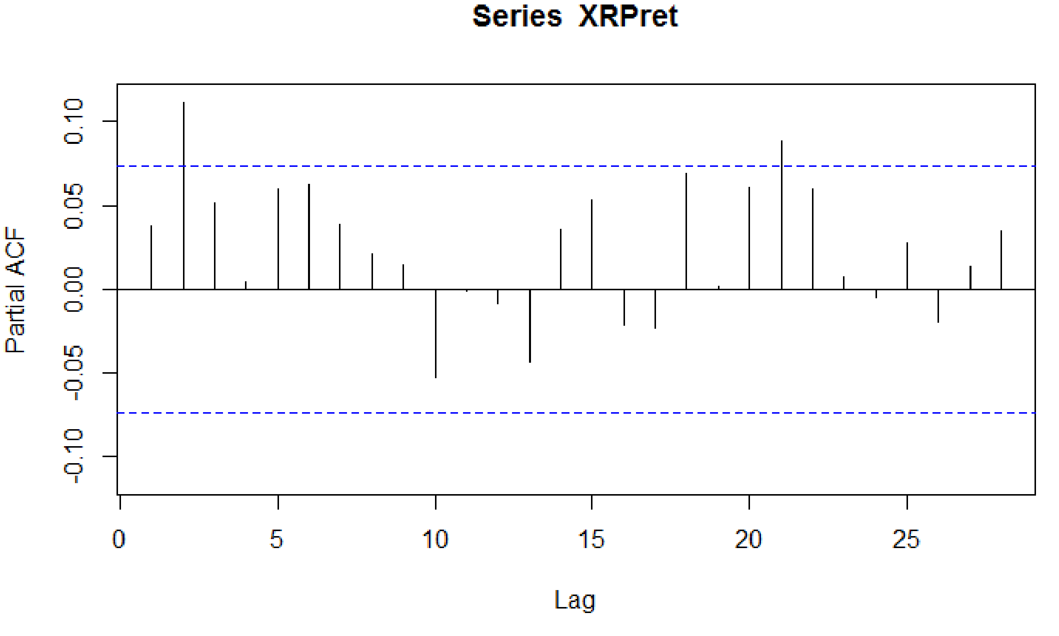


Source: author's computation

ARMA(p,q)-GARCH(1,1) results

Results of ARMA(p,q)-GARCH(1,1)

Currency	CNY	EUR	USD	BTC
Specification (p, I, q)	2, 0, 2	0, 0, 0	0, 0, 0	2, 0, 2
AR1	0.232528 (4.0e-06)***	N/A	N/A	0.777071 (0.0e+00)***
AR2	-0.867996 (0.0e+00)***	N/A	N/A	0.196833 (0.0e+00)***
MA1	-0.188370 (0.0e+00)***	N/A	N/A	-0.725715 (0.0e+00)***
MA2	0.924678 (0.0e+00)***	N/A	N/A	-0.275001 (0.0e+00)***
ω	0.000003 (4.1e-05)***	0.000002 (0.013498)**	0.000002 (0.45457)	0.000127 (7.9e-05)***
α	0.141436 (0.0e+00)***	0.065223 (0.000000)***	0.144066 (0.00000)***	0.219306 (0.0e+00)***
β	0.786488 (0.0e+00)***	0.890685 (0.000000)***	0.818035 (0.00000)***	0.718062 (0.0e+00)***
trend	N/A	N/A	N/A	0.000019 (0.0e+00)***
Ljung-Box test - z	[1] 0.1219 (0.7270)	[1] 0.4303 (0.5119)	[1] 0.1443 (0.7040)	[1] 2.37 (0.12365)
Ljung-Box test - z	[11] 5.4009 (0.8401)	[2] 0.4361 (0.7244)	[2] 0.2402 (0.8300)	[11] 7.20 (0.02844)**
Ljung-Box test - z	[19] 10.4011 (0.4031)	[5] 0.9088 (0.8800)	[5] 1.2282 (0.8062)	[19] 10.76 (0.34798)
Ljung-Box test - z^2	[1] 0.1111 (0.7389)	[1] 0.03465 (0.8523)	[1] 0.3726 (0.5416)	[1] 0.682 (0.4089)
Ljung-Box test - z^2	[5] 3.0916 (0.3906)	[5] 2.73137 (0.4583)	[5] 2.7080 (0.4630)	[5] 1.353 (0.7759)
Ljung-Box test - z^2	[9] 5.3988 (0.3732)	[9] 4.59061 (0.4919)	[9] 4.2032 (0.5548)	[9] 4.374 (0.5267)
ARCH-LM test - z	[3] 0.1594 (0.6897)	[3] 0.236 (0.6271)	[3] 0.1927 (0.6607)	[3] 0.4608 (0.4973)
ARCH-LM test - z	[5] 4.3272 (0.1466)	[5] 4.752 (0.1172)	[5] 3.3564 (0.2421)	[5] 0.8636 (0.7738)
ARCH-LM test - z	[7] 5.2115 (0.2040)	[7] 5.322 (0.1939)	[7] 3.8039 (0.3757)	[7] 3.4831 (0.4273)

Currency	DASH	LTC	XMR	XRP
Specification (p, I, q)	0, 0, 0	0, 0, 1	1, 0, 2	0, 0, 0

AR1	N/A	N/A	-0.923235 (0.000000)***	N/A
AR2	N/A	N/A	N/A	N/A
MA1	N/A	N/A	1.006373 (0.000000)***	N/A
MA2	N/A	N/A	0.041657 (0.000000)***	N/A
ω	0.000400 (0.002306)***	0.000299 (1.9e-05)***	0.000536 (0.000521)***	0.000842 (0.000009)***
α	0.394877 (0.000000)***	0.127203 (1.2e-05)***	0.254520 (0.000001)***	0.569829 (0.000000)***
β	0.604123 (0.000000)***	0.820928 (0.0e+00)***	0.719553 (0.000000)***	0.429171 (0.000000)***
trend	0.000008 (0.070504)*	N/A	0.000005 (0.420814)	-0.000014 (0.000661)***
Ljung-Box test - z	[1] 0.4249 (0.5145)	[1] 0.331 (0.5651)	[1] 1.095 (0.2954)	[1] 0.5738 (0.4488)
Ljung-Box test - z	[2] 0.9218 (0.5243)	[2] 0.365 (0.7606)	[8] 3.160 (0.9920)	[2] 0.7687 (0.5798)
Ljung-Box test - z	[5] 1.4405 (0.7545)	[5] 1.103 (0.8360)	[14] 5.081 (0.8884)	[5] 2.2844 (0.5529)
Ljung-Box test - z^2	[1] 0.02793 (0.8673)	[1] 0.02063 (0.8858)	[1] 1.266e-04 (0.991022)	[1] 0.01181 (0.9135)
Ljung-Box test - z^2	[5] 0.30927 (0.9827)	[5] 0.17084 (0.9945)	[5] 6.046e+00 (0.087754)*	[5] 0.65591 (0.9312)
Ljung-Box test - z^2	[9] 0.48813 (0.9986)	[9] 0.33071 (0.9996)	[9] 1.675e+01 (0.001336)***	[9] 1.03881 (0.9846)
ARCH-LM test - z	[3] 0.1608 (0.6884)	[3] 0.1677 (0.6821)	[3] 0.4794 (4.887e-01)***	[3] 0.08284 (0.7735)
ARCH-LM test - z	[5] 0.4571 (0.8962)	[5] 0.2571 (0.9514)	[5] 16.3955 (1.719e-04)***	[5] 0.52403 (0.8765)
ARCH-LM test - z	[7] 0.5207 (0.9765)	[7] 0.3391 (0.9905)	[7] 20.4248 (4.976e-05)***	[7] 0.65283 (0.9625)

Source: author's computation

Information criteria of ARMA(p,q)-GARCH(1,1) specification, ARMA diagnostics

CNY

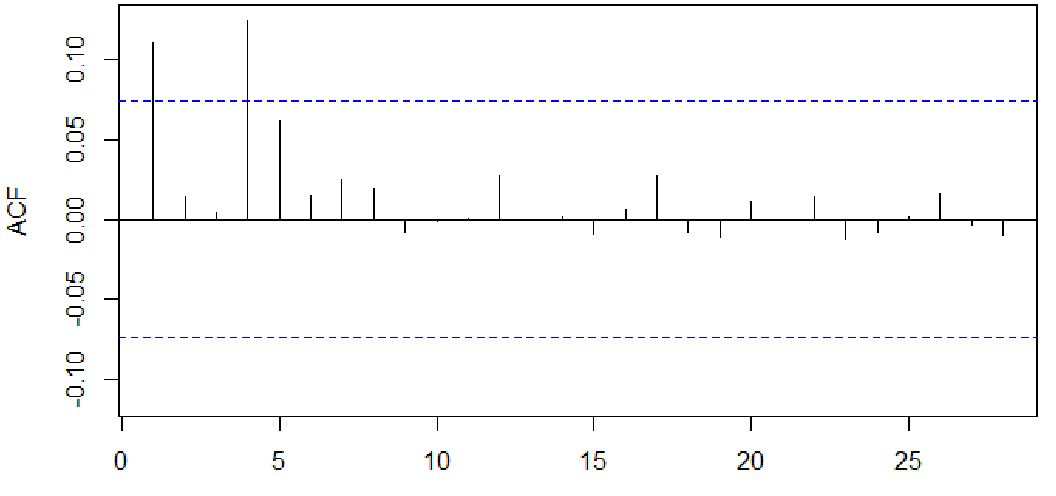
	Akaike	Bayes	Shibata	Hannan-Quinn

ARIMA_000_FALSE	-7.38421	-7.36477	-7.38425	-7.3767
ARIMA_001_FALSE	-7.38154	-7.35562	-7.3816	-7.37152
ARIMA_001__TRUE	-7.38087	-7.34847	-7.38097	-7.36834
ARIMA_002_FALSE	-7.37854	-7.34614	-7.37864	-7.36602
ARIMA_002__TRUE	-7.37769	-7.33881	-7.37783	-7.36266
ARIMA_100_FALSE	-7.38155	-7.35563	-7.38161	-7.37153
ARIMA_100__TRUE	-7.38087	-7.34847	-7.38097	-7.36835
ARIMA_101_FALSE	-7.37874	-7.34634	-7.37884	-7.36622
ARIMA_101__TRUE	-7.37805	-7.33918	-7.3782	-7.36303
ARIMA_102_FALSE	-7.37909	-7.34021	-7.37924	-7.36407
ARIMA_102__TRUE	-7.38032	-7.33496	-7.38052	-7.36279
ARIMA_200_FALSE	-7.37835	-7.34595	-7.37845	-7.36583
ARIMA_200__TRUE	-7.37754	-7.33867	-7.37769	-7.36252
ARIMA_201_FALSE	-7.37912	-7.34025	-7.37927	-7.3641
ARIMA_201__TRUE	-7.38037	-7.33501	-7.38056	-7.36284
ARIMA_202_FALSE	**-7.39888**	**-7.35352**	**-7.39908**	**-7.38135**
ARIMA_202__TRUE	-7.39767	-7.34583	-7.39792	-7.37763

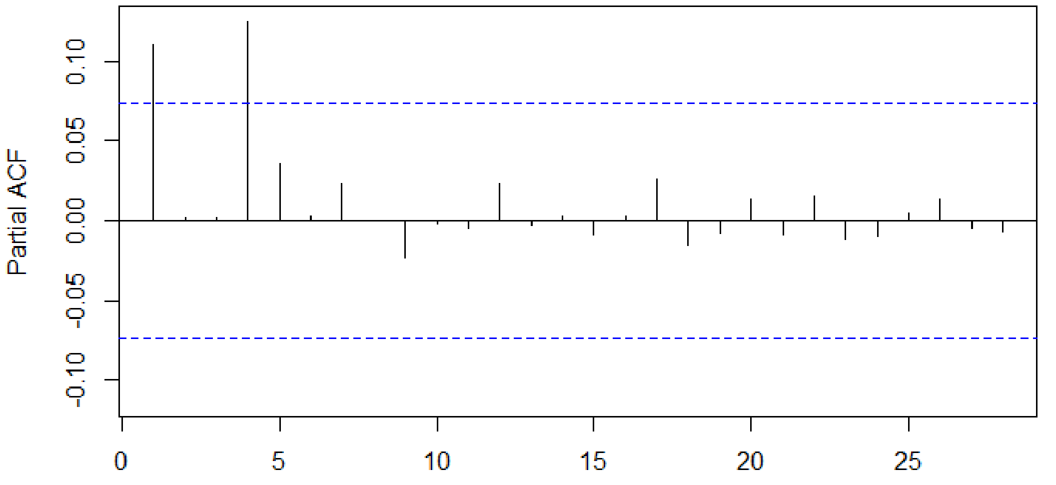
Source: author's computation

ARCH process diagnostics of ARMA's residuals:

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 21.531, df = 20, p-value = 0.3665



Source: author's computation



Source: author's computation

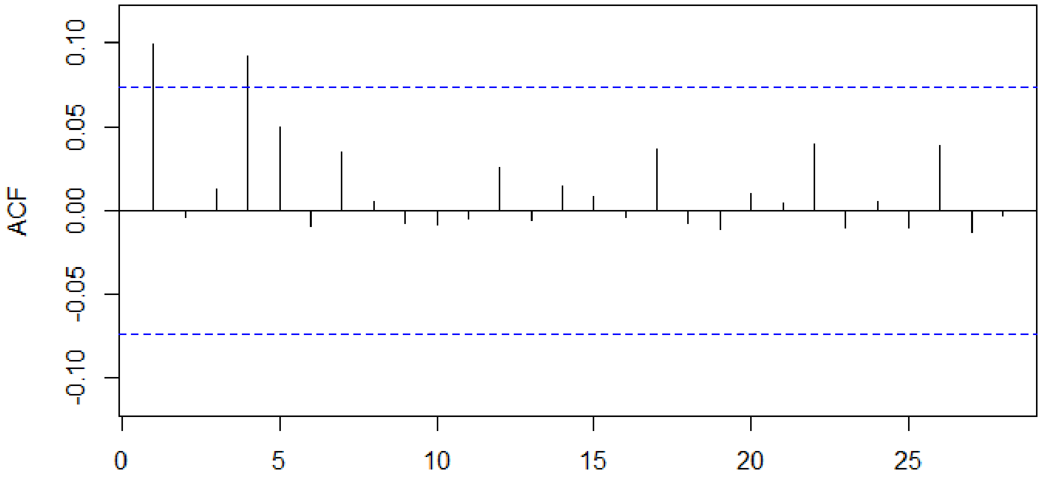
EUR

	Akaike	Bayes	Shibata	Hannan-Quinn
ARIMA_000_FALSE	**-7.28938**	**-7.26994**	**-7.28942**	**-7.28187**
ARIMA_001_FALSE	-7.28657	-7.26065	-7.28663	-7.27655
ARIMA_001__TRUE	-7.28407	-7.25167	-7.28417	-7.27155
ARIMA_002_FALSE	-7.28319	-7.25079	-7.28329	-7.27066
ARIMA_002__TRUE	-7.2807	-7.24182	-7.28085	-7.26568
ARIMA_100_FALSE	-7.28657	-7.26065	-7.28664	-7.27656
ARIMA_100__TRUE	-7.28409	-7.25169	-7.28419	-7.27156
ARIMA_101_FALSE	-7.28378	-7.25138	-7.28388	-7.27126
ARIMA_101__TRUE	-7.2813	-7.24243	-7.28145	-7.26628
ARIMA_102_FALSE	-7.28035	-7.24147	-7.28049	-7.26532
ARIMA_102__TRUE	-7.27789	-7.23253	-7.27808	-7.26036
ARIMA_200_FALSE	-7.28319	-7.25079	-7.28329	-7.27067
ARIMA_200__TRUE	-7.28072	-7.24184	-7.28086	-7.26569
ARIMA_201_FALSE	-7.28038	-7.2415	-7.28052	-7.26535
ARIMA_201__TRUE	-7.27789	-7.23253	-7.27808	-7.26036
ARIMA_202_FALSE	-7.27758	-7.23222	-7.27777	-7.26005
ARIMA_202__TRUE	-7.27508	-7.22324	-7.27533	-7.25504

Source: author's computation

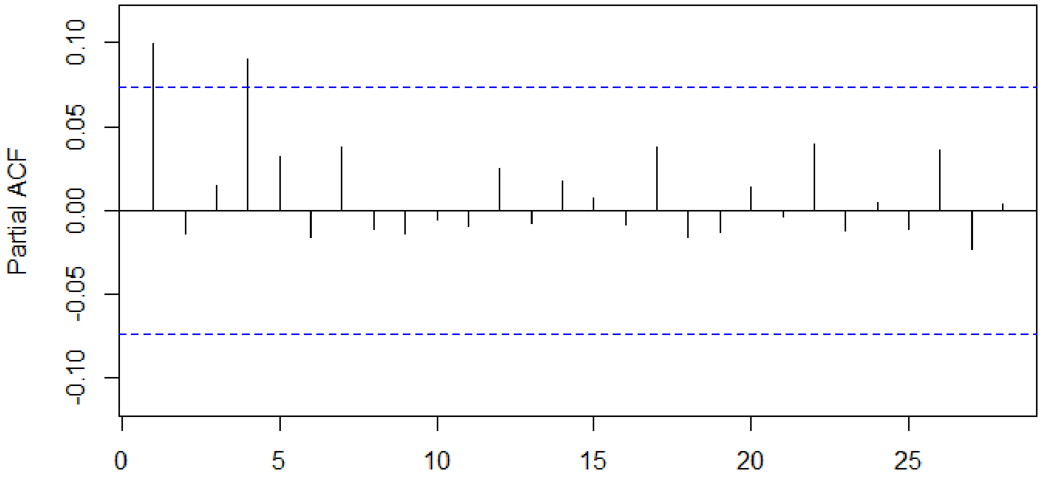
ARCH process diagnostics of returns

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 16.608, df = 20, p-value = 0.6782



ACF – EUR squared returns

Source: author's computation



PACF – EUR squared returns

Source: author's computation

USD

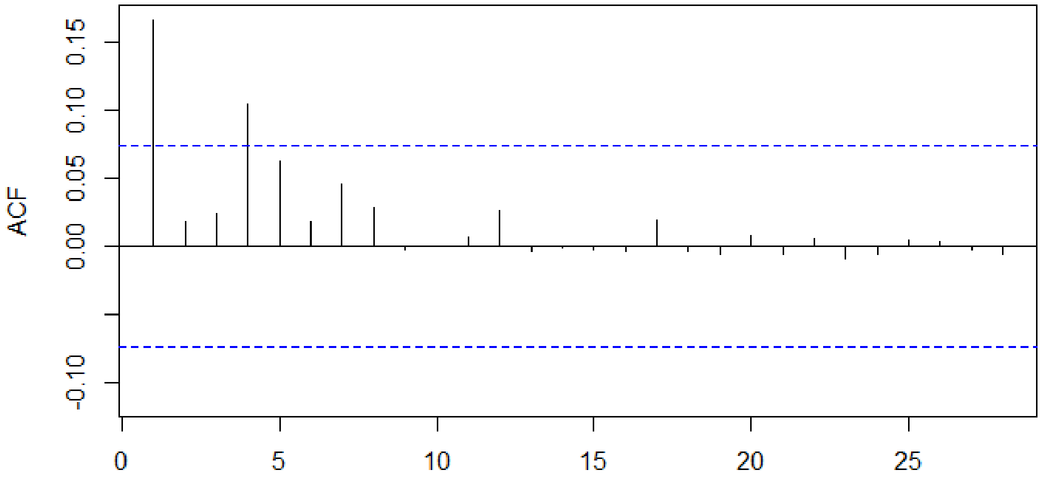
	Akaike	Bayes	Shibata	Hannan-Quinn
ARIMA_000_FALSE	**-7.3264**	**-7.30696**	**-7.32644**	**-7.31889**
ARIMA_001_FALSE	-7.32359	-7.29767	-7.32366	-7.31358

ARIMA_001__TRUE	-7.32658	-7.29418	-7.32668	-7.31406
ARIMA_002_FALSE	-7.3201	-7.2877	-7.3202	-7.30758
ARIMA_002__TRUE	-7.32332	-7.28444	-7.32346	-7.30829
ARIMA_100_FALSE	-7.32359	-7.29767	-7.32366	-7.31358
ARIMA_100__TRUE	-7.32658	-7.29418	-7.32668	-7.31406
ARIMA_101_FALSE	-7.32077	-7.28837	-7.32087	-7.30825
ARIMA_101__TRUE	-7.33065	-7.29177	-7.33079	-7.31562
ARIMA_102_FALSE	-7.31832	-7.27944	-7.31846	-7.30329
ARIMA_102__TRUE	-7.324	-7.27864	-7.3242	-7.30647
ARIMA_200_FALSE	-7.32009	-7.28769	-7.32019	-7.30757
ARIMA_200__TRUE	-7.32327	-7.28439	-7.32341	-7.30824
ARIMA_201_FALSE	-7.31845	-7.27957	-7.31859	-7.30342
ARIMA_201__TRUE	-7.32208	-7.27672	-7.32227	-7.30455
ARIMA_202_FALSE	-7.31581	-7.27045	-7.31601	-7.29828
ARIMA_202__TRUE	-7.32606	-7.27422	-7.32632	-7.30603

