UNIVERSITY OF PIRAEUS

SCHOOL OF FINANCE & STATISTICS

DEPARTMENT OF BANKING AND FINANCIAL MANAGEMENT

M.Sc. Program of «Banking & Finance» in «Finance & Investments»

M.Sc. Thesis title:

"ON THE RELATIVE BEHAVIOR OF CRYPTOCURRENCIES' VALUES"

of

ATHANASIOS D. PAPAFOTIS

Reg. Num.: MXAN1821

SUPERVISOR:

Professor

NIKOLAOS KOUROGENIS

EXAMINATION COMMITTEE:

Assistant Professor

MICHAIL ANTHROPELOS

Assistant Professor

NIKOLAOS ENGLEZOS

Piraeus, March 2021

Acknowledgments

I would like to express my deepest gratitude and appreciation to all the professors of the Master Program for their valuable knowledge and insight offered. I would especially like to thank Mr. Kourogenis Nikolaos that has given me the opportunity to explore such a fascinating subject while offering me guidance through the whole process of conducting this thesis.

Abstract

This study aimed to investigate the price behavior of five cryptocurrencies BTC, LTC, ETH, XMR, and XRP, their fluctuations, potential peaks, minimums, and whether there is a link, co-movement in the price behavior of the cryptocurrencies. For this reason, the daily prices of the five cryptocurrencies from 2013 until 2020 were retrieved from coinmarketcap.com. Initially, a correlation analysis was conducted with the use of a rolling window of 100 days of each pair of cryptocurrencies, BTC - LTC, BTC - ETH, BTC - XMR, BTC - XRP, LTC - ETH, LTC - XMR, LTC - XRP, ETH - XMR, ETH - XRP, and XMR – XRP. Also, a cointegration analysis was conducted with the use of the Johansen test. The rolling correlation analysis resulted that all five cryptocurrencies before the year 2017 presented an unstable pattern. Instead after 2017, the correlation level was higher than 0.6 for all five cryptocurrencies which is a sign of a stable and similar pattern among the cryptocurrencies. Finally, the Johansen test/cointegration analysis resulted that there was a cointegration equation for the time of 2017 until 2020. This result was consistent with the result of the rolling window analysis.

Keywords: blockchain technology, cryptocurrencies, rolling window, correlation, cointegration.

Περίληψη

Στόχος της παρούσας μελέτης ήταν η διερεύνηση της συμπεριφοράς των τιμών πέντε κρυπτονομισμάτων BTC, LTC, ETH, XMR και XRP, των διακυμάνσεων, των πιθανών μέγιστων τιμών, των ελάχιστων τιμών και εάν υπάρχει σύνδεση, συνεργασία στη συμπεριφορά των κρυπτονομισμάτων. Για τον λόγο αυτό, οι ημερήσιες τιμές των πέντε κρυπτονομισμάτων από το 2013 έως το 2020 ανακτήθηκαν από την ιστοσελίδα www.coinmarketcap.com. Αρχικά, πραγματοποιήθηκε ανάλυση συσχέτισης με τη χρήση κυλιόμενου παραθύρου 100 ημερών κάθε ζεύγους κρυπτονομισμάτων, BTC - LTC, BTC - ETH, BTC - XMR, BTC - XRP, LTC - ETH, LTC - XMR, LTC - XRP, ETH - XMR, ETH - XRP και XMR – XRP. Επίσης, πραγματοποιήθηκε μια ανάλυση συνολοκλήρωσης με τη χρήση της δοκιμής Johansen. Η ανάλυση κυλιόμενης συσχέτισης κατέληξε στο συμπέρασμα ότι και τα πέντε κρυπτονομίσματα πριν από το έτος 2017 παρουσίασαν ένα ασταθές μοτίβο. Εν αντιθέσει, μετά το 2017, το επίπεδο συσχέτισης ήταν υψηλότερο από 0,6 και για τα πέντε κρυπτονομίσματα το οποίο αποτελεί ένδειξη σταθερού και παρόμοιου μοτίβου μεταξύ των κρυπτονομισμάτων. Τέλος, η ανάλυση δοκιμής Johansen/συνολοκλήρωσης κατέληξε στο συμπέρασμα ότι υπήρξε μια εξίσωση συνολοκλήρωσης για την περίοδο 2017 έως το 2020. Αυτό το αποτέλεσμα ήταν σύμφωνο με το αποτέλεσμα της ανάλυσης κυλιόμενου παραθύρου.

Λέξεις κλειδιά: τεχνολογία blockchain, κρυπτονομίσματα, κυλιόμενο παράθυρο, συσχέτιση, συνολοκλήρωση.