Source: author's computation

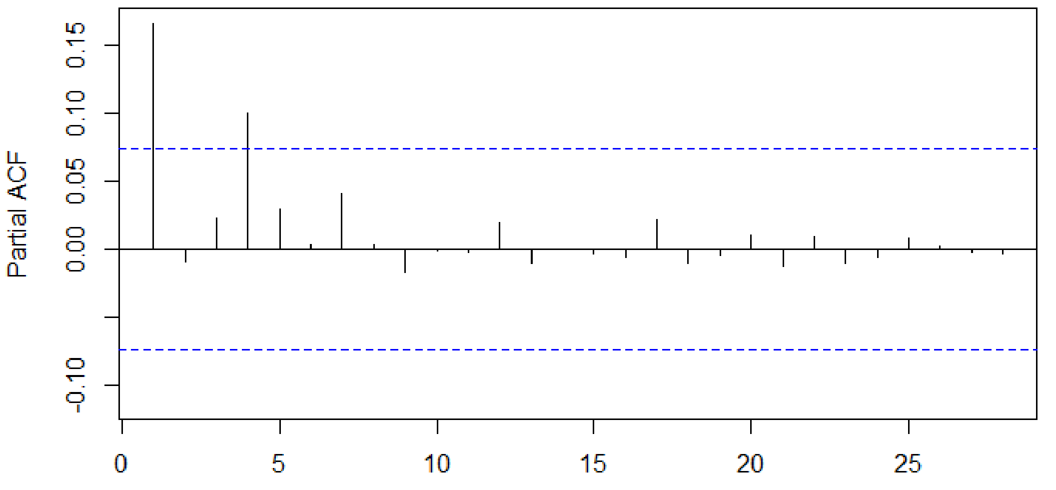
ARCH process diagnostics of returns

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 28.38, df = 20, p-value = 0.1007



ACF – USD squared returns

Source: author's computation



PACF – USD squared returns

Source: author's computation

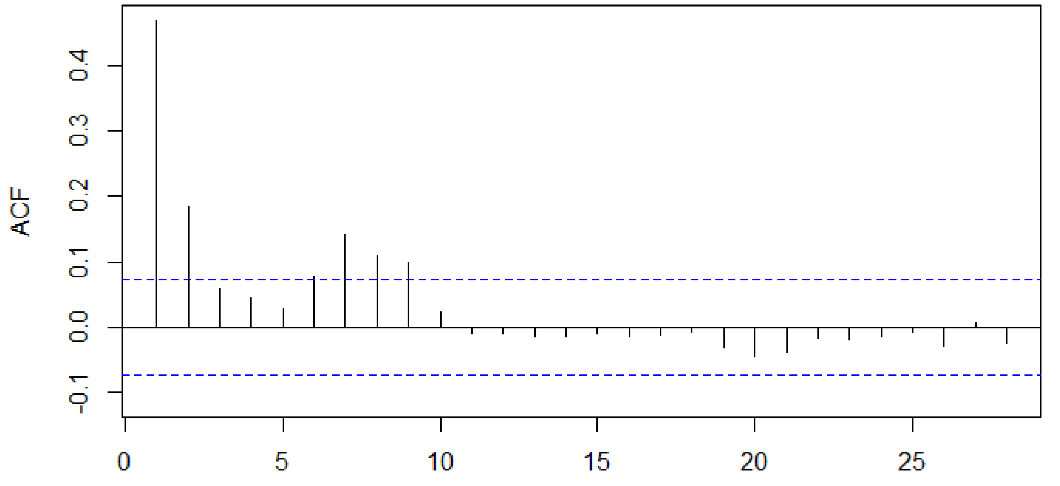
BTC

	Akaike	Bayes	Shibata	Hannan-Quinn
ARIMA_000_FALSE	-3.86477	-3.83885	-3.86483	-3.85475
ARIMA_001_FALSE	-3.86548	-3.83308	-3.86558	-3.85295
ARIMA_001__TRUE	-3.86507	-3.82619	-3.86521	-3.85004
ARIMA_002_FALSE	-3.86376	-3.82488	-3.8639	-3.84873
ARIMA_002__TRUE	-3.86365	-3.81829	-3.86385	-3.84612
ARIMA_100_FALSE	-3.86523	-3.83283	-3.86533	-3.8527
ARIMA_100__TRUE	-3.86481	-3.82594	-3.86496	-3.84979
ARIMA_101_FALSE	-3.86293	-3.82405	-3.86308	-3.84791
ARIMA_101__TRUE	-3.86261	-3.81725	-3.8628	-3.84508
ARIMA_102_FALSE	-3.86095	-3.81559	-3.86114	-3.84342
ARIMA_102__TRUE	-3.86092	-3.80908	-3.86117	-3.84088
ARIMA_200_FALSE	-3.86377	-3.82489	-3.86391	-3.84874
ARIMA_200__TRUE	-3.86381	-3.81845	-3.86401	-3.84628
ARIMA_201_FALSE	-3.86093	-3.81557	-3.86113	-3.8434
ARIMA_201__TRUE	-3.87173	-3.81989	-3.87199	-3.8517
ARIMA_202_FALSE	-3.85808	-3.80625	-3.85834	-3.83805
ARIMA_202__TRUE	**-3.86965**	**-3.81133**	**-3.86997**	**-3.84711**

Source: author's computation

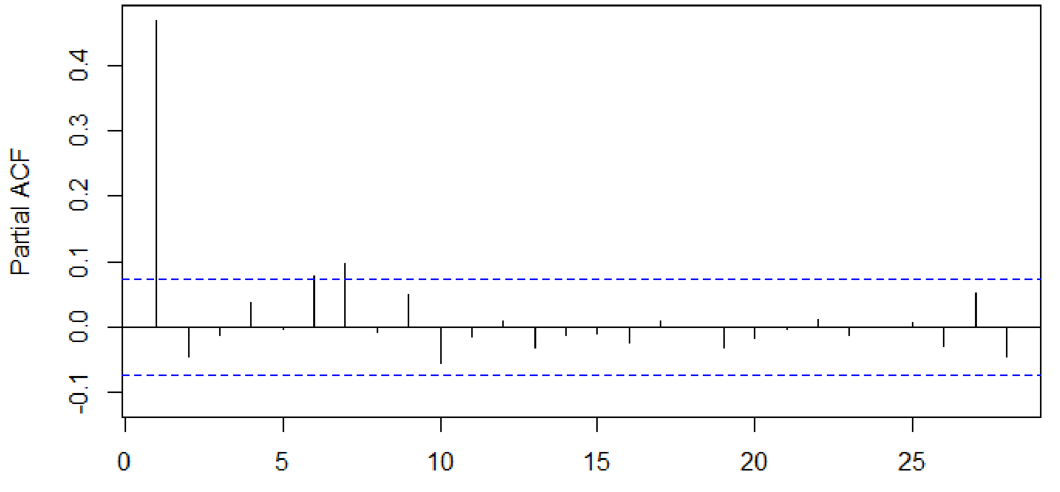
ARCH diagnostics of ARMA residuals

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 165, df = 20, p-value < 2.2e-16



ACF - BTC ARMA(2,2) squared residuals

Source: author's computation



PACF - BTC ARMA(2,2) squared residuals

Source: author's computation

DASH

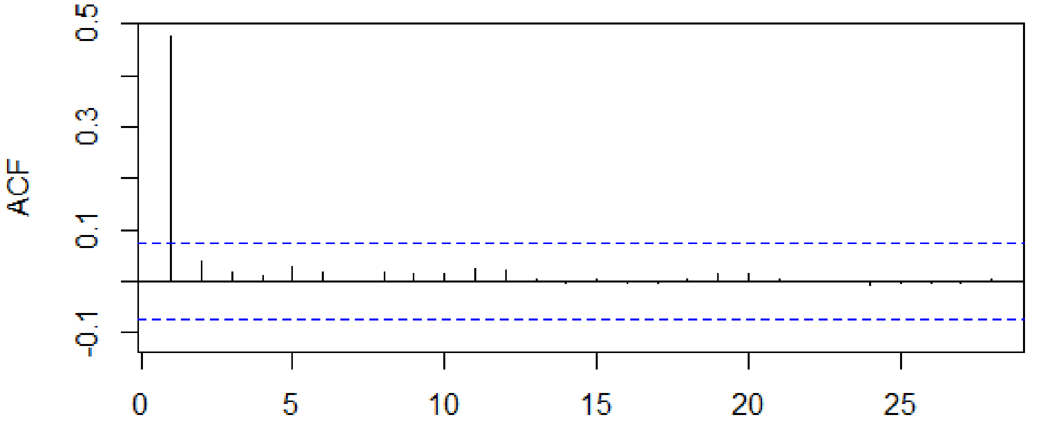
	Akaike	Bayes	Shibata	Hannan-Quinn
ARIMA_000_FALSE	**-2.60743**	**-2.58151**	**-2.60749**	**-2.59741**
ARIMA_001_FALSE	-2.60649	-2.57409	-2.60659	-2.59397
ARIMA_001__TRUE	-2.60627	-2.56739	-2.60641	-2.59124
ARIMA_002_FALSE	-2.58308	-2.5442	-2.58322	-2.56805
ARIMA_002__TRUE	-2.58144	-2.53608	-2.58164	-2.56391
ARIMA_100_FALSE	-2.6065	-2.5741	-2.6066	-2.59398
ARIMA_100__TRUE	-2.60631	-2.56744	-2.60646	-2.59129

ARIMA_101_FALSE	-2.60366	-2.56478	-2.6038	-2.58863
ARIMA_101__TRUE	-2.60347	-2.55811	-2.60367	-2.58594
ARIMA_102_FALSE	-2.58042	-2.53506	-2.58061	-2.56288
ARIMA_102__TRUE	-2.57875	-2.52691	-2.579	-2.55871
ARIMA_200_FALSE	-2.58106	-2.54218	-2.58121	-2.56604
ARIMA_200__TRUE	-2.57968	-2.53432	-2.57988	-2.56215
ARIMA_201_FALSE	-2.57846	-2.5331	-2.57866	-2.56093
ARIMA_201__TRUE	-2.57705	-2.52521	-2.5773	-2.55701
ARIMA_202_FALSE	-2.58142	-2.52958	-2.58168	-2.56139
ARIMA_202__TRUE	-2.5758	-2.51748	-2.57612	-2.55326

Source: author's computation

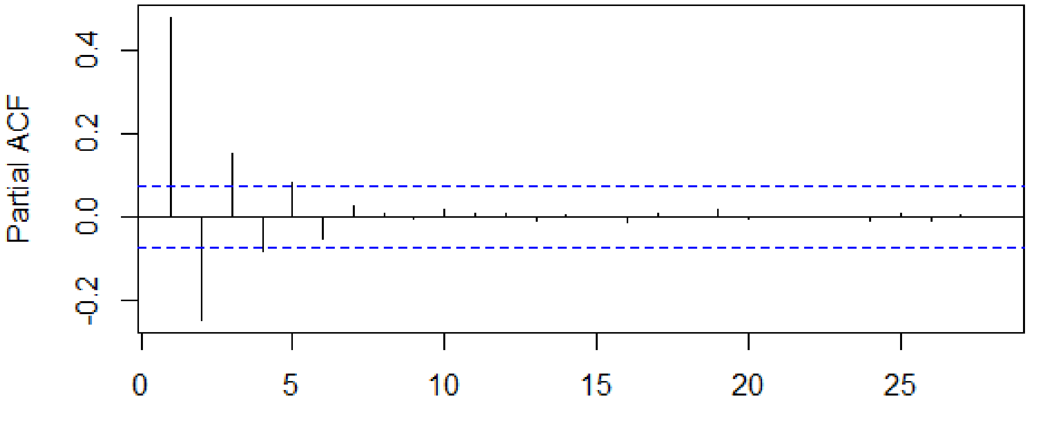
ARCH process diagnostics of returns

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 74.978, df = 20, p-value = 2.747e-08



ACF – DASH squared returns

Source: author's computation



PACF – DASH squared returns

Source: author's computation

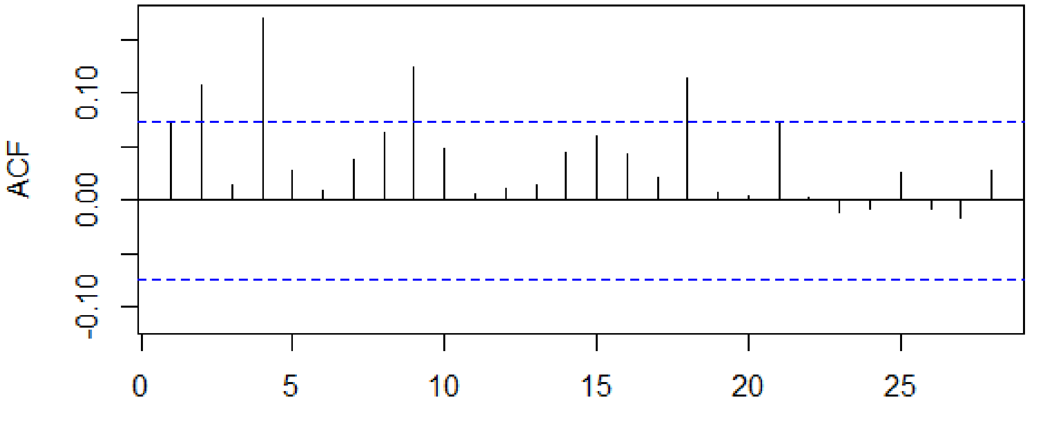
LTC

	Akaike	Bayes	Shibata	Hannan-Quinn
ARIMA_000_FALSE	**-2.76117**	**-2.74173**	**-2.7612**	**-2.75365**
ARIMA_001_FALSE	-2.75833	-2.73241	-2.75839	-2.74831
ARIMA_001__TRUE	-2.75549	-2.72309	-2.75559	-2.74297
ARIMA_002_FALSE	-2.76428	-2.73188	-2.76438	-2.75175
ARIMA_002__TRUE	-2.76143	-2.72255	-2.76157	-2.7464
ARIMA_100_FALSE	-2.75833	-2.73241	-2.75839	-2.74831
ARIMA_100__TRUE	-2.75549	-2.72309	-2.75559	-2.74297
ARIMA_101_FALSE	-2.75786	-2.72546	-2.75796	-2.74534
ARIMA_101__TRUE	-2.75754	-2.71866	-2.75768	-2.74251
ARIMA_102_FALSE	-2.76172	-2.72284	-2.76186	-2.74669
ARIMA_102__TRUE	-2.75887	-2.71352	-2.75907	-2.74134
ARIMA_200_FALSE	-2.76471	-2.73231	-2.76481	-2.75219
ARIMA_200__TRUE	-2.76186	-2.72298	-2.76201	-2.74684
ARIMA_201_FALSE	-2.76242	-2.72354	-2.76256	-2.74739
ARIMA_201__TRUE	-2.75957	-2.71421	-2.75977	-2.74204
ARIMA_202_FALSE	-2.7562	-2.71084	-2.75639	-2.73867
ARIMA_202__TRUE	-2.75834	-2.7065	-2.75859	-2.7383

Source: author's computation

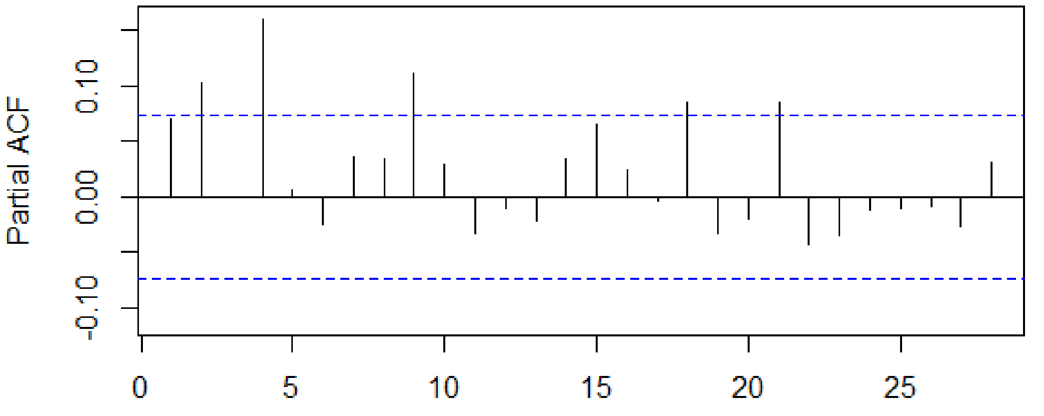
ARCH process diagnostics of returns

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 51.156, df = 20, p-value = 0.000151



ACF – LTC squared returns

Source: author's computation



PACF – LTC squared returns

Source: author's computation

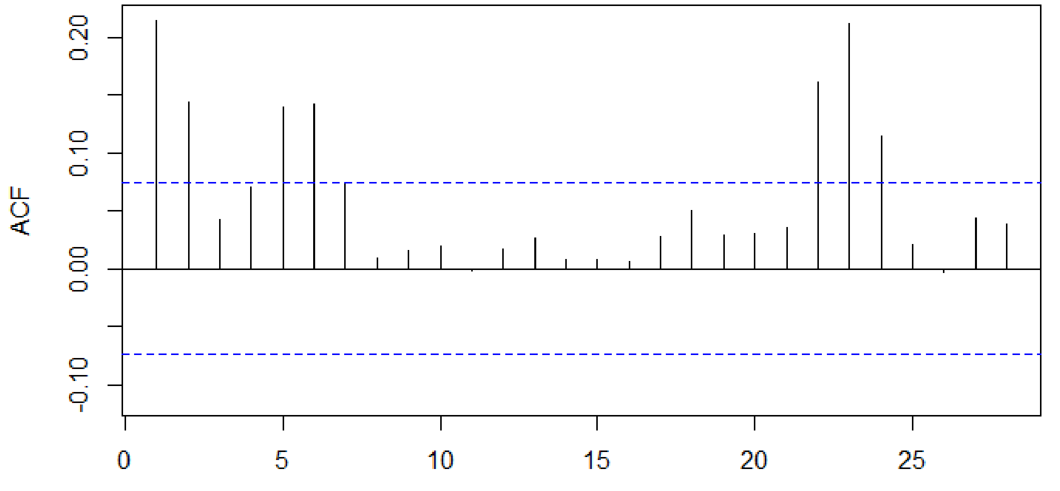
XRP

	Akaike	Bayes	Shibata	Hannan-Quinn
ARIMA_000_FALSE	**-2.60247**	**-2.57655**	**-2.60254**	**-2.59245**
ARIMA_001_FALSE	-2.59994	-2.56754	-2.60004	-2.58742
ARIMA_001__TRUE	-2.59743	-2.55856	-2.59758	-2.58241
ARIMA_002_FALSE	-2.6055	-2.56662	-2.60564	-2.59047
ARIMA_002__TRUE	-2.60366	-2.55831	-2.60386	-2.58613
ARIMA_100_FALSE	-2.59985	-2.56745	-2.59995	-2.58732
ARIMA_100__TRUE	-2.59729	-2.55842	-2.59744	-2.58227
ARIMA_101_FALSE	-2.59808	-2.5592	-2.59823	-2.58306
ARIMA_101__TRUE	-2.59537	-2.55001	-2.59556	-2.57784
ARIMA_102_FALSE	-2.60291	-2.55755	-2.6031	-2.58537
ARIMA_102__TRUE	-2.60103	-2.54919	-2.60129	-2.581
ARIMA_200_FALSE	-2.60233	-2.56345	-2.60247	-2.5873
ARIMA_200__TRUE	-2.6001	-2.55474	-2.6003	-2.58257
ARIMA_201_FALSE	-2.60426	-2.5589	-2.60446	-2.58673
ARIMA_201__TRUE	-2.61126	-2.55942	-2.61152	-2.59123
ARIMA_202_FALSE	-2.60258	-2.55074	-2.60283	-2.58254
ARIMA_202__TRUE	-2.60408	-2.54576	-2.6044	-2.58154

Source: author's computation

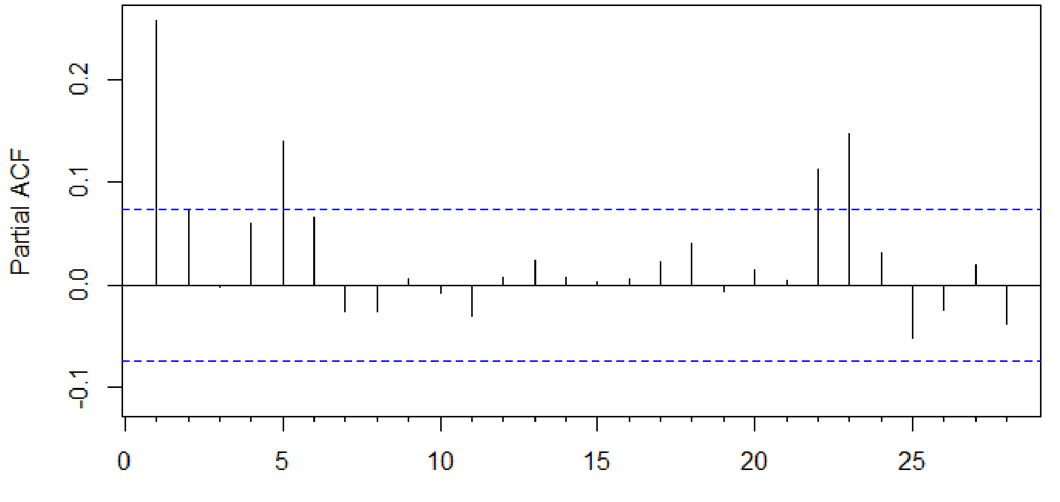
ARCH process diagnostics of returns

ARCH LM-test; Null hypothesis: no ARCH effects. Chi-squared = 68.119, df = 20, p-value = 3.683e-07



ACF – XRP squared returns

Source: author's computation



PACF – XRP squared returns

Source: author's computation

XMR

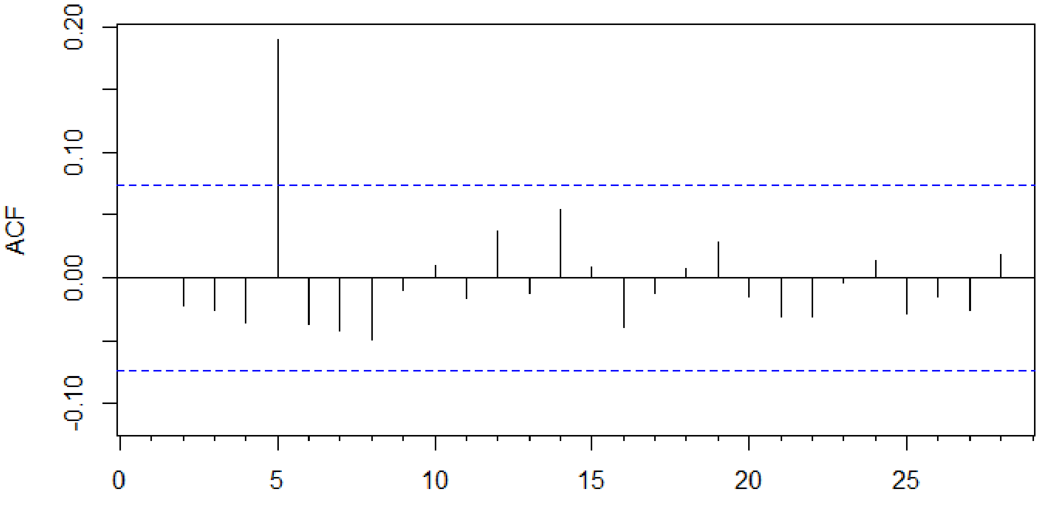
	Akaike	**Bayes**	**Shibata**	**Hannan-Quinn**
ARIMA_000_FALSE	-2.23777	-2.21185	-2.23783	-2.22775
ARIMA_001_FALSE	-2.23908	-2.20668	-2.23918	-2.22656
ARIMA_001__TRUE	-2.23821	-2.19933	-2.23835	-2.22318
ARIMA_002_FALSE	-2.23689	-2.19801	-2.23704	-2.22187
ARIMA_002__TRUE	-2.23605	-2.19069	-2.23625	-2.21852
ARIMA_100_FALSE	-2.23884	-2.20644	-2.23894	-2.22631
ARIMA_100__TRUE	-2.23797	-2.19909	-2.23811	-2.22294

ARIMA_101_FALSE	-2.24721	-2.20834	-2.24736	-2.23219
ARIMA_101__TRUE	-2.24694	-2.20158	-2.24713	-2.22941
ARIMA_102_FALSE	**-2.24535**	**-2.19999**	**-2.24555**	**-2.22782**
ARIMA_102__TRUE	-2.24489	-2.19305	-2.24514	-2.22485
ARIMA_200_FALSE	-2.23624	-2.19736	-2.23639	-2.22122
ARIMA_200__TRUE	-2.23548	-2.19012	-2.23567	-2.21794
ARIMA_201_FALSE	-2.24399	-2.19863	-2.24419	-2.22646
ARIMA_201__TRUE	-2.24369	-2.19185	-2.24395	-2.22366
ARIMA_202_FALSE	-2.24354	-2.1917	-2.24379	-2.2235
ARIMA_202__TRUE	-2.24236	-2.18405	-2.24269	-2.21982

Source: author's computation

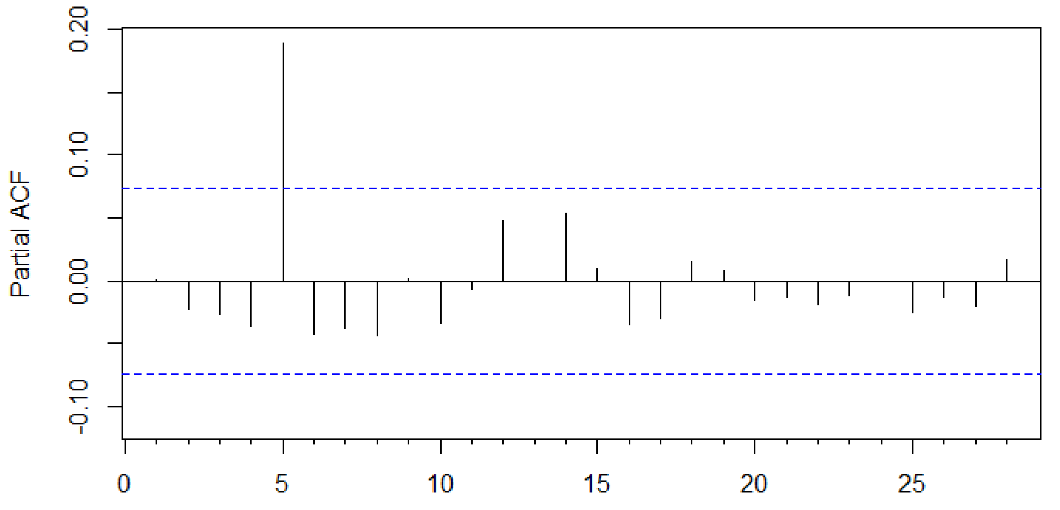
ARCH process diagnostics of ARMA residuals

ARCH LM-test; Null hypothesis: no ARCH effects, data: XMRret , Chi-squared = 90.484, df = 20, p-value = 6.1e-11



ACF – XMR ARMA(1,2)-GARCH(1,1) squared standardized residuals

Source: author's computation



PACF - XMR ARMA(1,2)-GARCH(1,1) squared standardized residuals

Source: author's computation

ARMA(p,q)-__GARCH(p,q) results

Results of ARMA(p,q)-__GARCH(p,q)

	CNY	EUR	USD	BTC	DASH
ARIMA (p, I, q)	2, 0, 2	0, 0, 0	0, 0, 0	2, 0, 2	0, 0, 0
GARCH spec.	gjrGARCH(1,1)	GARCH(1,1)	gjrGARCH(1,1)	GARCH(1,1)	csGARCH(0,1)
AR1	0.234151 (0.000004)***	N/A	N/A	0.777071 (0.0e+00)***	N/A
AR2	-0.877377 (0.000000)***	N/A	N/A	0.196833 (0.0e+00)***	N/A
MA1	-0.190752 (0.000000)***	N/A	N/A	-0.725715 (0.0e+00)***	N/A
MA2	0.928805 (0.000000)***	N/A	N/A	-0.275001 (0.0e+00)***	N/A
ω	0.000004 (0.000000)***	0.000002 (0.013498)**	0.000003 (0.000058)***	0.000127 (7.9e-05)***	0.00030 (2e-06)***
α1	0.069268 (0.000155)***	0.065223 (0.000000)***	0.066833 (0.000420)***	0.219306 (0.0e+00)***	N/A
α2	N/A	N/A	N/A	N/A	N/A
β	0.784295 (0.000000)***	0.890685 (0.000000)***	0.817368 (0.000000)***	0.718062 (0.0e+00)***	0.86926 (0e+00)***
γ	0.110126 (0.008601)***	N/A	0.127866 (0.001786)***	N/A	N/A
δ	N/A	N/A	N/A	N/A	N/A
η11	N/A	N/A	N/A	N/A	0.99911 (0e+00)***
η21	N/A	N/A	N/A	N/A	0.33906 (0e+00)***

trend	N/A	N/A	N/A	0.000019 (0.0e+00)***	N/A
ARCH-M	N/A	N/A	N/A	-0.116517 (0.0e+00)***	N/A
Ljung-Box test - z	[19] 9.93458 (0.4792)	[5] 0.9088 (0.8800)	[5] 1.0916 (0.8386)	[19] 10.76 (0.34798)	[5] 2.2932 (0.5509)
ARCH-LM test - z	[3] 0.05528 (0.81412)	[3] 0.236 (0.6271)	[3] 0.05768 (0.8102)	[3] 0.4608 (0.4973)	[2] 0.00349 (0.9529)
Unconditional variance	4.21E-05	4.61E-05	5.49E-05	0.002022689	0.337102
Persistence	0.908626	0.9559085	0.9481341	0.9373677	0.9991110
Transitory persistence	N/A	N/A	N/A	N/A	0.8692621

	DASH - shortened	**LTC**	**XMR**	**XRP**	**XRP - shortened**
ARIMA (p, I, q)	0, 0, 0	0, 0, 0	1, 0, 1	0, 0, 0	0, 0, 0
GARCH spec.	GARCH(1,1)	csGARCH(0,1)	GARCH(5,0)	csGARCH(1,1)	apARCH(1,1)
AR1	N/A	N/A	0.996308 (0.000000)***	N/A	N/A
AR2	N/A	N/A	N/A	N/A	N/A
MA1	N/A	N/A	-0.995725 (0.000000)***	N/A	N/A
MA2	N/A	N/A	N/A	N/A	N/A
ω	0.000257 (0.001261)***	0.00030 (0.009186)***	0.003215 (0.000000)***	0.000329 (0e+00)***	0.050689 (0.037653)**
α1	0.281549 (0.000000)***	N/A	0.380997 (0.000001)***	0.526611 (0e+00)***	0.472403 (0.000000)***
α2	N/A	N/A	α5 0.264916 (0.000004)***	N/A	N/A
β	0.704913 (0.000000)***	0.88289 (0.000000)***	N/A	0.440898 (0e+00)***	0.358331 (0.000000)***
γ	N/A	N/A	N/A	N/A	-0.531374 (0.000000)***
δ	N/A	N/A	N/A	N/A	0.684729 (0.000072)***
η11	N/A	0.95746 (0.000000)***	N/A	0.999148 (0e+00)***	N/A
η21	N/A	0.14174 (0.000097)***	N/A	0.320812 (0e+00)***	N/A
trend	N/A	N/A	0.000003 (0.312789)	-0.000015 (3e-06)***	0.000000 (0.924989)
ARCH-M	N/A	N/A	N/A	N/A	N/A
Ljung-Box test - z	[5] 1.9558 (0.6289)	[5] 1.1927 (0.8147)	[14] 9.820 (1.347e-01)***	[5] 2.626 (0.4796)	[5] 0.800260 (0.9030)
ARCH-LM test - z	[3] 0.8738 (0.3499)	[2] 0.0204 (0.8864)	[7] 0.4780 (0.4893)	[3] 0.02288 (0.8798)	[3] 0.001474 (0.9694)
Unconditional variance	0.01899591	0.007063666	0.009078277	0.3859852	0.007101712
Persistence	0.9864617	0.9574640	0.6459124	0.9991476	0.7242418
Transitory persistence	N/A	0.8828954	N/A	0.9675092	N/A

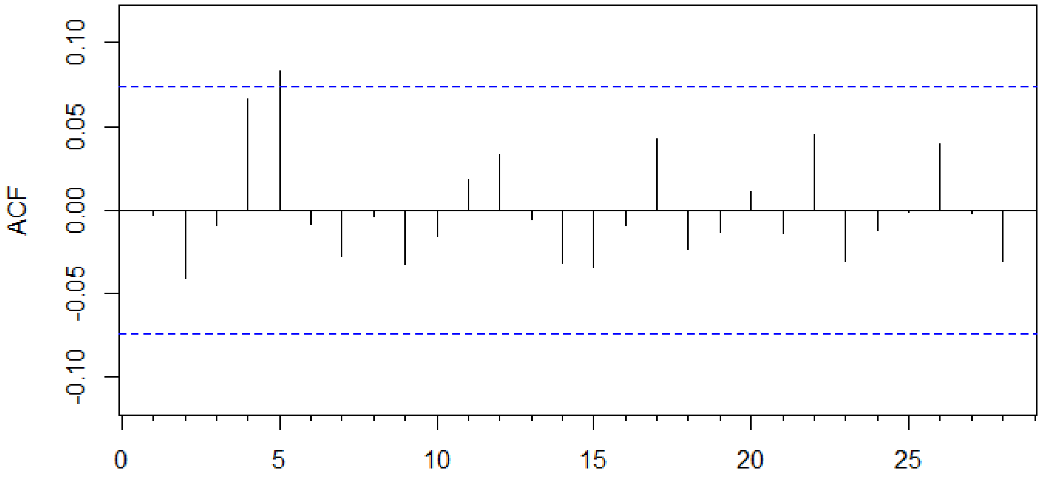
Source: author's computation

Information criteria, autocorrelograms, variance

CNY

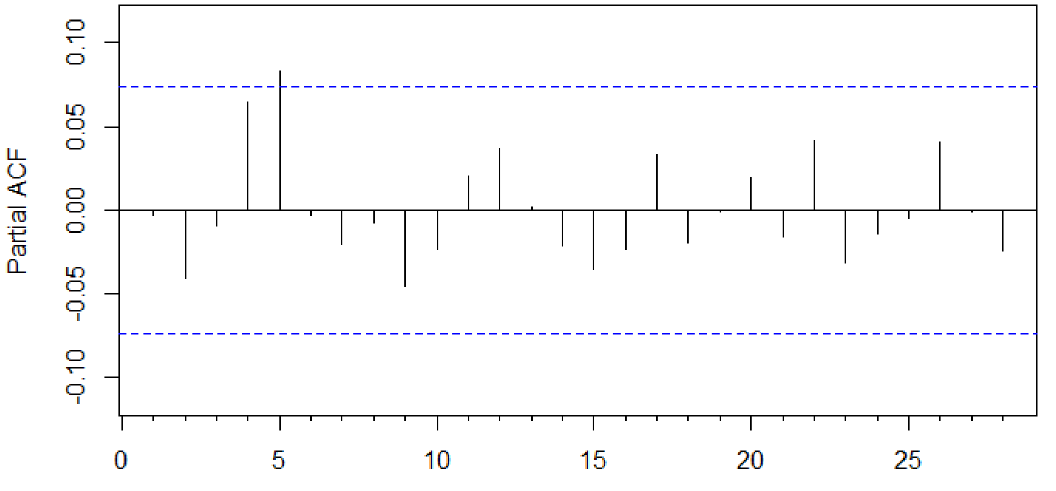
	Akaike	Bayes	Shibata	Hannan-Quinn
CNYARIMA_sGARCH11	-7.39888	-7.35352	-7.39908	-7.38135
CNYARIMA_sGARCH11	-7.39767	-7.34583	-7.39792	-7.37763
CNYARIMA_sGARCH21	-7.39769	-7.34585	-7.39795	-7.37766
CNYARIMA_sGARCH21	-7.39609	-7.33777	-7.39641	-7.37355
CNYARIMA_eGARCH11	-7.39891	-7.34707	-7.39917	-7.37888
CNYARIMA_eGARCH11	-7.39608	-7.33776	-7.3964	-7.37354
CNYARIMA_eGARCH21	-7.39667	-7.33187	-7.39706	-7.37162
CNYARIMA_eGARCH21	-7.39393	-7.32265	-7.39441	-7.36638
CNYARIMA_gjrGARCH	**-7.40383**	**-7.35199**	**-7.40409**	**-7.3838**
CNYARIMA_gjrGARCH	-7.40149	-7.34317	-7.40182	-7.37895
CNYARIMA_gjrGARCH	-7.38259	-7.31779	-7.38299	-7.35755
CNYARIMA_gjrGARCH	-7.39627	-7.325	-7.39675	-7.36873
CNYARIMA_apARCH11	-7.37054	-7.31222	-7.37086	-7.348
CNYARIMA_apARCH11	-7.37457	-7.30977	-7.37496	-7.34952
CNYARIMA_apARCH21	-7.37556	-7.30428	-7.37604	-7.34801
CNYARIMA_apARCH21	-7.35977	-7.28201	-7.36034	-7.32972
CNYARIMA_iGARCH11	-7.3873	-7.34843	-7.38745	-7.37228
CNYARIMA_iGARCH11	-7.37459	-7.32923	-7.37478	-7.35706
CNYARIMA_iGARCH21	-7.38891	-7.34355	-7.3891	-7.37138
CNYARIMA_iGARCH21	-7.37304	-7.3212	-7.37329	-7.353
CNYARIMA_csGARCH1	-7.36448	-7.30616	-7.3648	-7.34194
CNYARIMA_csGARCH1	-7.3588	-7.29401	-7.3592	-7.33376
CNYARIMA_csGARCH2	-7.36761	-7.30281	-7.36801	-7.34257
CNYARIMA_csGARCH2	-7.35459	-7.28331	-7.35507	-7.32704
CNYARIMA_sGARCH10	-0.28334	-0.24446	-0.28349	-0.26832
CNYARIMA_eGARCH01	-7.23796	-7.19908	-7.2381	-7.22293
CNYARIMA_eGARCH01	-7.23634	-7.19098	-7.23653	-7.21881
CNYARIMA_gjrGARCH	17.48086	17.52622	17.48066	17.49839
CNYARIMA_apARCH10	-7.326	-7.27416	-7.32625	-7.30596
CNYARIMA_apARCH10	-7.325	-7.26668	-7.32532	-7.30246
CNYARIMA_apARCH01	-7.21547	-7.17011	-7.21567	-7.19794
CNYARIMA_apARCH01	-7.21141	-7.15957	-7.21167	-7.19138
CNYARIMA_iGARCH01	-7.24076	-7.20836	-7.24086	-7.22824
CNYARIMA_iGARCH01	-7.23913	-7.20025	-7.23927	-7.2241

Source: author’s computation



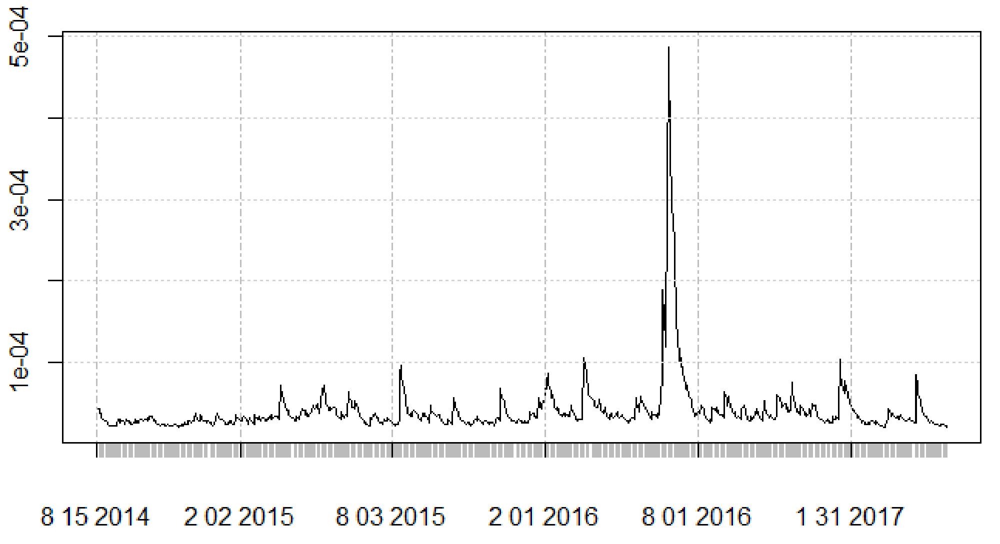
ACF – CNY ARMA(2,2)-gjrGARCH(1,1) squared standardized residuals

Source: author's computation



PACF – CNY ARMA(2,2)-gjrGARCH(1,1) squared standardized residuals

Source: author's computation



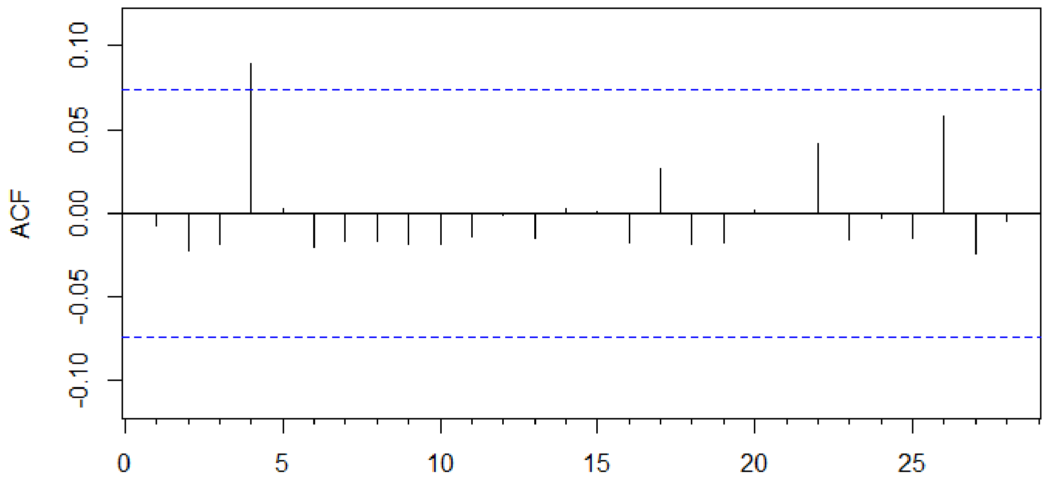
CNY conditional variance

Source: author's computation

EUR

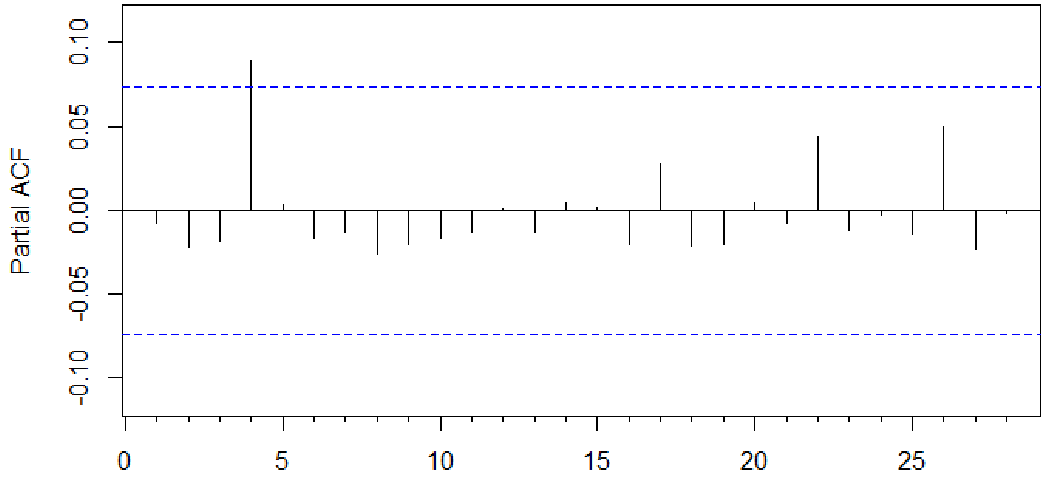
	Akaike	Bayes	Shibata	Hannan-Quinn
EURARIMA000_sGARCH11	**-7.289384**	**-7.269944**	**-7.28942**	**-7.281871**
EURARIMA000_sGARCH21	-7.291273	-7.265354	-7.291337	-7.281256
EURARIMA000_eGARCH11	-7.290819	-7.264899	-7.290883	-7.280801
EURARIMA000_eGARCH21	-7.297043	-7.258163	-7.297187	-7.282017
EURARIMA000_gjrGARCH11	-7.297079	-7.271159	-7.297143	-7.287061
EURARIMA000_gjrGARCH21	-7.295352	-7.256472	-7.295496	-7.280325
EURARIMA000_apARCH11	-7.291047	-7.258648	-7.291147	-7.278525
EURARIMA000_apARCH21	-7.286824	-7.241465	-7.28702	-7.269294
EURARIMA000_iGARCH11	-7.284029	-7.271069	-7.284045	-7.27902
EURARIMA000_iGARCH21	-7.283937	-7.264497	-7.283973	-7.276424
EURARIMA000_csGARCH11	-7.272934	-7.240534	-7.273034	-7.260412
EURARIMA000_csGARCH21	-7.273758	-7.234878	-7.273902	-7.258732
EURARIMA000_sGARCH10	-7.258306	-7.245346	-7.258322	-7.253297
EURARIMA000_sGARCH01	-7.251955	-7.238995	-7.251971	-7.246946
EURARIMA000_eGARCH01	-7.252259	-7.239299	-7.252275	-7.24725
EURARIMA000_gjrGARCH01	-7.251955	-7.238995	-7.251971	-7.246946
EURARIMA000_apARCH10	-7.249308	-7.223389	-7.249373	-7.239291
EURARIMA000_apARCH01	-7.23907	-7.21963	-7.239106	-7.231557
EURARIMA000_iGARCH01	-7.254267	-7.247787	-7.254271	-7.251763
EURARIMA000_csGARCH01	-7.268716	-7.242796	-7.26878	-7.258698