Table of Contents

Table of Figures

Tables

Equations

Introduction

The purpose of this paper is to study the relative behavior of cryptocurrencies ’values. The work consists of five chapters. The first chapter, entitled Blockchain Technology, attempts a brief introduction to Bitcoin and Blockchain Technology and then outlines Blockchain technology, presenting the double-spending problem and the consensus mechanisms, as well as regulatory approaches on blockchain technology and its potential uses in various industries. The second chapter attempts a bibliographic review of the issue focusing on Volatility relationships in the cryptocurrency market, the efficiency of the cryptocurrency market, and the impact of Covid-19 on the cryptocurrency market. The third chapter analyzes the cryptocurrency market and specifically bitcoin and altcoins. The fourth chapter describes the methodology on which the present research was based, and the fifth chapter presents the results of the study. The work is completed with the conclusions.

Chapter 1 Blockchain Technology

1.1 A brief introduction to Bitcoin and Blockchain Technology

The introduction of Bitcoin back in 2009 by Satoshi Nakamoto in his white paper "Bitcoin: A Peer-to-Peer Electronic Cash System", paved the way for every single implementation of blockchain technology available until this day.

Cryptocurrencies, which are based on blockchain technology, have received a great deal of attention the last decade, growing from nearly nothing to over $300 billion in market capitalization in only a few years, with Bitcoin, Ether, and Ripple being the most distinguished.

Bitcoin, which is the most popular cryptocurrency, with a market capitalization over $160 billion (as of July 2020)[1], appeared amid the financial crisis to fill the gap of trust that had been created between major financial institutions and the public, by providing a system of decentralized trust for value transfer based on cryptographic proof (Nakamoto 2008). The mechanism through which Bitcoin accomplishes decentralization is not solely technical, but it is a combination of technical methods and astute incentive engineering.

Bitcoin's blockchain technology in which many cryptocurrencies are based on is essentially a digital public ledger that keeps track of all user committed transactions in a list of blocks. The database is: a) immutable, meaning that computers building the blocks can only add information to the blockchain over time but cannot erase it, b) distributed, in a sense that any computer can access and maintain the information within, contrary to most databases that delegate access to selected users only, c) cryptographically secured, since blockchain relies heavily on cryptographic consensus algorithms to maintain virtual security.

The distributed consensus and anonymity are two crucial characteristics of blockchain technology, enabling it to serve specific purposes for various industries. For example, it can be used in numerous financial services such as digital payments, remittances, (Peters, Panayi, & Chapelle, 2015), and asset trading (Casino, Dasaklis, & Patsakis, 2019). Furthermore, it can be applied to other non-financial areas including healthcare, education, the Internet of Things, and privacy and security services (Casino, Dasaklis, & Patsakis, 2019).

Although the implications are fascinating, several technological, regulatory, and societal issues must be addressed for blockchain technology to be universally adopted. However, many of these obstacles will likely be surmounted in the near future, with companies that facilitate financial services having already steered in this direction.

---

[1] Bitcoin's market capitalization data from www://coinmarketcap.com

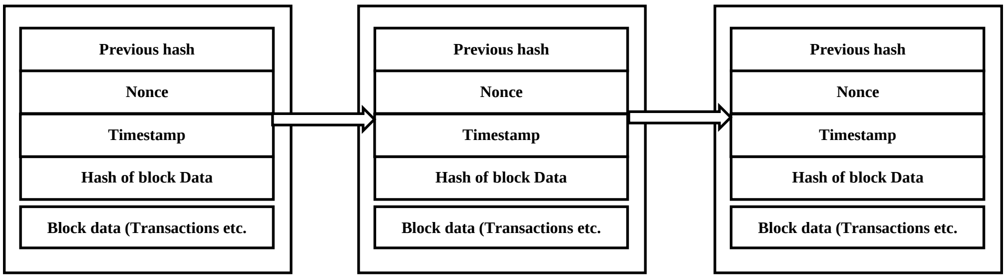
1.2 Blockchain technology outline

The scope of this chapter is to provide an overview of blockchain architecture by discussing some key components that make blockchain technology innovative and at the same time to explain how cryptocurrencies are implemented in the overall structure.

Blockchain is, in essence, an ever-expanding array of blocks. Transactions are stored in each block chronologically, along with the hash value of the previous block and a cryptographic nonce, a number which serves as a partial solution to the cryptographic hash function used. The hash value of the entire block is derived by proof of work (PoW), a consensus algorithm[1] which in essence is a predefined validation method that enables all network participants to determine the correct sequence of blocks (Natarajan, Krause, & Gradstein, 2017). This value typically begins with several predetermined zero bits. The time interval at which new blocks are generated is maintained through a constant difficulty adjustment of the computation required by the miners when they join the network or when they invest in increasing their computing power for the mining process. The block structure is depicted in the following figure.