Source: author's computation



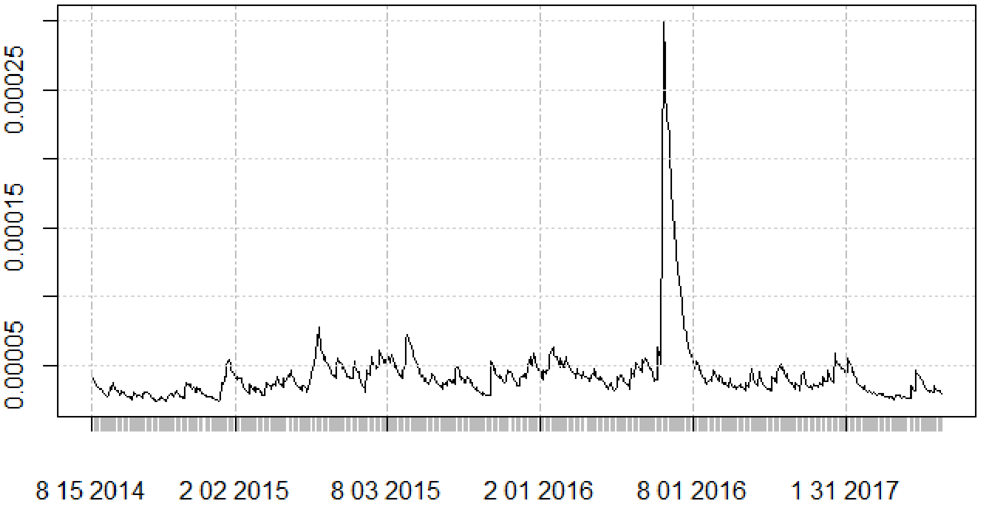
ACF – EUR GARCH(1,1) squared standardized residuals

Source: author's computation



PACF – EUR GARCH(1,1) squared standardized residuals

Source: author's computation



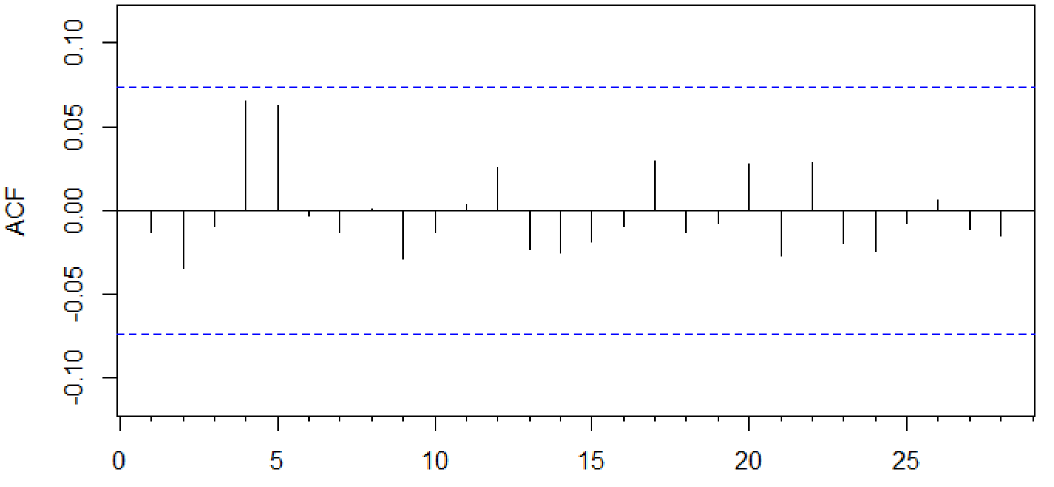
EUR conditional variance

Source: author's computation

USD

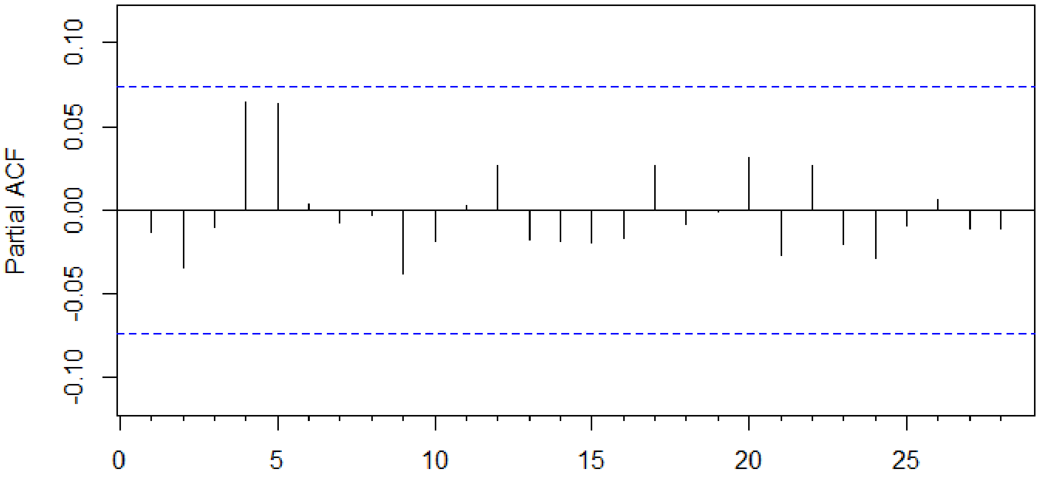
	Akaike	Bayes	Shibata	Hannan-Quinn
USDARIMA000_sGARCH11	-7.3264	-7.30696	-7.32644	-7.31889
USDARIMA000_sGARCH21	-7.33381	-7.30789	-7.33388	-7.32379
USDARIMA000_eGARCH11	-7.32887	-7.30295	-7.32893	-7.31885
USDARIMA000_eGARCH21	-7.3559	-7.31703	-7.35605	-7.34088
USDARIMA000_gjrGARCH11	**-7.33468**	**-7.30876**	**-7.33474**	**-7.32466**
USDARIMA000_gjrGARCH21	-7.34141	-7.30253	-7.34155	-7.32638
USDARIMA000_apARCH11	-7.31389	-7.28149	-7.31399	-7.30136
USDARIMA000_apARCH21	-7.31645	-7.2711	-7.31665	-7.29892
USDARIMA000_iGARCH11	-7.3244	-7.31144	-7.32442	-7.31939
USDARIMA000_iGARCH21	-7.32972	-7.31028	-7.32976	-7.32221
USDARIMA000_csGARCH11	-7.01897	-6.98657	-7.01907	-7.00645
USDARIMA000_csGARCH21	-7.32066	-7.28178	-7.3208	-7.30563
USDARIMA000_sGARCH10	-7.18698	-7.17402	-7.187	-7.18197
USDARIMA000_sGARCH01	-7.12985	-7.11689	-7.12987	-7.12484
USDARIMA000_eGARCH01	-7.13074	-7.11778	-7.13076	-7.12574
USDARIMA000_gjrGARCH01	-7.12985	-7.11689	-7.12987	-7.12484
USDARIMA000_apARCH10	-7.15196	-7.12604	-7.15202	-7.14194
USDARIMA000_apARCH01	-7.10282	-7.08338	-7.10286	-7.09531
USDARIMA000_iGARCH01	-7.13343	-7.12695	-7.13343	-7.13092
USDARIMA000_csGARCH01	-7.24941	-7.22349	-7.24948	-7.23939

Source: author's computation



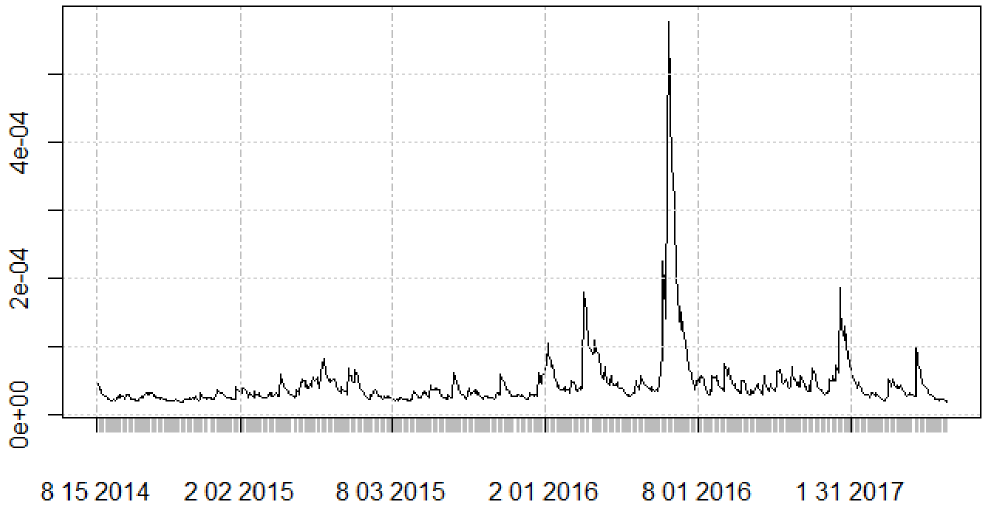
ACF – USD gjrGARCH(1,1) squared standardized residuals

Source: author's computation



PACF – USD gjrGARCH(1,1) squared standardized residuals

Source: author's computation



USD conditional variance

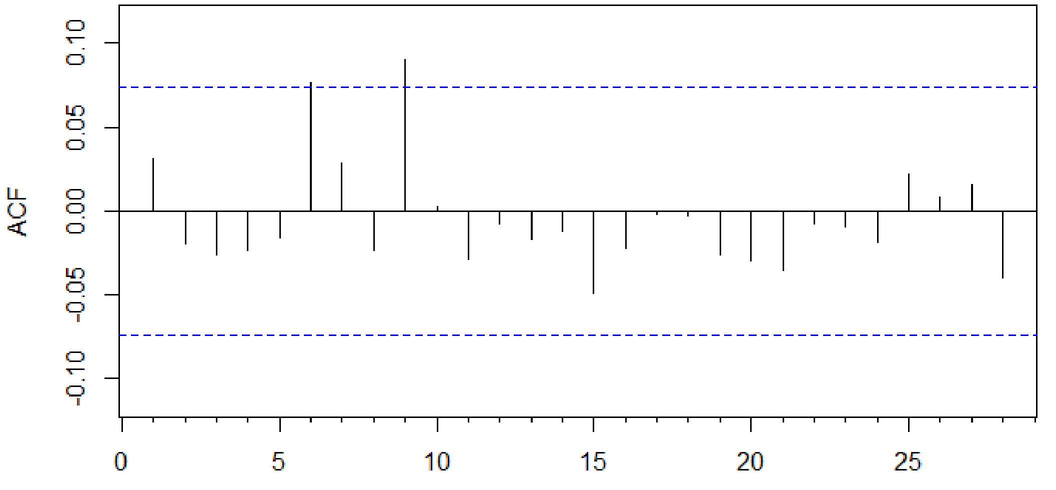
Source: author's computation

BTC

	Akaike	Bayes	Shibata	Hannan-Quinn
BTCARIMA000_sGARCH11	-3.85808	-3.80625	-3.85834	-3.83805
BTCARIMA000_sGARCH11	**-3.86965**	**-3.81133**	**-3.86997**	**-3.84711**
BTCARIMA000_sGARCH21	-3.87179	-3.81347	-3.87211	-3.84925
BTCARIMA000_sGARCH21	-3.87144	-3.80664	-3.87184	-3.8464
BTCARIMA000_eGARCH11	-3.87879	-3.82048	-3.87912	-3.85625
BTCARIMA000_eGARCH11	-3.87661	-3.81181	-3.87701	-3.85157
BTCARIMA000_eGARCH21	-3.90364	-3.83236	-3.90412	-3.87609
BTCARIMA000_eGARCH21	-3.90416	-3.8264	-3.90473	-3.87411
BTCARIMA000_gjrGARCH11	-3.87353	-3.81521	-3.87385	-3.85099
BTCARIMA000_gjrGARCH11	-3.87269	-3.80789	-3.87309	-3.84765
BTCARIMA000_gjrGARCH21	-3.89694	-3.82566	-3.89742	-3.86939
BTCARIMA000_gjrGARCH21	-3.8968	-3.81904	-3.89737	-3.86675
BTCARIMA000_apARCH11	-3.86026	-3.79546	-3.86066	-3.83522
BTCARIMA000_apARCH11	-3.85935	-3.78807	-3.85983	-3.8318
BTCARIMA000_apARCH21	-3.86552	-3.78776	-3.86609	-3.83547
BTCARIMA000_apARCH21	-3.8664	-3.78216	-3.86707	-3.83384
BTCARIMA000_iGARCH11	-3.85845	-3.8131	-3.85865	-3.84092
BTCARIMA000_iGARCH11	-3.8579	-3.80606	-3.85815	-3.83786
BTCARIMA000_iGARCH21	-3.87089	-3.81905	-3.87114	-3.85085
BTCARIMA000_iGARCH21	-3.86404	-3.80572	-3.86436	-3.8415
BTCARIMA000_csGARCH11	-3.87104	-3.80625	-3.87144	-3.846
BTCARIMA000_csGARCH11	-3.87011	-3.79883	-3.87059	-3.84256
BTCARIMA000_csGARCH21	-3.8682	-3.79692	-3.86868	-3.84066
BTCARIMA000_csGARCH21	-3.86727	-3.78951	-3.86784	-3.83721

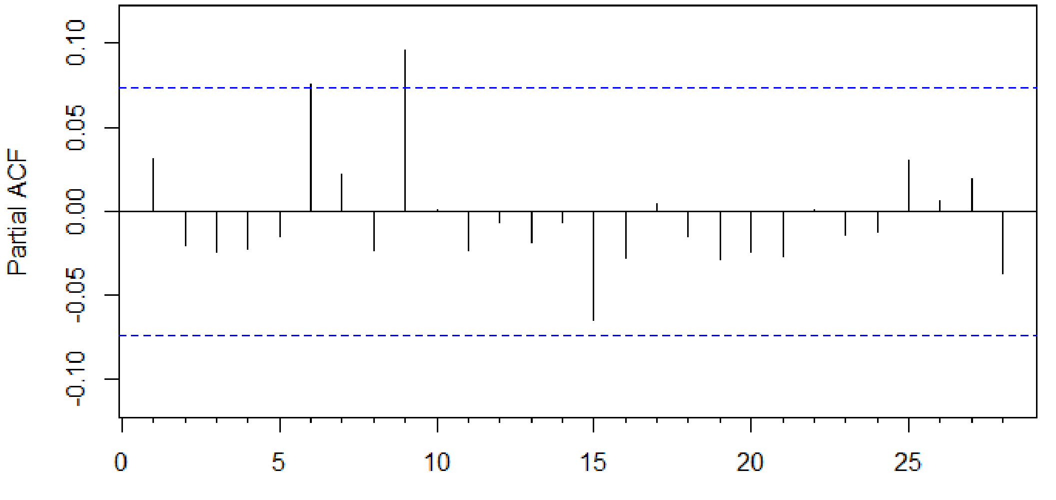
BTCARIMA000_eGARCH01	-3.58738	-3.54202	-3.58757	-3.56985
BTCARIMA000_eGARCH01	-3.58787	-3.53603	-3.58813	-3.56784
BTCARIMA000_gjrGARCH10	-3.76438	-3.70606	-3.7647	-3.74184
BTCARIMA000_apARCH10	235.7503	235.8151	235.7499	235.7753
BTCARIMA000_apARCH01	-3.60826	-3.54994	-3.60858	-3.58572
BTCARIMA000_iGARCH01	-3.5899	-3.55102	-3.59005	-3.57488
BTCARIMA000_iGARCH01	-3.51612	-3.47076	-3.51631	-3.49859
BTCARIMA000_csGARCH01	-3.85599	-3.79768	-3.85632	-3.83346
BTCARIMA000_csGARCH01	-3.85877	-3.79397	-3.85917	-3.83373

Source: author's computation



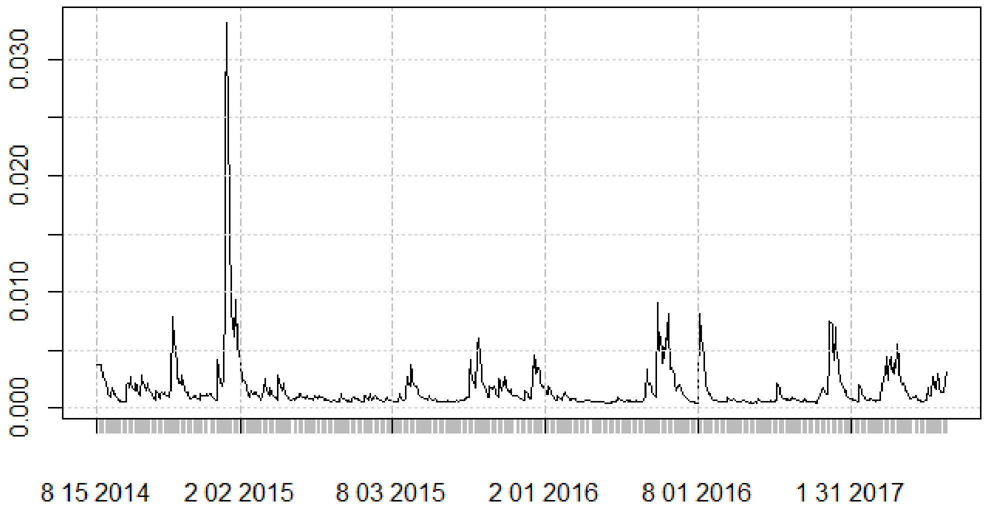
ACF – BTC ARMA(2,2)-GARCH(1,1) squared standardized residuals

Source: author's computation



PACF – BTC ARMA(2,2)-GARCH(1,1) squared standardized residuals

Source: author's computation



BTC conditional variance

Source: author's computation

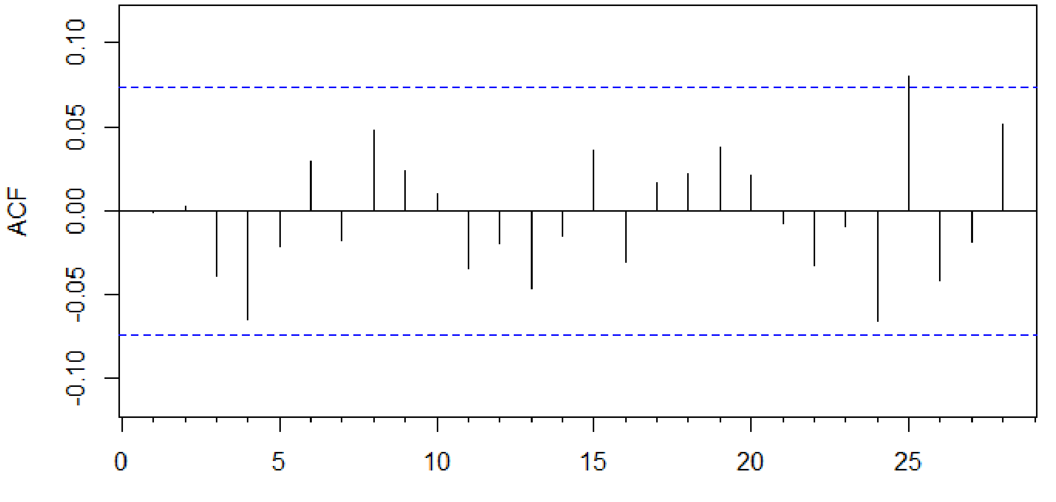
DASH

	Akaike	Bayes	Shibata	Hannan-Quinn
DASHARIMA000_sGARCH11	-2.605647	-2.586207	-2.605683	-2.598134
DASHARIMA000_sGARCH21	-2.580883	-2.554963	-2.580947	-2.570865
DASHARIMA000_eGARCH11	-2.608701	-2.582781	-2.608765	-2.598683
DASHARIMA000_eGARCH21	-2.593212	-2.554333	-2.593356	-2.578186
DASHARIMA000_gjrGARCH11	-2.605221	-2.579301	-2.605285	-2.595203
DASHARIMA000_gjrGARCH21	-2.577986	-2.539107	-2.57813	-2.56296
DASHARIMA000_apARCH11	-2.680655	-2.648255	-2.680755	-2.668133
DASHARIMA000_apARCH21	-2.687398	-2.642039	-2.687594	-2.669868
DASHARIMA000_iGARCH11	-2.608561	-2.595601	-2.608577	-2.603552
DASHARIMA000_iGARCH21	-2.582318	-2.562878	-2.582354	-2.574805
DASHARIMA000_csGARCH11	-2.731281	-2.698881	-2.731381	-2.718759
DASHARIMA000_csGARCH21	-2.72908	-2.690201	-2.729224	-2.714054
DASHARIMA000_sGARCH10	-2.48559	-2.47263	-2.485606	-2.480581
DASHARIMA000_sGARCH01	-2.248205	-2.235245	-2.248221	-2.243196
DASHARIMA000_eGARCH01	-2.247409	-2.23445	-2.247425	-2.242401
DASHARIMA000_gjrGARCH10	-2.500192	-2.480752	-2.500228	-2.492679
DASHARIMA000_gjrGARCH01	-2.248205	-2.235245	-2.248221	-2.243196
DASHARIMA000_apARCH10	-2.502126	-2.476206	-2.50219	-2.492108
DASHARIMA000_apARCH01	-2.456657	-2.437218	-2.456694	-2.449144
DASHARIMA000_iGARCH01	-2.179021	-2.172541	-2.179025	-2.176516
DASHARIMA000_csGARCH01	**-2.731978**	**-2.706058**	**-2.732042**	**-2.72196**

Source: author's computation

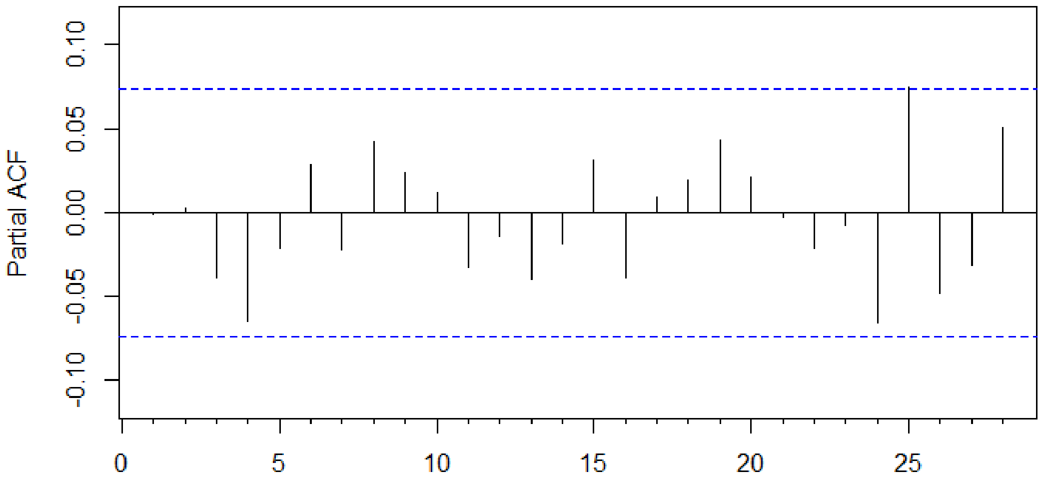
	Akaike	Bayes	Shibata	Hannan-Quinn
DASHARIMA000_sGARCH11	**-2.80079**	**-2.780701**	**-2.800829**	**-2.793011**
DASHARIMA000_sGARCH21	-2.797976	-2.771191	-2.798046	-2.787604
DASHARIMA000_eGARCH11	-2.797946	-2.771161	-2.798016	-2.787574
DASHARIMA000_eGARCH21	-2.798487	-2.758309	-2.798643	-2.782929
DASHARIMA000_gjrGARCH11	-2.800575	-2.77379	-2.800645	-2.790203
DASHARIMA000_gjrGARCH21	-2.794898	-2.754721	-2.795054	-2.77934
DASHARIMA000_apARCH11	-2.797608	-2.764127	-2.797717	-2.784643
DASHARIMA000_apARCH21	-2.791894	-2.745021	-2.792107	-2.773743
DASHARIMA000_iGARCH11	-2.803499	-2.790107	-2.803517	-2.798313
DASHARIMA000_iGARCH21	-2.800688	-2.7806	-2.800728	-2.79291
DASHARIMA000_csGARCH11	-2.793269	-2.759788	-2.793378	-2.780304
DASHARIMA000_csGARCH21	-2.789277	-2.7491	-2.789433	-2.773719
DASHARIMA000_sGARCH10	-2.665674	-2.652281	-2.665691	-2.660488
DASHARIMA000_sGARCH01	-2.562379	-2.548987	-2.562397	-2.557193
DASHARIMA000_eGARCH01	-2.56123	-2.547837	-2.561247	-2.556044
DASHARIMA000_gjrGARCH10	-2.664538	-2.644449	-2.664577	-2.656759
DASHARIMA000_gjrGARCH01	-2.562379	-2.548987	-2.562397	-2.557193
DASHARIMA000_apARCH10	-2.662221	-2.635436	-2.662291	-2.651849
DASHARIMA000_apARCH01	-2.570422	-2.550334	-2.570462	-2.562643
DASHARIMA000_iGARCH01	-2.564103	-2.557407	-2.564107	-2.56151
DASHARIMA000_csGARCH01	-2.795817	-2.769032	-2.795887	-2.785445

Source: author's computation



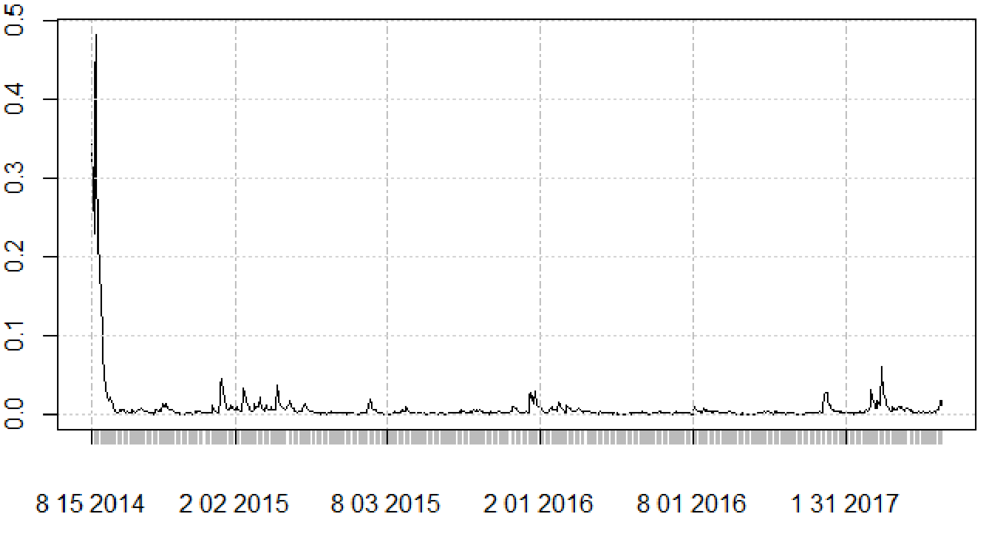
PACF – DASH cGARCH(0,1) squared standardized residuals

Source: author's computation



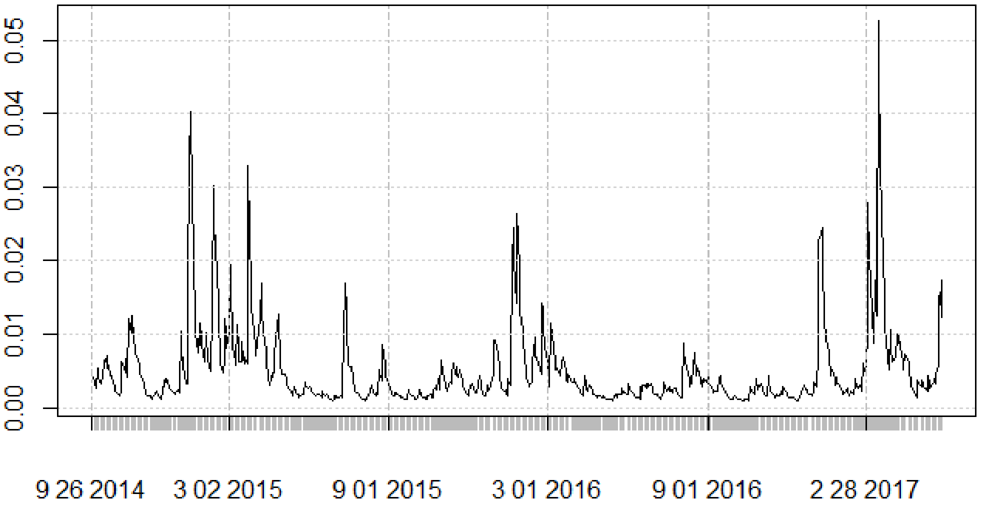
PACF – DASH cGARCH(0,1) squared standardized residuals

Source: author's computation



DASH conditional variance

Source: author's computation

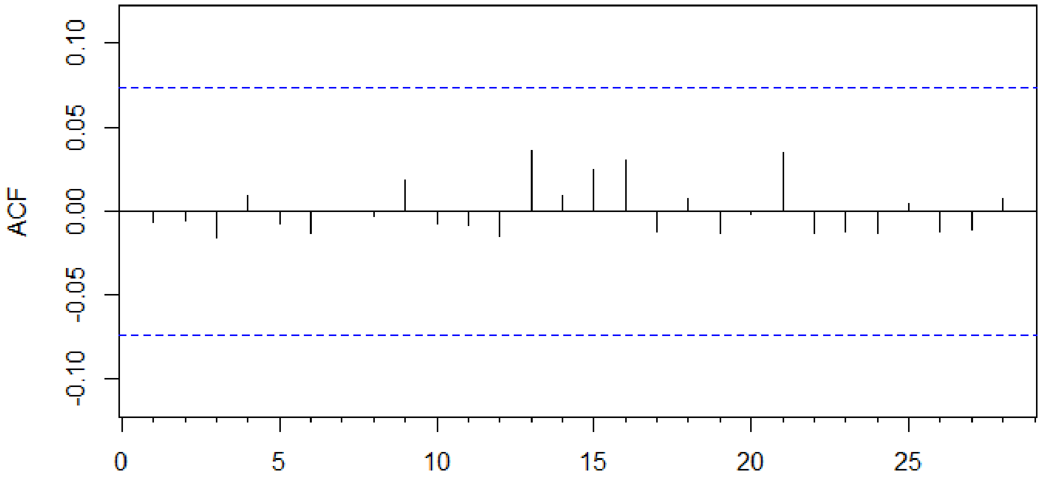


DASH conditional variance – restricted sample

Source: author's computation

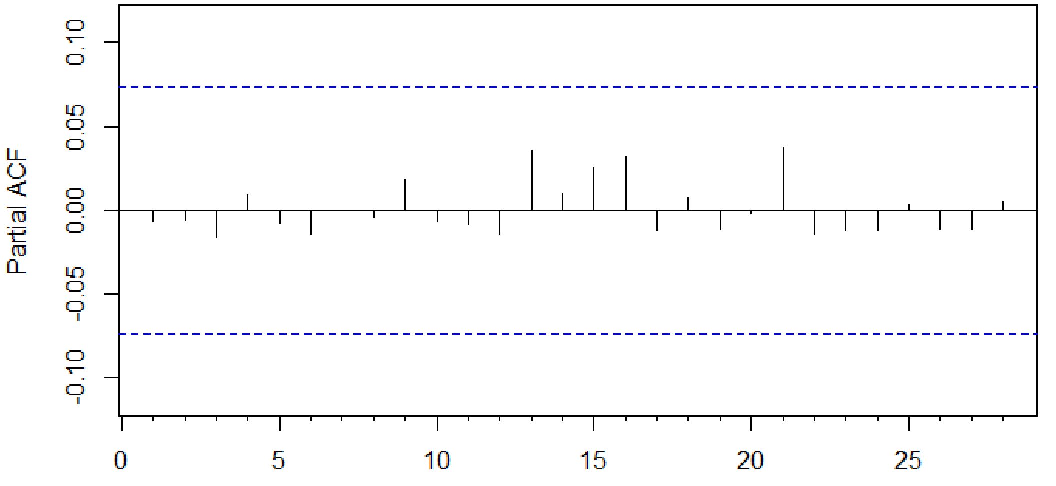
LTC

	Akaike	Bayes	Shibata	Hannan-Quinn
LTCARIMA000_sGARCH11	-2.761166	-2.741726	-2.761202	-2.753653
LTCARIMA000_sGARCH21	-2.761249	-2.735329	-2.761313	-2.751231
LTCARIMA000_eGARCH11	-2.786711	-2.760791	-2.786775	-2.776693
LTCARIMA000_eGARCH21	-2.80212	-2.763241	-2.802264	-2.787094
LTCARIMA000_gjrGARCH11	-2.763783	-2.737863	-2.763847	-2.753765
LTCARIMA000_gjrGARCH21	-2.761313	-2.722434	-2.761457	-2.746287
LTCARIMA000_apARCH11	-2.761019	-2.728619	-2.761119	-2.748497
LTCARIMA000_apARCH21	-2.75887	-2.713511	-2.759066	-2.74134
LTCARIMA000_iGARCH11	-2.752885	-2.739926	-2.752902	-2.747877
LTCARIMA000_iGARCH21	-2.75342	-2.733981	-2.753456	-2.745907
LTCARIMA000_csGARCH11	-2.76717	-2.73477	-2.76727	-2.754648
LTCARIMA000_csGARCH21	-2.765727	-2.726848	-2.765872	-2.750701
LTCARIMA000_sGARCH10	-2.655927	-2.642967	-2.655943	-2.650918
LTCARIMA000_sGARCH01	-2.495119	-2.48216	-2.495135	-2.490111
LTCARIMA000_eGARCH01	-2.495069	-2.482109	-2.495085	-2.49006
LTCARIMA000_gjrGARCH10	-2.669864	-2.650424	-2.6699	-2.662351
LTCARIMA000_gjrGARCH01	-2.495119	-2.48216	-2.495135	-2.490111
LTCARIMA000_apARCH10	-2.702208	-2.676288	-2.702272	-2.69219
LTCARIMA000_apARCH01	-2.513334	-2.493894	-2.51337	-2.505821
LTCARIMA000_iGARCH01	-2.49753	-2.491051	-2.497534	-2.495026
LTCARIMA000_csGARCH01	**-2.770856**	**-2.744936**	**-2.77092**	**-2.760838**



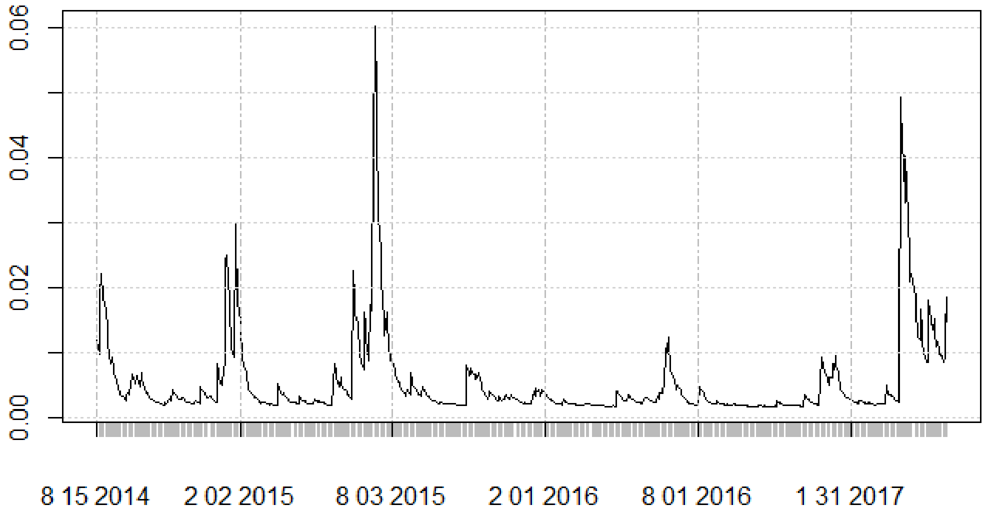
ACF – LTC cGARCH(0,1) squared standardized residuals

Source: author's computation



PACF – LTC cGARCH(0,1) squared standardized residuals

Source: author's computation



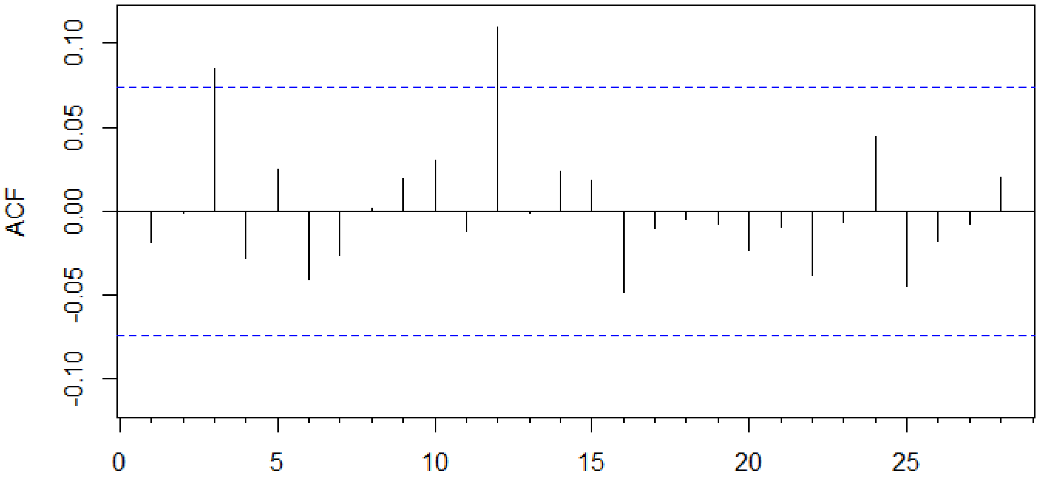
LTC conditional variance

Source: author's computation

XMR

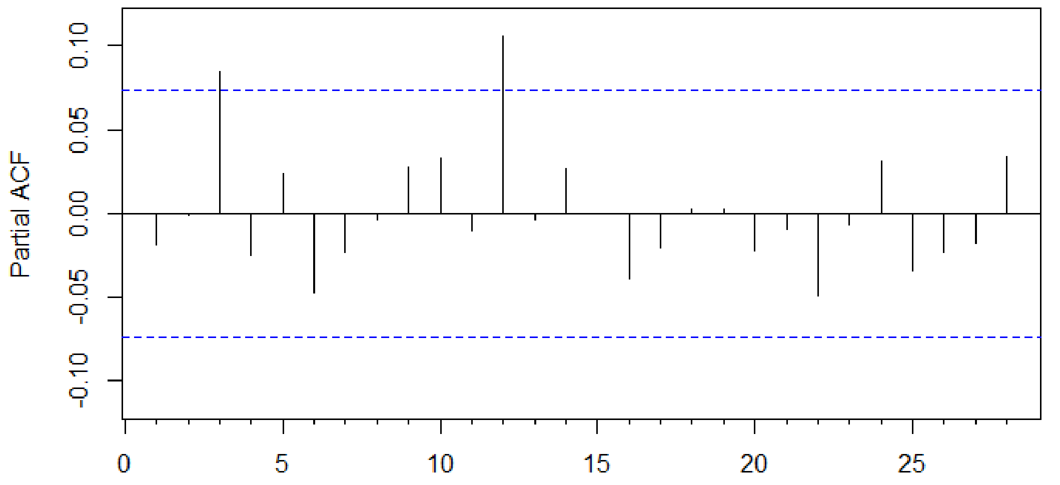
	Akaike	Bayes	Shibata	Hannan-Quinn
XMRARIMA101_sGARCH51	-2.295743	-2.224465	-2.296223	-2.268196
XMRARIMA101_sGARCH51	-2.298797	-2.221038	-2.299367	-2.268744
XMRARIMA101_sGARCH51	-2.295743	-2.224465	-2.296223	-2.268196
XMRARIMA101_sGARCH51	-2.298797	-2.221038	-2.299367	-2.268744
XMRARIMA101_eGARCH51	-2.319257	-2.215579	-2.320262	-2.279187
XMRARIMA101_eGARCH51	-2.321896	-2.211738	-2.323029	-2.279322
XMRARIMA101_eGARCH51	-2.319257	-2.215579	-2.320262	-2.279187
XMRARIMA101_eGARCH51	-2.321896	-2.211738	-2.323029	-2.279322
XMRARIMA101_gjrGARCH51	-2.241193	-2.137515	-2.242199	-2.201123
XMRARIMA101_gjrGARCH51	-2.310876	-2.200718	-2.312009	-2.268302
XMRARIMA101_gjrGARCH51	-2.241193	-2.137515	-2.242199	-2.201123
XMRARIMA101_gjrGARCH51	-2.310876	-2.200718	-2.312009	-2.268302
XMRARIMA101_apARCH51	-2.310336	-2.200178	-2.311469	-2.267762
XMRARIMA101_apARCH51	-2.308825	-2.192187	-2.310093	-2.263746
XMRARIMA101_apARCH51	-2.310336	-2.200178	-2.311469	-2.267762
XMRARIMA101_apARCH51	-2.308825	-2.192187	-2.310093	-2.263746
XMRARIMA101_iGARCH51	-2.291355	-2.226556	-2.291752	-2.266311
XMRARIMA101_iGARCH51	-2.295063	-2.223784	-2.295542	-2.267515
XMRARIMA101_iGARCH51	-2.291355	-2.226556	-2.291752	-2.266311
XMRARIMA101_iGARCH51	-2.295063	-2.223784	-2.295542	-2.267515
XMRARIMA101_csGARCH51	-2.289141	-2.204903	-2.289809	-2.256585
XMRARIMA101_csGARCH51	-2.292291	-2.201573	-2.293064	-2.25723
XMRARIMA101_csGARCH51	-2.289141	-2.204903	-2.289809	-2.256585
XMRARIMA101_csGARCH51	-2.292291	-2.201573	-2.293064	-2.25723