Figure 1

Block structure



Source: https://nvlpubs.nist.gov/nistpubs/ir/2018/NIST.IR.8202.pdf page 17

Asymmetric key cryptography is implemented by blockchain that acts as a trust mechanism between entities in the network. Each transaction is digitally signed, meaning that a private key is used to encrypt a transaction such that anyone with the public key can decrypt it (Yaga, Mell, Roby, & Scarfone, 2019). Upon verification, the transaction is broadcasted to all participants in the network, which are called nodes, and then is appended to the blockchain permanently.

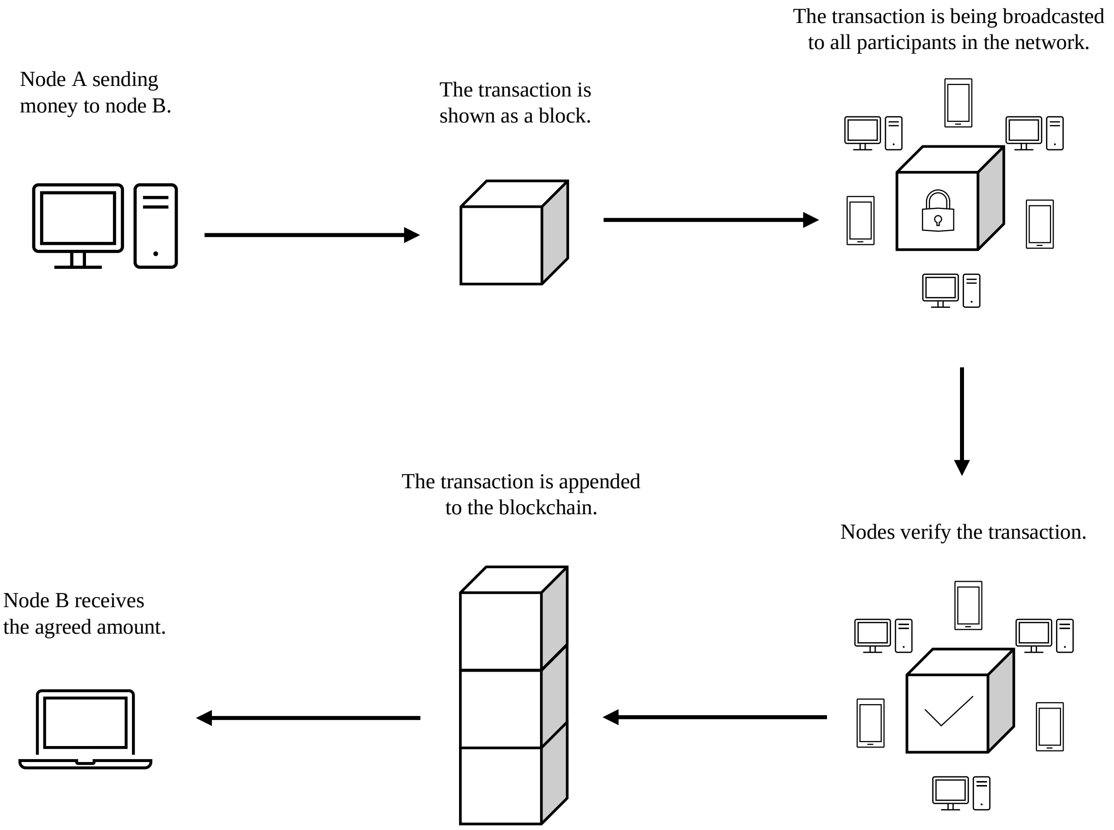
For transactions to be stored in the blockchain, a verifying node has to certify the validity of each one of them, acting as a trusted third party between a spender and a receiver of a cryptocurrency. In particular, verifying nodes have to confirm the spender

[1] Proof of work is the most widely used algorithm by many cryptocurrecies. Different consesus algorithms will be explained further in this chapter.

actually owns the cryptocurrency by reviewing his digital signature, at the verification phase. Also, a further inspection of all his past registered transactions in the blockchain is carried out, to ensure that his account balance suffices the number of cryptocurrencies spent. Figure 2 illustrates how transactions are propagated and verified on the network.

Figure 2

Blockchain transaction process illustration



Source https://smartpayments.com/corporate-payments/how-blockchain-works/

1.3 Double spending problem

Cryptocurrencies, by design, face an inherent risk unique to all digital currency schemes, known as the double-spending problem. The double-spending problem is a potential imperfection in a cryptocurrency or other digital cash design whereby the same single digital token can be spent more than once, and this is possible because a digital token is contained in a digital file that can be replicated or tampered (Chohan, 2017).

In the current financial market infrastructures, banks, and clearing institutions like Fedwire, CHIPS, and SWIFT intermediate between transaction parties, offering clearing and settlement services of transferred funds. Anyone participating in the transaction can easily confirm the previous ownership and authenticity of the physical currency.

With the absence of a third trusted party, there is no guarantee that the sequence of transactions received, matches the exact chronological order they were created. As in the case of counterfeit money, double spending can potentially destabilize the value of cryptocurrencies compared to other currency units through applied inflationary pressure caused by the increased supply of fraudulent currencies. This in turn undermines their demand in the long run as reliability diminishes.

To tackle this problem, Nakamoto (2008), as we mentioned earlier proposed a peer two peer distributed timestamp server in which the chronological order of transactions is determined by computational proof. The concept behind this is that for double-spending to occur, a malicious node would have to repeat all the calculations performed previously by all the other nodes, to detect the block which contains the original transaction, and then compute again all the successive blocks in the chain.

However, the risk of a node accumulating transactions that have not been confirmed is still present. Since multiple blocks can be generated simultaneously by different nodes in the network, the assortment of blocks cannot be perceived as strict. This means that two or more branches of blocks can be established in the blockchain. The publication rate of a block is roughly ten minutes, so the branch that obtains the next block of confirmations first will be appended to the blockchain. The number of confirmations needed depends on the nature of the transaction, where six is a feasible number of transactions after which the realization of double-spending attacks is negligible.

Although the possibility of such attacks is minimal, their threat becomes quite significant when an attacker has a time advantage towards falsified block generation and possesses enough computational power (Pinzón & Rocha, 2016). Further, Karame et al. (2015) showed that double-spending attacks can be accomplished with minor expenses when the exchange of currency and goods happens in a short time. To address this issue, they proposed a modification to the current Bitcoin design that aids the detection of double-spending attacks against fast payments.

1.4 Applications of Blockchain Technology

In addition to a decentralized means of payment without the need for intermediaries, blockchain technology has also potential applications in several financial services. For example, the traditional way of processing and clearing transactions, in addition to being expensive, is also complicated and therefore slow, as more parties may be involved in completing a transaction, such as agents, custodians, clearing managers, and so on. Each of these parties keeps its record, which in addition to practicality issues increases the chances of errors and inconsistencies. Blockchain technology greatly simplifies the process while eliminating the need for intermediaries. The time of confirmation and settlement of transactions is dramatically reduced, regardless of the geographical location of the counterparties. Most international financial institutions are piloting the new technology in order to take advantage of its potential in the full range of services they provide (Miraz & Ali, 2018).

As a means of processing payments, blockchain technology will be able to simplify and speed up the payment confirmation process. For example, in international freight transport under the term Cash Against Documents (CAD), the consignee must wait several hours to several days to receive the goods, until the carrier receives a confirmation on behalf of the sender that the price has been paid. In a system based on blockchain technology, the confirmation will be immediate (a few minutes) and can even be done directly from the recipient to the sender, without the mediation of third parties (bank).

Blockchain technology can be particularly useful in the processing of insurance claims, as these can be extremely complex for various reasons, such as fraudulent claims of policyholders, fragmented data, inactive insurance policies, etc. These issues can be addressed through the use of registers in which data will be registered with safety while the continuity of all relevant information will be preserved (Pilkington, 2016).

Record keeping

Since blockchain technology is essentially a new way of entering and storing information in an interconnected data chain that prevents duplicate and malicious entries, its most obvious application is in record keeping, such as, company register, tax register, intellectual property rights register (see below), etc. In addition, the technology could be applied to company accounting records, as it significantly reduces the likelihood of errors and ensures, at least to a greater extent than current practices, the integrity of records. Modifying entries once they are registered in the blockchain database will be extremely difficult, if not impossible, even for the registrar.

In all the above cases, the data entered can be combined with additional functionalities which are integrated into the respective platform. For example, in a pilot application of the technology from the NASDAQ stock exchange in 2016, users' ownership of securities, as held by the central authority (CSD), was registered, and then voting rights were assigned via tokens so that users could "spend" tokens and vote in assemblies if they were also holders of the corresponding voting right (Pilkington, 2016).

Blockchain technology can also be of particular importance in the registration of intellectual property rights where their proof of ownership and time priority can be difficult and costly to track, in contrast to blockchain technology, which can provide reliance for such registrations. This information can also be extremely useful in dealing with counterfeit products by allowing the use of secure and non-modifiable certificates by customs and police authorities.