XMRARIMA101_sGARCH50	**-2.298588**	**-2.23379**	**-2.298986**	**-2.273545**
XMRARIMA101_sGARCH50	-2.294958	-2.223679	-2.295438	-2.26741
XMRARIMA101_sGARCH51	-2.295743	-2.224465	-2.296223	-2.268196
XMRARIMA101_sGARCH51	-2.298797	-2.221038	-2.299367	-2.268744
XMRARIMA101_eGARCH51	-2.319257	-2.215579	-2.320262	-2.279187
XMRARIMA101_eGARCH51	-2.321896	-2.211738	-2.323029	-2.279322
XMRARIMA101_gjrGARCH50	-2.318754	-2.221555	-2.319639	-2.281188
XMRARIMA101_gjrGARCH51	-2.241193	-2.137515	-2.242199	-2.201123
XMRARIMA101_gjrGARCH51	-2.310876	-2.200718	-2.312009	-2.268302
XMRARIMA101_apARCH50	-2.313568	-2.20989	-2.314573	-2.273498
XMRARIMA101_apARCH50	-2.299176	-2.189018	-2.300309	-2.256602
XMRARIMA101_apARCH51	-2.310336	-2.200178	-2.311469	-2.267762
XMRARIMA101_apARCH51	-2.308825	-2.192187	-2.310093	-2.263746
XMRARIMA101_iGARCH51	-2.291355	-2.226556	-2.291752	-2.266311
XMRARIMA101_iGARCH51	-2.295063	-2.223784	-2.295542	-2.267515
XMRARIMA101_csGARCH51	-2.289141	-2.204903	-2.289809	-2.256585
XMRARIMA101_csGARCH51	-2.292291	-2.201573	-2.293064	-2.25723
XMRARIMA101_sGARCH50	-2.298588	-2.23379	-2.298986	-2.273545
XMRARIMA101_sGARCH50	-2.294958	-2.223679	-2.295438	-2.26741
XMRARIMA101_gjrGARCH	-2.318754	-2.221555	-2.319639	-2.281188
XMRARIMA101_apARCH50	-2.313568	-2.20989	-2.314573	-2.273498
XMRARIMA101_apARCH50	-2.299176	-2.189018	-2.300309	-2.256602



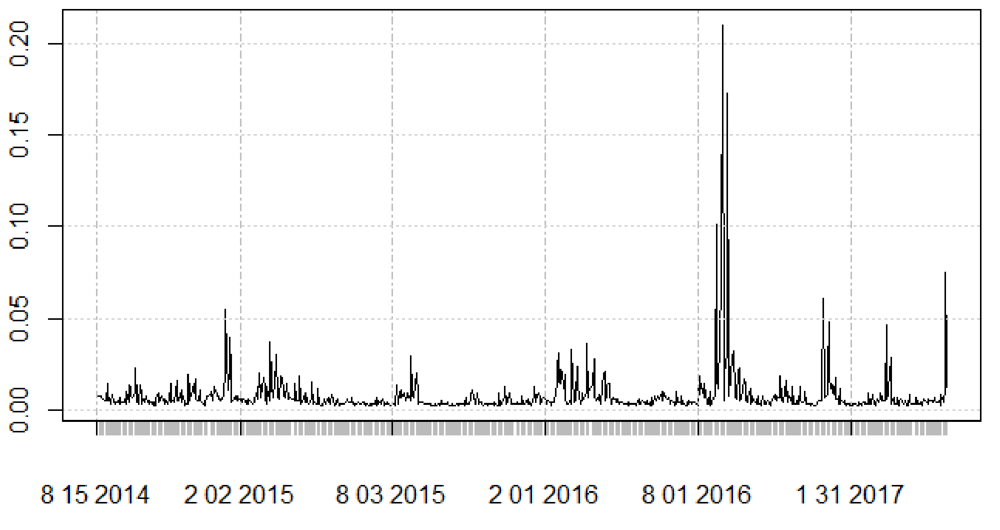
ACF – XMR ARMA(1,1)-GARCH(5,0) squared standardized residuals

Source: author's computation



PACF – XMR ARMA(1,1)-GARCH(5,0) squared standardized residuals

Source: author's computation



XMR conditional variance

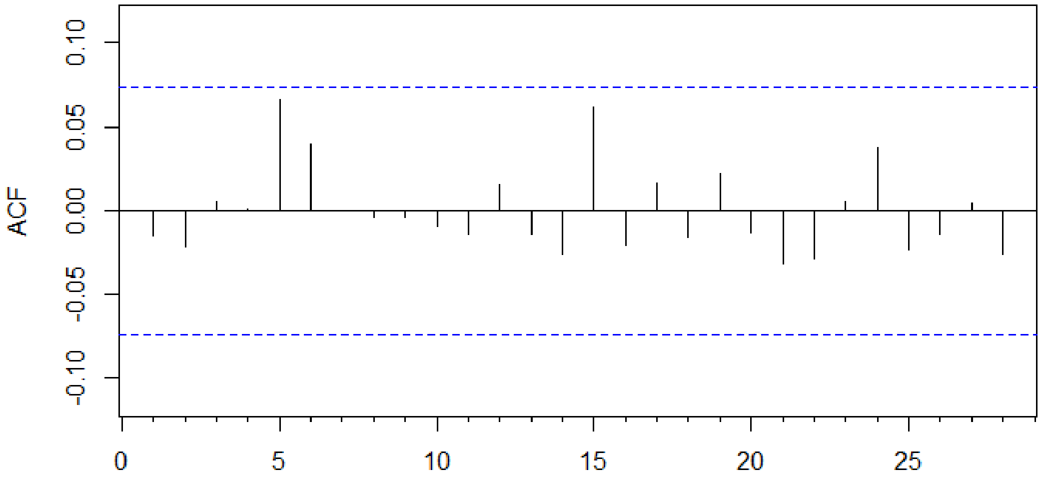
Source: author's computation

XRP

	Akaike	Bayes	Shibata	Hannan-Quinn
XRPARIMA000_sGARCH11	-2.602472	-2.576552	-2.602536	-2.592454
XRPARIMA000_sGARCH21	-2.597488	-2.565088	-2.597588	-2.584966
XRPARIMA000_eGARCH11	-2.62824	-2.595841	-2.62834	-2.615718
XRPARIMA000_eGARCH21	-2.64068	-2.595321	-2.640876	-2.62315
XRPARIMA000_gjrGARCH11	-2.634922	-2.602523	-2.635023	-2.622401
XRPARIMA000_gjrGARCH21	-2.630129	-2.584769	-2.630324	-2.612598
XRPARIMA000_apARCH11	-2.632561	-2.593682	-2.632705	-2.617535

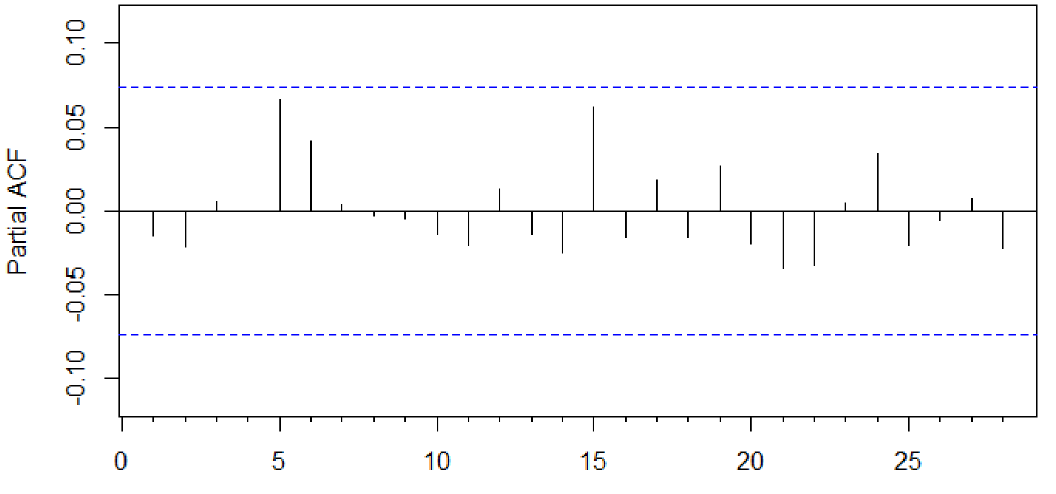
XRPARIMA000_apARCH21	-2.6102	-2.558361	-2.610455	-2.590165
XRPARIMA000_iGARCH11	-2.605349	-2.585909	-2.605385	-2.597836
XRPARIMA000_iGARCH21	-2.600372	-2.574452	-2.600436	-2.590354
XRPARIMA000_csGARCH11	**-2.691978**	**-2.653098**	**-2.692122**	**-2.676952**
XRPARIMA000_csGARCH21	-2.688463	-2.643104	-2.688659	-2.670933
XRPARIMA000_sGARCH10	-2.516888	-2.497448	-2.516924	-2.509375
XRPARIMA000_sGARCH01	-2.115602	-2.096163	-2.115638	-2.108089
XRPARIMA000_eGARCH01	-2.119032	-2.099592	-2.119068	-2.111519
XRPARIMA000_gjrGARCH10	-2.531186	-2.505267	-2.53125	-2.521169
XRPARIMA000_gjrGARCH01	-2.115602	-2.096163	-2.115638	-2.108089
XRPARIMA000_apARCH10	-2.500569	-2.46817	-2.500669	-2.488047
XRPARIMA000_apARCH01	-2.153742	-2.127822	-2.153806	-2.143724
XRPARIMA000_iGARCH01	-2.120415	-2.107455	-2.120431	-2.115406
XRPARIMA000_csGARCH01	-2.631876	-2.599477	-2.631976	-2.619354

	Akaike	Bayes	Shibata	Hannan-Quinn
XRPARIMA000_sGARCH11	-2.776802	-2.749608	-2.776875	-2.766262
XRPARIMA000_sGARCH21	-2.773293	-2.739301	-2.773406	-2.760118
XRPARIMA000_eGARCH11	-2.817733	-2.78374	-2.817846	-2.804558
XRPARIMA000_eGARCH21	-2.832144	-2.784555	-2.832366	-2.8137
XRPARIMA000_gjrGARCH11	-2.810668	-2.776676	-2.810782	-2.797494
XRPARIMA000_gjrGARCH21	-2.539749	-2.49216	-2.53997	-2.521305
XRPARIMA000_apARCH11	**-2.834658**	**-2.793867**	**-2.83482**	**-2.818848**
XRPARIMA000_apARCH21	-2.829673	-2.775286	-2.829961	-2.808594
XRPARIMA000_iGARCH11	-2.779696	-2.759301	-2.779737	-2.771791
XRPARIMA000_iGARCH21	-2.776191	-2.748997	-2.776264	-2.765651
XRPARIMA000_csGARCH21	-2.830674	-2.783085	-2.830895	-2.812229
XRPARIMA000_sGARCH10	-2.715079	-2.694684	-2.71512	-2.707175
XRPARIMA000_sGARCH01	-2.403882	-2.383487	-2.403923	-2.395977
XRPARIMA000_eGARCH01	-2.406762	-2.386367	-2.406803	-2.398858
XRPARIMA000_gjrGARCH10	-2.730797	-2.703603	-2.73087	-2.720257
XRPARIMA000_gjrGARCH01	-2.403882	-2.383487	-2.403923	-2.395977
XRPARIMA000_apARCH10	-2.752556	-2.718564	-2.752669	-2.739381
XRPARIMA000_apARCH01	58.667174	58.694367	58.667101	58.677713
XRPARIMA000_iGARCH01	-2.405559	-2.391962	-2.405577	-2.400289



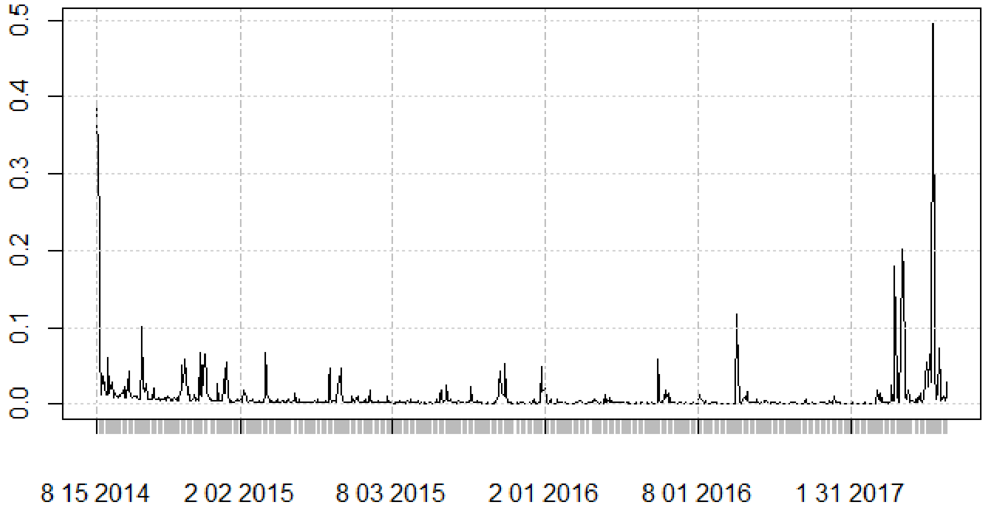
ACF – XRP cGARCH(1,1) squared standardized residuals

Source: author's computation



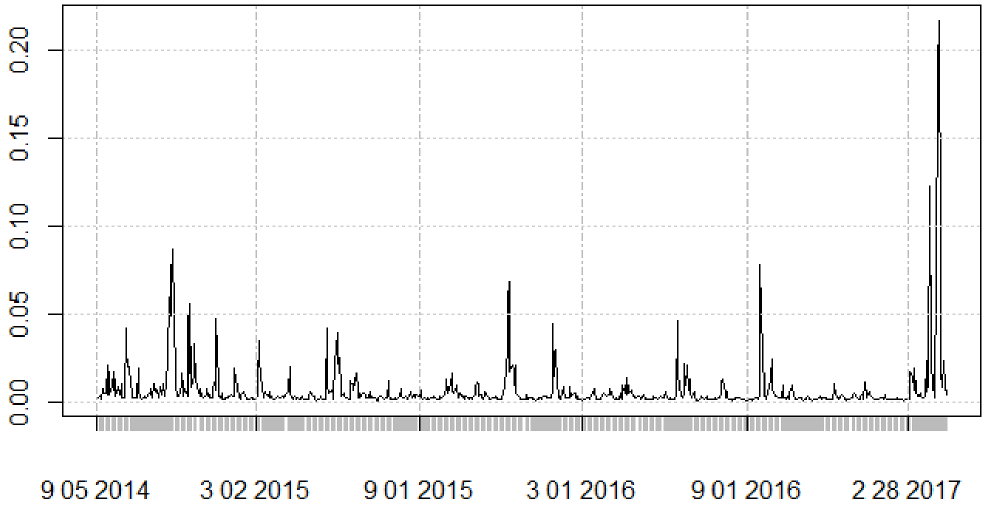
PACF – XRP cGARCH(1,1) squared standardized residuals

Source: author's computation



XRP conditional variance

Source: author's computation



XRP conditional variance – restricted sample

Source: author's computation

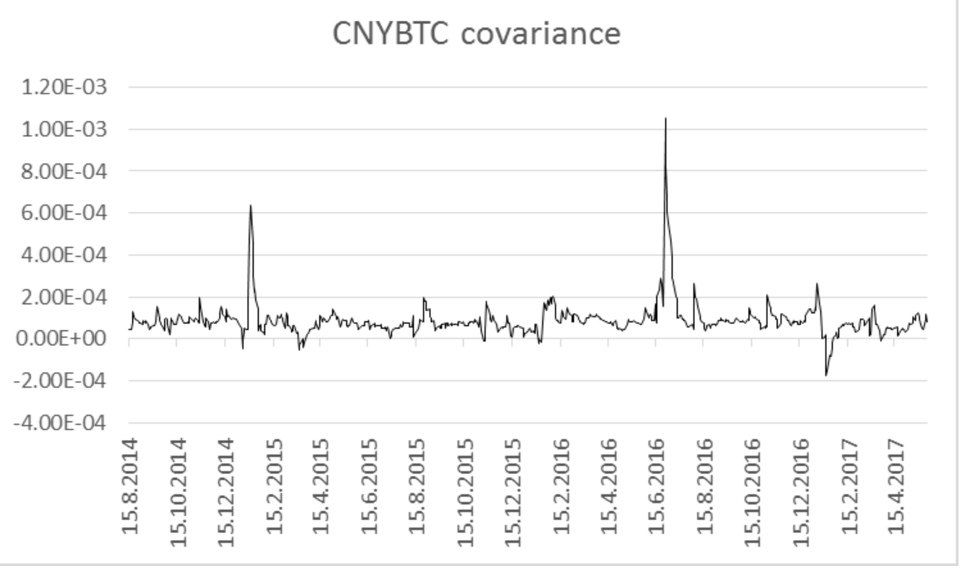
Multivariate models

BTC – CNY results

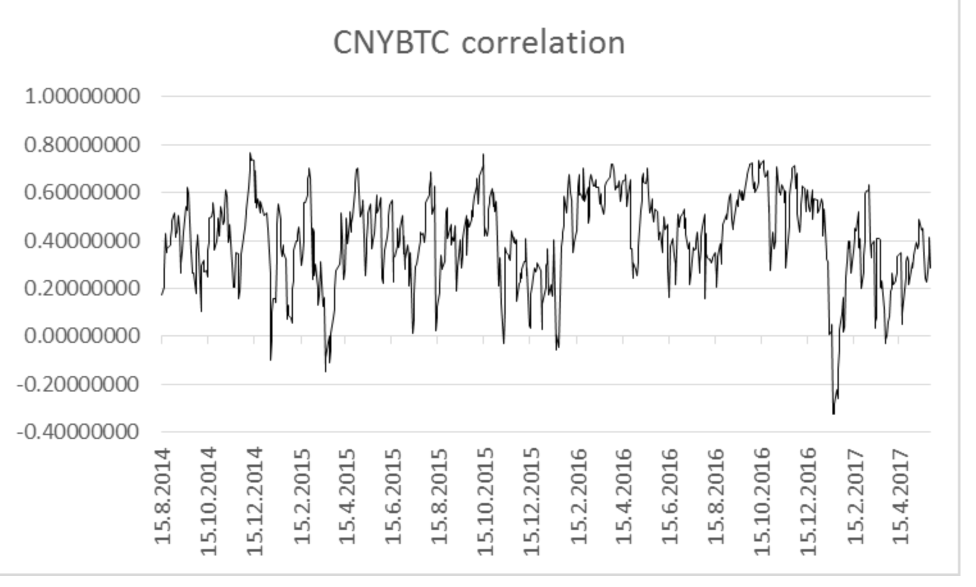
BEKK(1,1) BTC-CNY parameters

mu1.CNY	0.000171
mu2.BTC.close	0.002618
A011	0.001864
A021	0.002634
A022	0.009293
A11	0.311161
A21	-0.36826
A12	0.005259
A22	0.482117
B11	0.90822
B21	0.036244
B12	-0.00212
B22	0.865129