Smart contracts

Smart contracts, as opposed to what the term implies, are not legal agreements but digitized contracts embedded in the form of If - [this] - then - will - that (IFTTT), that ensure the conformity of contractual provisions by implementing an orderly sequence of their execution if the conditions set are met. They were first conceptualized by Nick Szabo in 1994[1]. In a later article[2] Szabo uses a vending machine as an example to illustrate the functionality of smart contracts. The vending machine is in control of the ownership of the product stored in it and it transfers it to the consumer, only if the latter inserts the predefined unit of currency in the slot. Another typical case of use of smart contracts is the so-called starter interrupter, that is, a device that has a built-in contract, which is executed automatically in case of violation of the terms of financing for the acquisition of the car, which does not allow the engine to start (Kim & Deka, 2020).

The integration of the operation of smart contracts through blockchain technology enhances their functionality since blockchain technology acts as an intermediary which ensures that the counterparties adhere to the predefined terms of the contract and once the contract has been executed the result is publicly visible and cannot be tampered with. The parties to a smart contract negotiate the basic terms, such as product specifications, quantity, price, time, and place of fulfillment through the blockchain, in a process that is similar to trading derivative contracts on an electronic OTC platform. If millions of computers confirm that Alice is paying Bob 100 Euros on April 8 at 4 p.m. and these computers are neutral and do not make computational errors, then one can assume with an extremely high degree of certainty that this payment took place.

The example of the start switch is even more typical of the possibilities of combining smart contracts and blockchain technology. Instead of contractor programming being determined by the lender, it will be defined and executed by the blockchain platform. Neither party needs to trust the other to execute the contract but the neutral blockchain platform, which will execute the relevant contractual terms when the pre-agreed conditions are met (Pilkington, 2016).

The application of this new technology can reduce costs and credit risks for lenders, as the execution of the terms of the contracts will be automated and the recovery rate of the collateral will be higher. This in turn will reduce the cost of financing, with lower interest rates, at least for those borrowers who accept the rigor and rigidity of the terms of a smart contract.

---

[1] Szabo, N. "Smart Contracts," 1994
http://www.fon.hum.uva.nl/rob/Courses/InformationInSpeech/CDROM/Literature/LOTwinterschool2006/szabo.best.vwh.net/smart.contracts.html

2 http://web.archive.org/web/20140406003401/szabo.best.vwh.net/idea.html

Governance

Digital governance and e-voting can be much more secure as data is encrypted in a way that makes it extremely difficult to falsify it, thus, transparency is ensured by all participants in the voting process.

Digital identity management

Creating a digital identity with blockchain technology will allow better protection (as a triptych involving the confidentiality, integrity, and availability) of personal data through encryption, but above all will allow users to manage them exclusively according to their own needs according to the circumstances. The new technology allows the storage of encrypted personal data in the blockchain, which will be selectively shared by their owner. The hash number of authentication data can be provided to a service provider without the need to access or store personal data. This user-centered approach is often referred to as "self-sovereign identity".

In addition, it will be possible to merge more identification data (identity card, passport, driver's license, passwords, social security registers, etc.) into one digital ID which will allow registration in any register.

Internet of Things

Devices that are connected to the internet, interacting with their owner and with each other, constantly providing and receiving data are characterized as smart. These devices can be controlled remotely, therefore, they achieve more efficient performance and optimal energy consumption, while at the same time they are kept in better condition. Encrypting the data of these devices in a blockchain database provides a higher level of protection and transmission of information (Kim & Deka, 2020).

Supply chain management

The immutable nature of blockchain technology makes it suitable for purposes such as tracking products as they change ownership in the supply chain. Entries in the blockchain database can be used to route events in the supply chain (such as distributing products as they arrive at a port in different containers). Blockchain technology offers a dynamic new way to organize and track data and products.

Additionally, sensors placed on products deliver complete transparency and accurate knowledge of the product procurement process since they provide real-time data on their location and status as they are transported to the global market. Blockchain technology will store, manage, protect and transfer this smart information in the best way, providing real-time transparency as all participants (computers) will keep a fully updated file of this data.

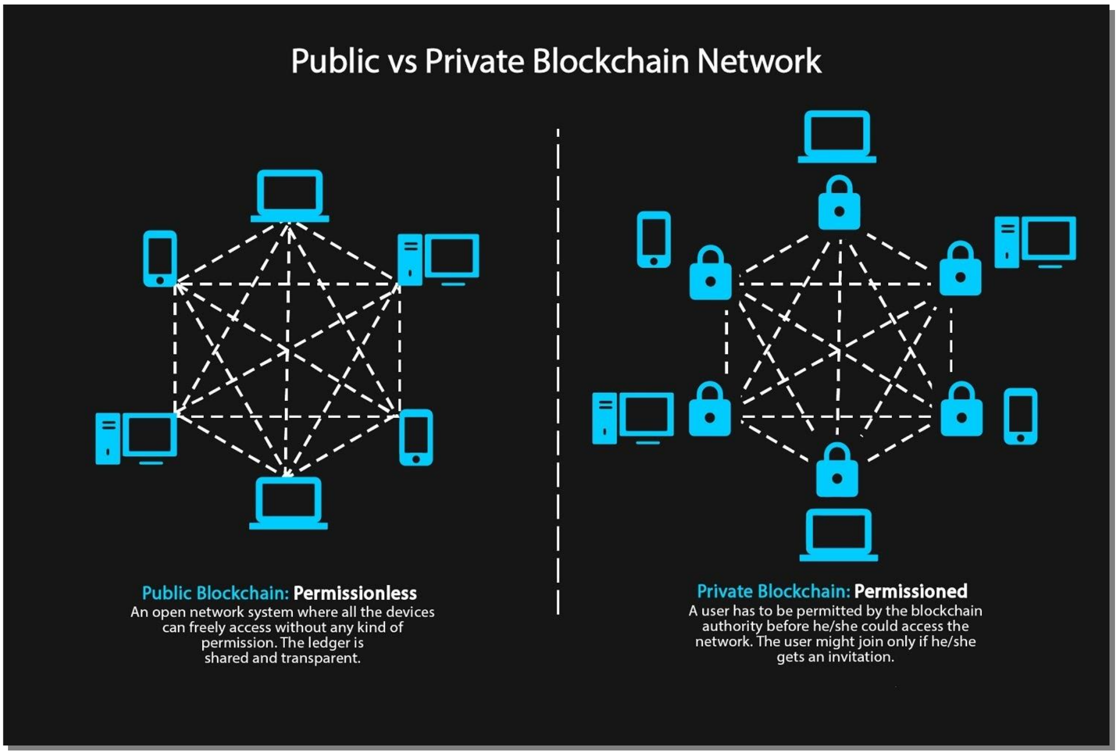
Copyright management

One of the key issues in the field of copyright management is the complexity of the acquisition rights, the distribution of remuneration, and the transparency of the operation of collective management bodies. Blockchain technology combined with smart contracts can provide a complete and accurate copyright database ensuring a transparent real-time pay distribution to all beneficiaries at different levels. The use of digital currencies for the immediate payment of fees by users will further facilitate the optimal management of these rights (Pilkington, 2016).

1.4.1. Public and Private blockchains

The only difference between a public and a private Blockchain network is who is allowed to join the network (Yang et al., 2020).

Figure 3



Source: https://zephyrnet.com/public-or-private-blockchain-best-for-your-supply-chain/

In the case of public blockchain networks, everyone is allowed to participate. This means that every user can have a copy of the Blockchain and watch all transactions happen in real-time. Public networks have an incentive mechanism that encourages more participants to participate. Bitcoin is an example of a public blockchain network (Lai & Chuen, 2018).

A public blockchain network requires a significant amount of computing power, as participants are asked to solve complex cryptographic problems called Proof of Work to verify transactions and keep everyone on the same page (Lai & Chuen, 2018).

In private blockchain networks, participants can only be added by invitation and usually, the network is licensed. This means that unlike public blockchain networks, not everyone is allowed to participate while the scope of participants is also limited. Hyperledger Fabric is an example of a private blockchain network (Yang et al., 2020).

Private blockchain networks are highly targeted at business use. Private blockchains can be created in such a way that only the entities involved in the transaction have access to it while the access for other entities is restricted (Yang et al., 2020).

1.5 Consensus mechanisms

This sub-section provides an overview of various consensus algorithms that form the backbone of blockchain technology and are utilized in different cryptocurrency schemes. The differences among these protocols may pose several implications on the price formation, volatility, and liquidity of the cryptocurrency markets.

1.5.1 Proof of Work (PoW)

Proof of Work (PoW) consensus mechanism was introduced by Bitcoin in 2009 and it is the most utilized consensus mechanism by current blockchains. Some examples of cryptocurrencies that employ the PoW consensus mechanism is Bitcoin, Ethereum, Litecoin, Monero, Dash, Dogecoin, and Zcash.