Source: author's computation



Source: author's computation



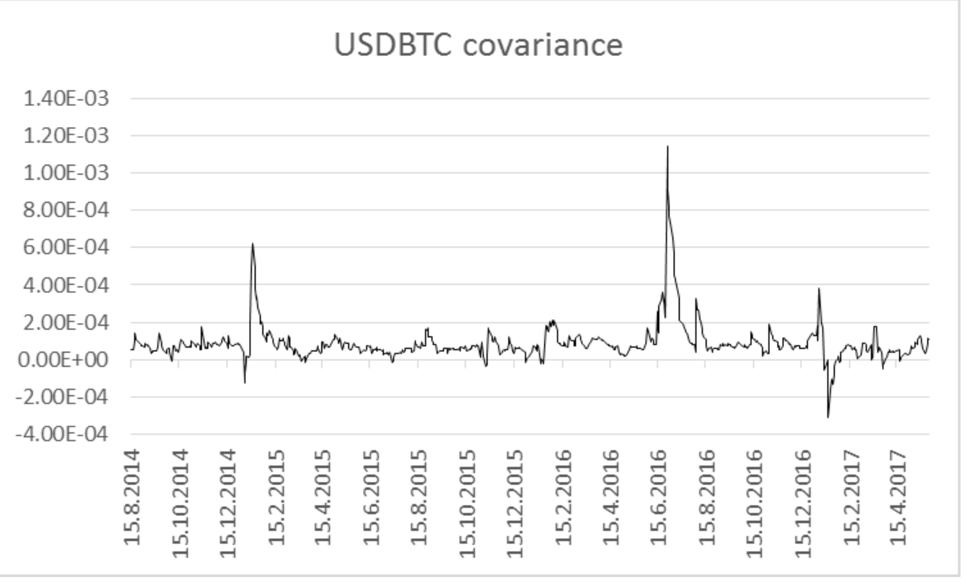
Source: author's computation

USD - BTC results

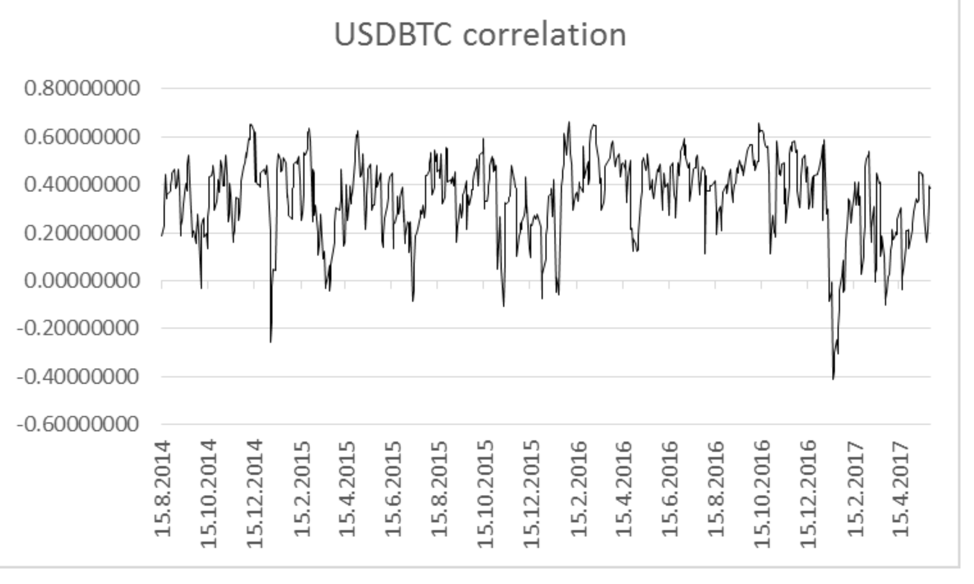
BEKK(1,1) BTC-USD parameters

mu1.USD	0.00036
mu2.BTC.close	0.00264
A011	0.00153
A021	0.001519
A022	0.009695
A11	0.330315
A21	-0.4037
A12	0.004221
A22	0.494375
B11	0.920814
B21	0.095309
B12	-0.00021
B22	0.860019

Source: author's computation



Source: author's computation



Source: author's computation

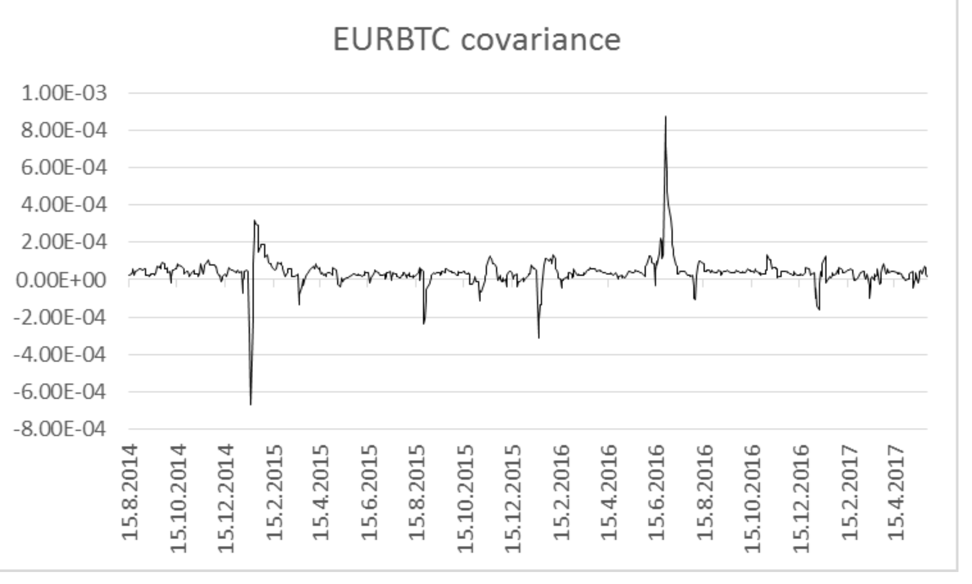
EUR – BTC results

BEKK(1,1) BTC-EUR parameters

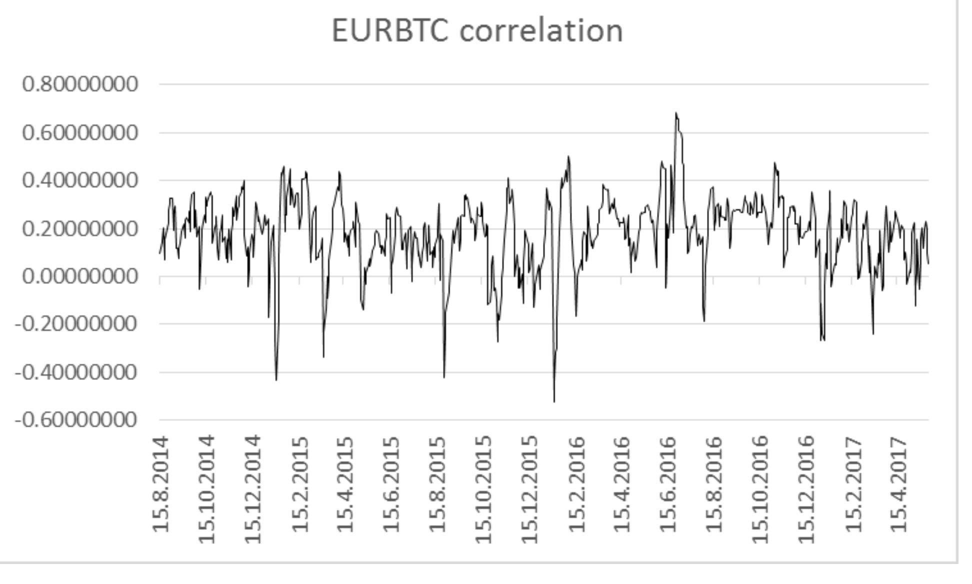
mu1.EUR	0.000105
mu2.BTC.close	0.002996
A011	0.002356
A021	0.000787
A022	0.012199
A11	0.245001
A21	-0.17654
A12	-0.01069

A22	0.468243
B11	0.888857
B21	-0.10133
B12	0.010585
B22	0.844086

Source: author's computation



Source: author's computation



Source: author's computation

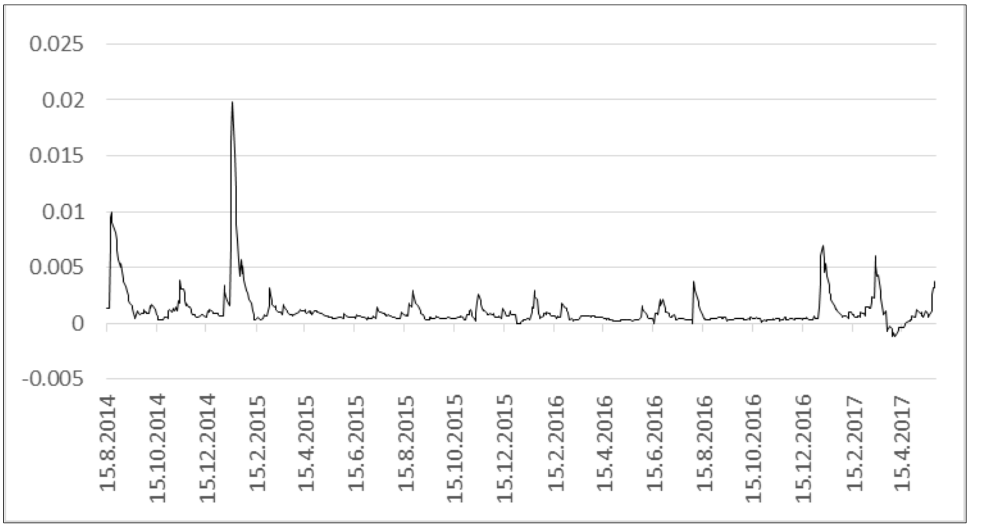
BTC-FIAT-CRYPTO BEKK(1,1) results

DASH

BEKK(1,1 DASH parameters

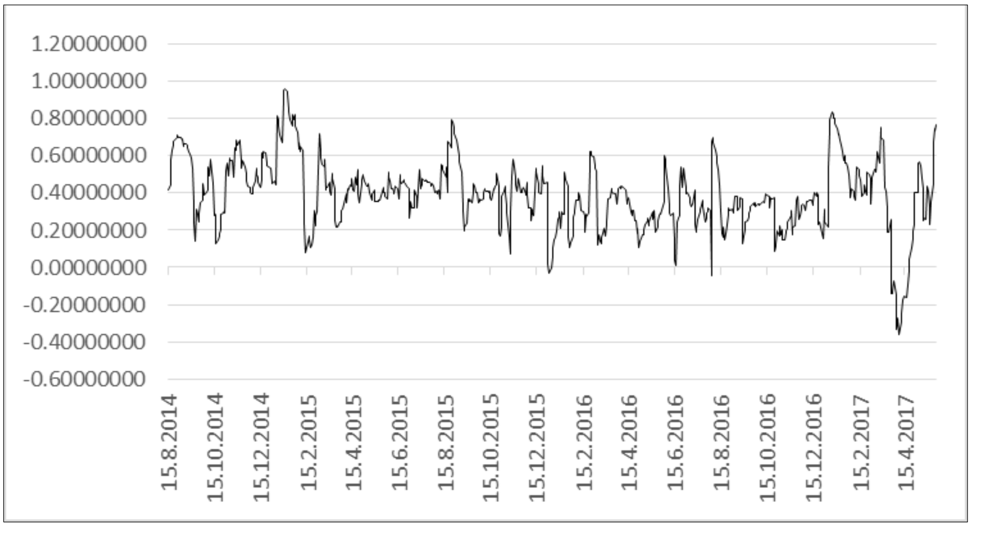
	CNY-BTC.DASH	USD-BTC.DASH	EUR-BTC.DASH
mu1.CNY	0.000143983	0.00027243	-6.35E-05
mu2.BTC.close	0.003051807	0.002229912	0.001445889
mu3.DASH.close	0.00326485	0.003383001	0.002946136
A011	0.003320412	0.003386964	0.003296439
A021	0.007709325	0.008355907	0.000787338
A031	0.003750804	0.001730975	0.004618132
A022	0.007932519	0.009301365	0.013511127
A032	0.006670523	0.006987169	0.006682883
A033	0.016350318	0.017512542	0.017026857
A11	0.000647324	0.060232555	0.208851395
A21	-0.05122459	-0.150289235	-0.027706906
A31	0.000489661	-0.13127304	-0.09890606
A12	0.040891564	0.034139585	-0.021379113
A22	0.358351935	0.481259775	0.40610423
A32	0.043662589	0.166668865	0.176467109
A13	-0.003193915	-0.001082418	0.001425587
A23	-0.007736444	0.001042692	0.004449284
A33	0.316812438	0.415478976	0.310020593
B11	0.811996324	0.829471677	0.817693188
B21	0.098551549	0.164596452	-0.182709945
B31	0.029202106	-0.035363052	-0.008057833
B12	-0.040332811	-0.04316987	0.021185145
B22	0.876003346	0.825893436	0.841631714
B32	-0.048310942	-0.054003352	-0.044240169
B13	0.005046987	0.007504037	-0.002986455
B23	0.011595686	0.001415211	0.002780999
B33	0.904770228	0.86776061	0.896814099

Source: author's computation



BTC-DASH covariance

Source: author's computation

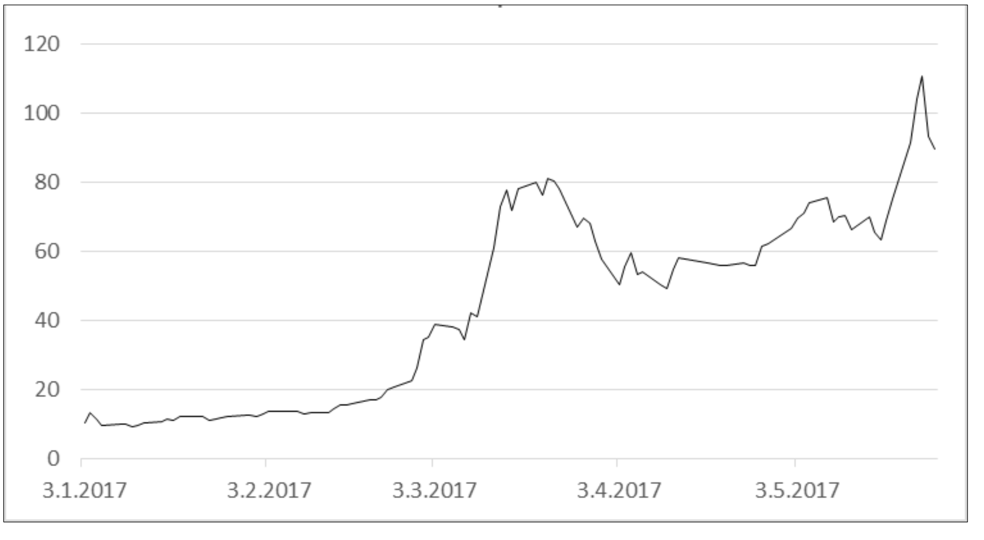


BTC-DASH correlation coefficient

Source: author's computation

BTC-DASH correlation coefficient (2017)

Source: author's computation



DASH/GBP exchange rate (2017)

Source: author's computation

DASH – BTC subsamples

		I	II*	III	IV*	V	VI*	Whole sample
CNY	**Average**	**0.4208**	**0.3238**	**0.3177**	**0.5183**	**0.5218**	**0.1734**	**0.3929**
	Min	**-0.0317**	**-0.0437**	**0.0860**	**0.1539**	**0.3170**	**-0.3606**	**-0.3606**
	Max	**0.9595**	**0.6050**	**0.7018**	**0.8362**	**0.7753**	**0.7652**	**0.9595**
	St.dev	**0.1701**	**0.1305**	**0.1172**	**0.2856**	**0.1244**	**0.3245**	**0.1912**
USD	**Average**	0.3978	0.3810	0.2420	0.5512	0.5264	0.1539	0.3710
	Min	-0.1658	-0.1368	-0.1296	0.0807	0.2367	-0.5129	-0.5129
	Max	0.9800	0.7833	0.8273	0.8976	0.8306	0.8419	0.9800
	St.dev	0.2237	0.2073	0.1688	0.3360	0.1666	0.4142	0.2475

EUR	**Average**	0.4186	0.4292	0.2897	0.5792	0.5352	0.2268	0.4001
	Min	0.0191	0.0549	0.0409	0.1980	0.3049	-0.3263	-0.3263
	Max	0.9704	0.7547	0.8120	0.8788	0.8123	0.8046	0.9704
	St.dev	0.1838	0.1717	0.1415	0.2792	0.1395	0.3346	0.2040

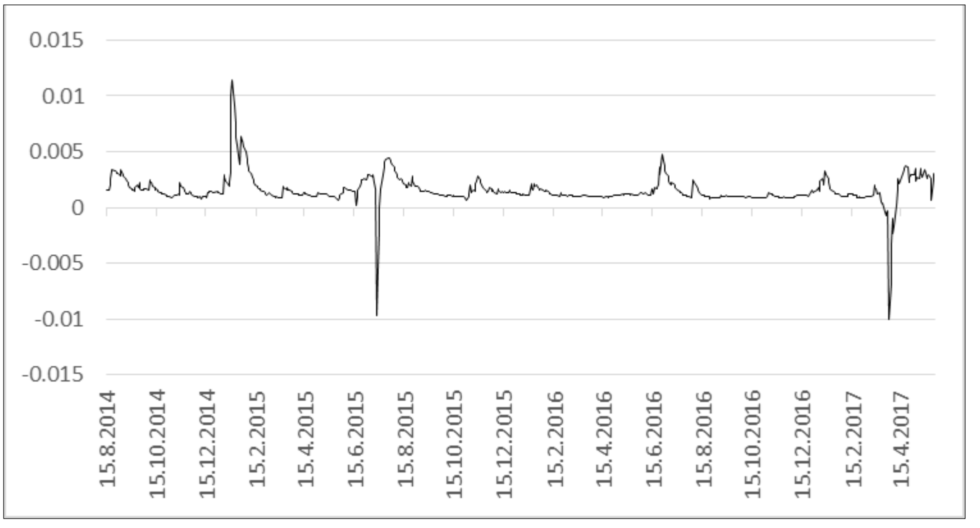
Source: author's computation

LTC BEKK(1,1) results

BEKK(1,1) LTC results

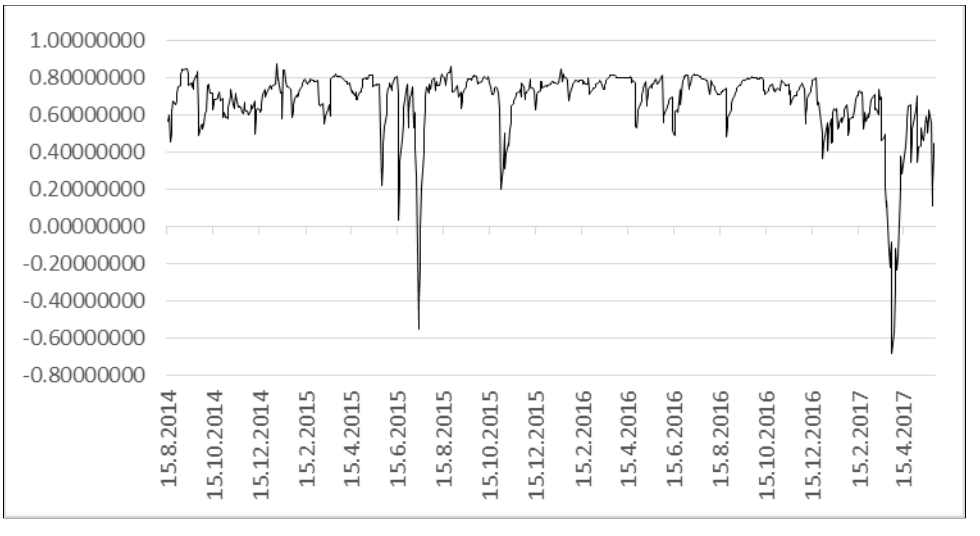
	CNY	USD	EUR
mu1.CNY	0.000231	0.000393	6.68E-05
mu2.BTC.close	-0.00043	0.001178	0.003151
mu3.LTC.close	-0.00343	-0.0016	0.000989
A011	0.001951	0.002181	0.003706
A021	0.001402	0.001519	0.00244
A031	0.001693	0.00245	0.001209
A022	0.010434	0.018726	0.014443
A032	0.013027	0.025284	0.01737
A033	0.011468	0.011465	0.011473
A11	0.276936	0.366698	0.107073
A21	0.033225	0.000219	0.055291
A31	0.04957	0.048492	0.040813
A12	0.006262	-0.00841	0.036177
A22	0.331998	0.422891	0.3646
A32	-0.14169	-0.12957	-0.10057
A13	-0.00204	0.006767	-0.00758
A23	-0.0672	-0.04149	-0.04435
A33	0.406641	0.493162	0.37518
B11	0.913342	0.866842	0.79634
B21	-0.01193	-0.02728	0.031195
B31	0.015373	0.031471	0.00712
B12	0.000145	0.010989	-0.01996
B22	0.881475	0.748248	0.834436
B32	-0.03682	-0.20907	-0.08794
B13	-0.0004	-0.00349	0.004875
B23	0.035774	0.038863	0.028203
B33	0.922	0.86504	0.916329