The main idea behind PoW is to prevent users from disrupting and controlling the services of a shared resource by forcing them to compute a moderately hard, but not intractable, function (Dwork & Naor, 1992)[1]. The term "Proof-of-work" was first introduced by Markus Jakobsson and Ari Juels in 1999[2]. Bitcoin's PoW is a variant of the computational puzzle implemented in Hashcash[3] by its inventor Adam Back in 1996.

PoW, as mentioned earlier, involves solving a complex mathematical problem in a way that meets specific predetermined criteria. This acts as a safety lock mechanism and ensures the validity of transactions (blocks) in the network. The mathematical computation is carried out continuously by miners of the network. This process is random

[1] See Dwork, C., & Naor, M. (1992, August). Pricing via processing or combatting junk mail. In *Annual International Cryptology Conference* (pp. 139-147). Springer, Berlin, Heidelberg.
[2] See Jakobsson, M., & Juels, A. (1999). Proofs of Work and Bread Pudding Protocols (Extended Abstract). Secure Information Networks (s. 258-272).
[3] Hashcash is a proof-of-work system that has been designed by Adam Back in 1996 to deter spam-email and denial-of-service attacks. See Back, A. (2002). Hashcash-a denial of service countermeasure.

and upon successful completion, the miners are being rewarded with new coins and transaction fees for their contribution to expanding the blockchain. Moreover, as new miners enter the network and their aggregate computational power increases, the difficulty of the PoW computation adjusts accordingly.

PoW mechanism has been receiving major criticism due to the substantial amount of money needed to invest in electrical power and mining infrastructure. The ever-increasing need for scarce resources is detrimental to the viability of a PoW based system in the long-term. Furthermore, it raises the issue of whether a group of miners that holds a significant fraction of computing power in the network collaborates to maximize their earnings. This strategy is called “selfish mining” and can shake the very foundations of decentralization on which cryptocurrencies have been established. Meanwhile, the accumulation of mining pools[1] observed globally raises concerns about the security of a PoW system, as entities who control over 51% of the mining power can potentially pose a threat to the security of the network.

1.5.2 Proof of Stake (PoS)

Proof of Stake (PoS) is an alternative consensus mechanism to PoW. It was first implemented by the Peercoin[2] cryptocurrency in 2012. The main idea behind PoS is to address the problem of large energy consumption the PoW demands. This is achieved by compensating miners in proportion to the coins they already possess instead of their mining power. An advantage over PoW is that in PoS a potential attack is dissuasive to a miner that holds a 51% stake since this would ultimately devalue the share he already owns.

The core problem of PoS lies in the initial issuance of coins. In PoS developers of a new cryptocurrency can manipulate the very first distribution of coins, so that is favorable to them while in PoW, miners are awarded based on their computing power. Some cryptocurrencies utilize both PoS and PoW consensus mechanisms to overcome the problems inherent to both designs. For example, the PoW is being utilized at the early stages of a cryptocurrency’s deployment, while the PoS mechanism gradually assumes the mining process. Peercoin, MintCoin, and Novacoin are some of the cryptocurrencies that use a PoW/PoS hybrid consensus mechanism. Another issue is that PoS by design benefits the accumulation of wealth by rich individuals as they have a greater chance to successfully mine the next block in the chain.

[1] Hashrate distribution amongst the larget mining pools can be found here: https://www.blockchain.com/charts/pools

[2] King, S., & Nadal, S. (2012). Ppcoin: Peer-to-peer crypto-currency with proof-of-stake. *self-published paper, August 19*, 1.

1.5.3 Delegated Proof of Stake (DPoS)

A variation of PoS named Delegated Proof of Stake (DPoS) was proposed by Dan Lanimer in 2014 and was first implemented in the Bitshares blockchain-based financial platform. DPoS seeks to tackle the problem of wealthy entities in the network becoming increasingly wealthy by selecting the nodes for the mining process via a deterministic mechanism based on voting rather than on coins possessed. DPoS is currently being used by the cryptocurrencies Bitshares, Cardano, and Nano.

1.5.4 Proof of Burn (PoB)

Proof of Burn (PoB) protocol was introduced in 2014[1] as a way to resolve the issue of excessive expenditure on electrical power in PoW systems. PoB seeks to bootstrap one cryptocurrency off another. Miners of the network send their proof-of-work-mined coins to a randomly generated public addresses where they are placed out of circulation. This process referred to as coin burning encourages users to commit to the sustainability of the network, by granting them the right to participate in the mining process through investing in coin burns instead of physical resources as in PoW.

Further, the coin burning process nurtures market scarcity by virtually stimulating the price of coins burned. To avoid the accumulation of wealth to inaugural users the value of burned coins diminishes over time. However, as in PoS, this protocol also aids the uneven distribution of wealth among users.