Source: author's computation



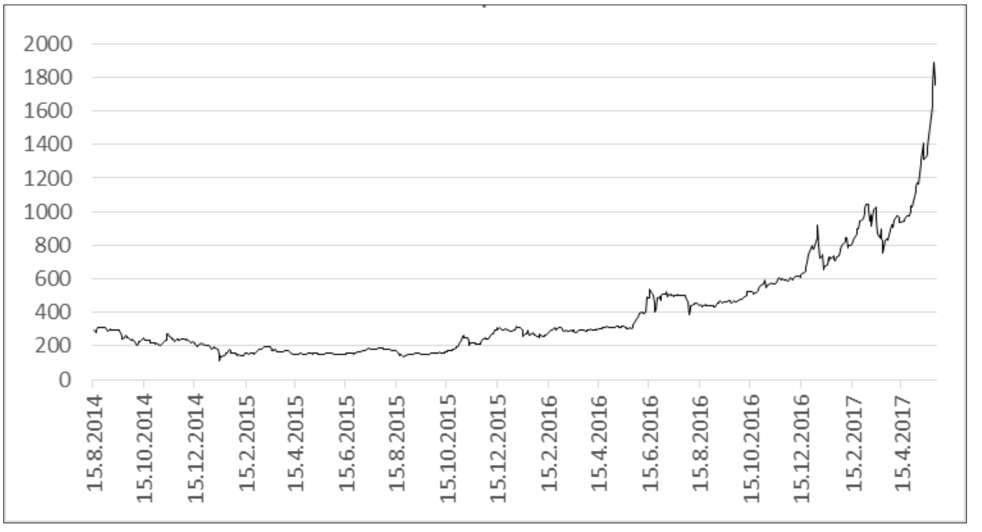
BTC-LTC covariance

Source: author's computation



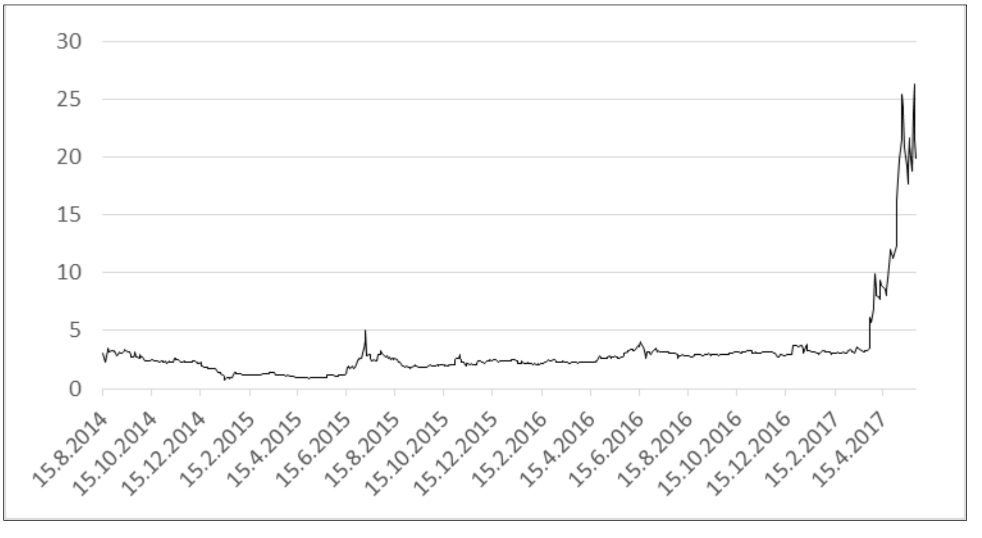
BTC-LTC correlation coefficient

Source: author's computation



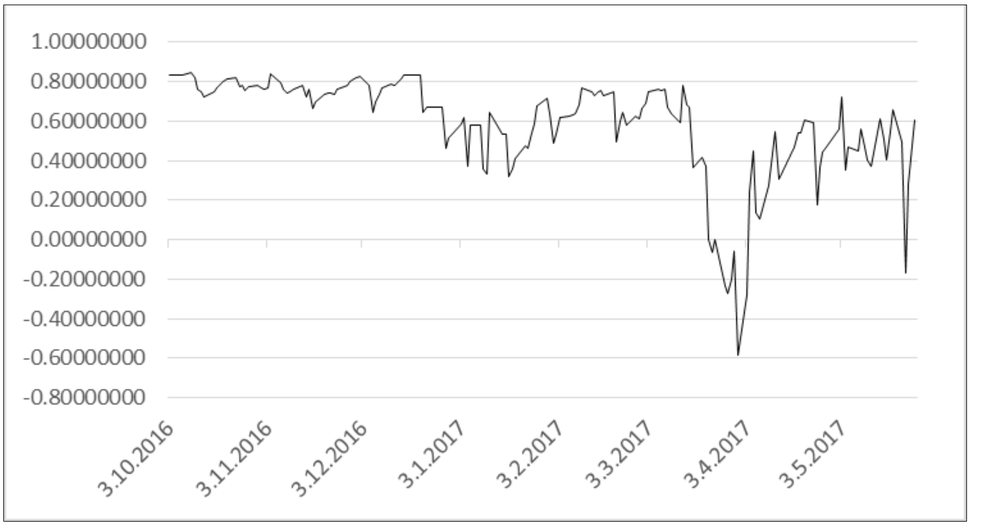
BTC/GBP exchange rate

Source: author's computation



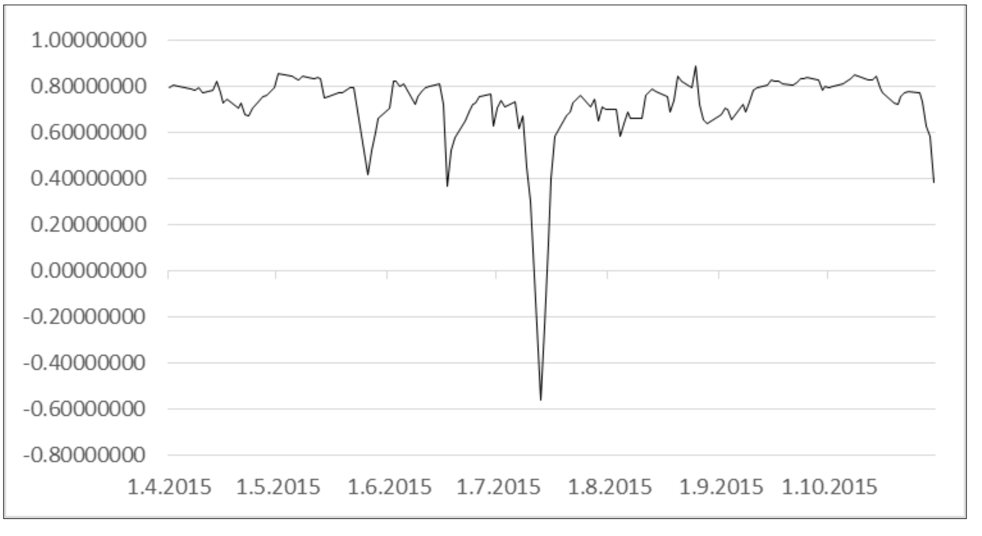
LTC/GBP exchange rate

Source: author's computation



BTC-LTC correlation coefficient (October 2016 – May 2017)

Source: author's computation



BTC-LTC correlation coefficient (April 2015 – October 2015)

Source: author's computation

LTC – BTC subsamples

		I	II**	III	IV*	Whole sample
CNY	**Average**	**0.7036**	**0.6173**	**0.7341**	**0.7264**	**0.6732**
	Min	**0.2212**	**-0.5548**	**0.1986**	**0.4883**	**-0.6802**
	Max	**0.8766**	**0.8623**	**0.8436**	**0.8187**	**0.8766**
	St.dev	**0.0978**	**0.2899**	**0.0964**	**0.0948**	**0.1871**
USD	**Average**	0.7016	0.6583	0.7553	0.7106	0.686919
	Min	0.2452	-0.5578	0.3222	0.2241	-0.58433
	Max	0.9348	0.8895	0.8926	0.8596	0.934776
	St.dev	0.1194	0.2296	0.0946	0.1367	0.181222

EUR	**Average**	0.6984	0.6162	0.7323	0.7078	0.670591
	Min	0.3974	-0.5084	0.3554	0.4266	-0.57599
	Max	0.9074	0.8667	0.8429	0.8221	0.907435
	St.dev	0.0851	0.2520	0.0824	0.0971	0.1717

		V	**VI***	**VII**	**VIII***	**Whole sample**
CNY	**Average**	**0.7376**	**0.5180**	**0.6082**	**0.2777**	**0.6732**
	Min	**0.4789**	**0.3677**	**0.2035**	**-0.6802**	**-0.6802**
	Max	**0.8025**	**0.6693**	**0.7375**	**0.7028**	**0.8766**
	St.dev	**0.0577**	**0.0946**	**0.0931**	**0.3483**	**0.1871**
USD	**Average**	0.7647	0.5404	0.6007	0.312989	0.686919
	Min	0.4810	0.3319	-0.0026	-0.58433	-0.58433
	Max	0.8431	0.6723	0.7809	0.720502	0.934776
	St.dev	0.0797	0.1223	0.1514	0.30496	0.181222
EUR	**Average**	0.7381	0.5469	0.6082	0.279655	0.670591
	Min	0.5284	0.3994	0.1931	-0.57599	-0.57599
	Max	0.7998	0.6643	0.7594	0.641284	0.907435
	St.dev	0.0512	0.0884	0.1019	0.3012	0.1717

Source: author's computation

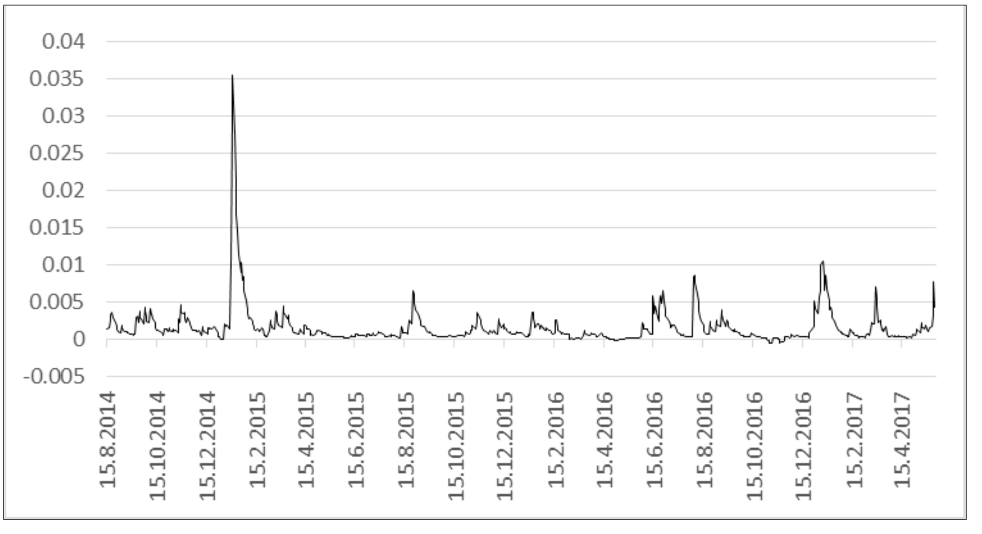
XMR BEKK(1,1) results

BEKK(1,1) XMR parameters

	CNY	USD	EUR
mu1.CNY	0.000194	0.000398	0.000102
mu2.BTC.close	0.002084	0.002865	0.001914
mu3.XMR.close	0.002605	0.004651	0.00305
A011	0.00191	0.001372	0.005333
A021	0.002142	0.00163	0.00433
A031	0.002162	0.002139	0.000117
A022	0.009094	0.009787	0.012571
A032	0.006889	0.00688	0.014796
A033	0.02341	0.026729	0.020837
A11	0.302127	0.278664	1.00E-06
A21	-0.0271	-0.00474	-0.00031
A31	0.031917	0.029646	0.10365
A12	0.000893	0.000528	0.01658
A22	0.424583	0.389754	0.207957
A32	0.144604	0.066139	0.074386
A13	0.00182	0.001371	-0.00862
A23	0.009756	0.005325	-0.0057
A33	0.333314	0.363553	0.249712
B11	0.908334	0.941006	0.519595
B21	-0.0318	-0.00063	0.024643

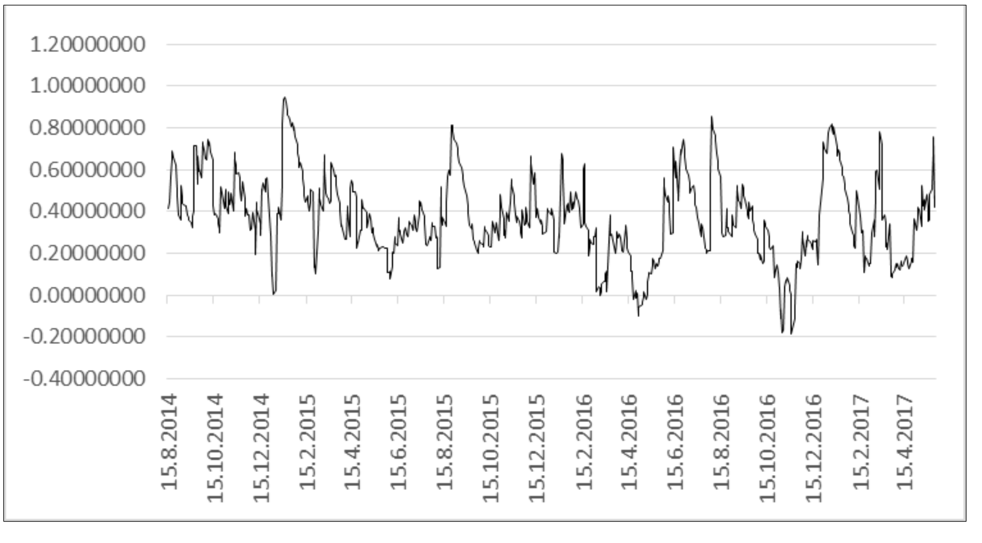
B31	0.050366	0.021841	0.003141
B12	-0.00026	0.000285	-0.02344
B22	0.888755	0.889292	0.899906
B32	-0.03003	-0.01275	-0.09407
B13	-0.00048	-0.00045	0.004208
B23	-0.00202	0.000157	0.000938
B33	0.900131	0.875368	0.917388

Source: author's computation



BTC-XMR covariance

Source: author's computation



BTC-XMR correlation coefficient

Source: author's computation

XMR – BTC subsamples

		I	II*	III	IV**	Whole sample
CNY	**Average**	**0.3821**	**0.4495**	**0.7423**	**0.2909**	**0.3738**
	Min	**-0.0967**	**0.1730**	**0.6056**	**-0.1805**	**-0.1856**
	Max	**0.9453**	**0.7427**	**0.8578**	**0.5677**	**0.9453**
	St.dev	**0.1877**	**0.1648**	**0.0937**	**0.1544**	**0.1996**
USD	**Average**	0.3578	0.4034	0.7037	0.2794	0.348729
	Min	-0.0894	0.1918	0.5580	-0.2324	-0.23237
	Max	0.9378	0.6850	0.8359	0.5524	0.937754
	St.dev	0.1767	0.1383	0.1045	0.1562	0.188164
EUR	**Average**	0.3447	0.3808	0.5868	0.2366	0.336211
	Min	0.1050	0.2849	0.4593	-0.0071	-0.00705
	Max	0.8737	0.5833	0.7109	0.4354	0.873714
	St.dev	0.1060	0.0819	0.0952	0.0846	0.1162

		V	VI*	VII	VIII*	Whole sample
CNY	**Average**	**0.1316**	**0.6728**	**0.4239**	**0.2890**	**0.3738**
	Min	**-0.1856**	**0.1435**	**0.1099**	**0.0837**	**-0.1856**
	Max	**0.3021**	**0.8185**	**0.7797**	**0.7587**	**0.9453**
	St.dev	**0.1430**	**0.1998**	**0.1911**	**0.1692**	**0.1996**
USD	**Average**	0.1425	0.6451	0.3839	0.253058	0.348729
	Min	-0.1990	0.1315	0.0826	-0.02263	-0.23237
	Max	0.2991	0.8049	0.7538	0.71473	0.937754
	St.dev	0.1482	0.2000	0.1885	0.160094	0.188164
EUR	**Average**	0.2244	0.5240	0.3787	0.270352	0.336211
	Min	0.0672	0.3026	0.2106	0.105966	-0.00705
	Max	0.3349	0.6793	0.6297	0.499663	0.873714
	St.dev	0.0797	0.1250	0.0987	0.1001	0.1162

Source: author's computation

XRP BEKK(1,1) results

BEKK(1,1) XRP parameters

	CNY	USD	EUR
mu1.CNY	0.000164	0.000303	6.11E-05
mu2.BTC.close	0.003489	0.002255	0.002099
mu3.XRP.close	0.002643	-0.00265	0.00107
A011	0.002582	0.001372	0.002705
A021	0.007709	0.001519	0.003157
A031	0.001388	0.001873	0.00056
A022	0.017312	0.012158	0.012714
A032	0.003169	0.009994	0.010716
A033	0.019534	0.021648	0.025513
A11	0.136351	0.272138	0.170207
A21	0.028717	0.004705	0.00099
A31	0.020113	0.022999	0.02903
A12	0.030034	-0.00222	-0.00431
A22	1.00E-06	0.340871	0.357345
A32	0.02536	-0.013	-0.05837
A13	-0.01021	0.003385	-0.0088
A23	-0.06495	0.047971	0.066817
A33	0.287587	0.498033	0.504396
B11	0.882873	0.945362	0.885609
B21	0.008284	0.004417	-0.00038
B31	0.011082	0.014652	0.008819
B12	-0.01356	0.000836	0.002181
B22	0.838754	0.875179	0.864413
B32	-0.07292	-0.06409	0.012008
B13	0.005252	-0.0007	0.005211
B23	0.059902	-0.02363	-0.05098
B33	0.928277	0.835059	0.785237

Source: author’s computation

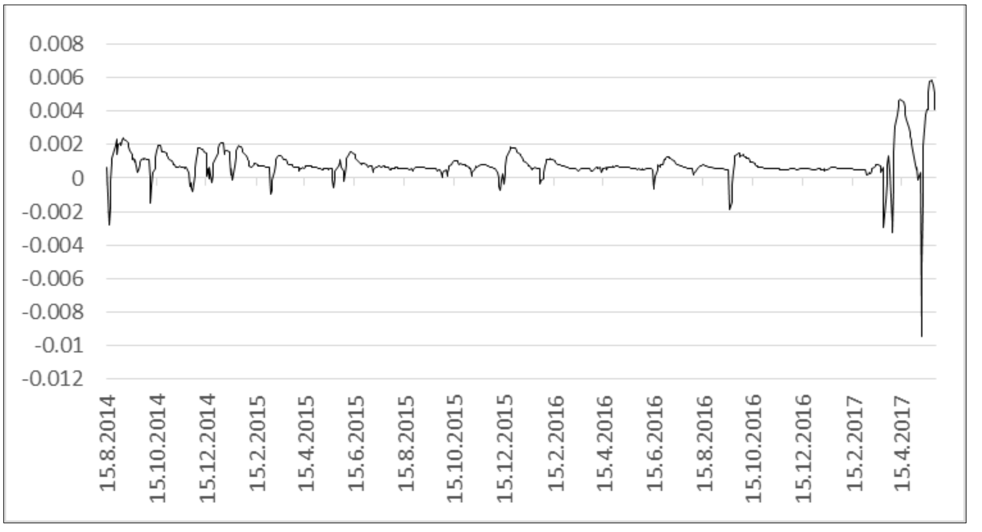


Figure 0.1: BTC-XRP covariance

Source: author's computation

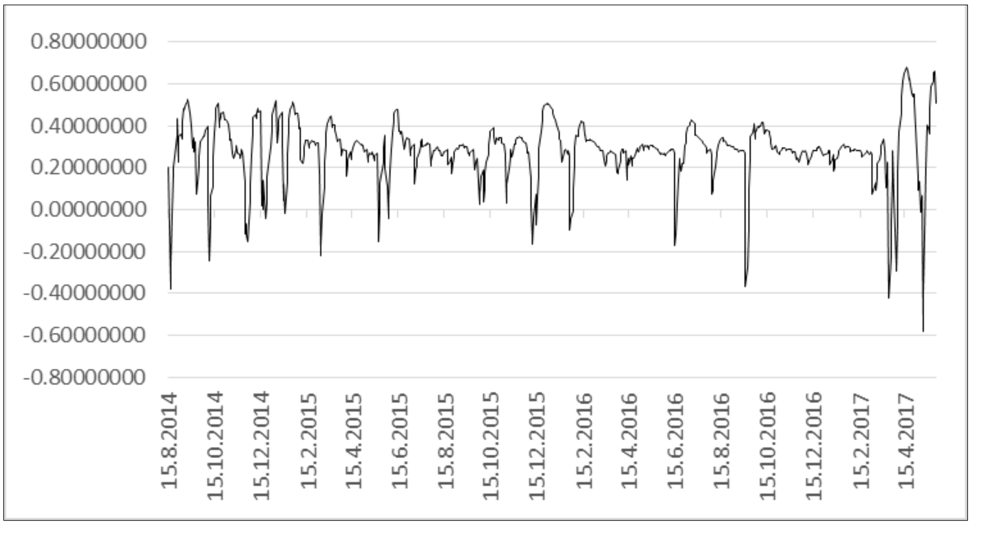


Figure 0.2: BTC-XRP correlation coefficient

Source: author's computation

Table 8: XRP –BTC subsamples

		I	II**	III	IV*	Whole sample
CNY	**Average**	**0.3010**	**0.2806**	**0.2736**	**0.2801**	**0.2772**
	Min	**-0.3783**	**-0.2228**	**-0.1630**	**-0.1723**	**-0.5827**
	Max	**0.5254**	**0.5191**	**0.5096**	**0.4269**	**0.6777**
	St.dev	**0.1881**	**0.1683**	**0.1074**	**0.1161**	**0.1498**
USD	**Average**	0.1303	0.0943	0.1880	0.0760	0.151311
	Min	-0.5217	-0.3925	-0.2781	-0.2991	-0.52168
	Max	0.5084	0.8697	0.6902	0.3227	0.904413
	St.dev	0.1933	0.2678	0.1709	0.1208	0.198851

EUR	**Average**	0.1383	0.1440	0.1938	0.1314	0.16605
	Min	-0.4508	-0.3832	-0.2464	-0.2653	-0.48169
	Max	0.5496	0.8838	0.7350	0.3992	0.920083
	St.dev	0.1966	0.2829	0.1743	0.1145	0.2052

		V	**VI***	**VII**	**VIII***	**Whole sample**
CNY	**Average**	**0.2780**	**0.2547**	**0.2570**	**0.2813**	**0.2772**
	Min	**-0.3686**	**0.1811**	**0.0749**	**-0.5827**	**-0.5827**
	Max	**0.4180**	**0.3002**	**0.3363**	**0.6777**	**0.6777**
	St.dev	**0.1120**	**0.0365**	**0.0611**	**0.3489**	**0.1498**
USD	**Average**	0.1710	0.0769	0.1006	0.198165	0.151311
	Min	-0.0355	-0.1847	-0.1222	-0.27924	-0.52168
	Max	0.7794	0.4347	0.4266	0.904413	0.904413
	St.dev	0.1554	0.1401	0.1294	0.319042	0.198851
EUR	**Average**	0.1761	0.0658	0.1587	0.134029	0.16605
	Min	-0.2200	-0.2389	-0.0139	-0.48169	-0.48169
	Max	0.7600	0.3951	0.4545	0.920083	0.920083
	St.dev	0.1691	0.1469	0.1056	0.3604	0.2052

Source: author's computation