1.5.5 Proof of Importance (PoI)

Proof of Importance (PoI) is another consensus mechanism used for transaction validation in a digital currency scheme. It was first implemented by the cryptocurrency NEM in 2018[2] to compensate for the shortcoming of the PoS mechanism which favors users to store coins excessively instead of circulating them. While in the pure PoS system miners with small stakes are at a disadvantageous position in terms of collecting a reward, in PoI protocol the priority is given to miners based on the number of coins they already hold as well as on their frequency of transactions and their interaction with other transacting parties within the network.

However, this protocol is also benefiting wealthy users since the reward system is based on the total number of coins obtained and transactions performed. Further, security

[1] Proof of Burn - Bitcoin Wiki. https://en.bitcoin.it/wiki/Proof_of_burn.
[2] NEM, T. (2018). Nem technical reference. *URL* *https://nemplatform.com/wp-content/uploads/2020/05/NEM_techRef.pdf*

implications might arise since PoI neglects the fact that a group of users might engage in virtual transactions between themselves.

1.5.6 Proof of Space (PoSpace)

Dziembowski et al. (2015) proposed an alternative consensus algorithm to PoW named Proof of Space (PoSpace) also known as Proof of Capacity to solve the issue of resource scarcity and wealth inequality among users. In PoSpace users can generate the next block in the blockchain by providing disk or memory space instead of computational power like in PoW. The overall computing work needed in a PoSpace system is performed into two separate phases called plotting and mining. Plotting involves storing nonce values permanently in a pre-allocated space of the hard drive through a repeating hashing process. These nonce values will then be used in the mining phase to verify each new block. Nodes have to mine a new block in a given time window. The node that finds the solution first, gets to mine the next block in the blockchain and collects the reward.

PoSpace is much more energy-efficient than PoW and requires less investment in specialized hardware since hard drives are available by everyone. This also achieves greater decentralization as far more users are able to join the network. However, this affordability in energy and equipment can also promote the disruptive behavior of users in the network. Burstcoin and Spacemint are some examples of cryptocurrencies utilizing the PoSpace algorithm.

1.5.7 Proof of Activity (PoA)

Proof of Activity[1] is essentially a combination of PoW and PoS protocols executed in two stages. The first stage is the equivalent of a PoW system. Miners compete by utilizing their computational resources to create a new block in the blockchain and then broadcast it over the network. However, this newly generated block is partially obsolete since it does not contain any transactions yet. In the next stage of the algorithm, much like in PoS, a group of validators is selected to sign the new block based on the number of coins they already own. The block is appended in the blockchain as soon as it has been signed by all validators. To incentivize both miners and validators in expanding the blockchain, the PoA protocol rewards both groups of users.

Considering that PoA is based on PoW and PoS algorithm designs, it suffers from the same inherent problems. In particular, the energy requirements remain high in the PoW stage, while groups of users who engage in coin hoarding are still favored in the collection of rewards.

[1] Bentov, I., Lee, C., Mizrahi, A., & Rosenfeld, M. (2014). Proof of activity: Extending bitcoin's proof of work via proof of stake [extended abstract] y. *ACM SIGMETRICS Performance Evaluation Review*, *42*(3), 34-37.

1.5.8 Proof of Elapsed Time (PoET)

Proof of Elapsed Time was developed by Intel Corporation in 2016 under the Hyperledger Sawtooth[1] open source project to address the issue of excessive coin accumulation by users, which may ultimately lead to the centralization of a blockchain network. In PoET, each node must remain inactive for a randomly generated period. The node with the shortest waiting time assigned is then prioritized in the creation of the new block. This operation is iterative and the protocol safeguards the fair election of nodes in the mining process. The main advantage of PoET is that its energy demand is lower compared to PoW.

1.5.9 Byzantine Fault Tolerance Consensus Algorithms (BFT)

Byzantine Fault Tolerance Consensus Algorithms (BFT) belong to another category of consensus protocols under which the election of nodes for the mining process is based on a voting mechanism instead of computational capacity. In distributed systems, Byzantine Fault Tolerance refers to the ability of a network to withstand the influence of malicious or failing nodes until the required level of agreement between users is met. BFT protocols developed to solve the Byzantine Generals Problem introduced by Lamport et al. (1982) which provide an analogy based on the Byzantine army to explain how the lack of communication among participants of a distributed network can be surpassed to achieve network integrity.

Several variations of Byzantine Consensus protocols (BCP) have been implemented by known cryptocurrency platforms. For Example, the Delegated Byzantine Fault Tolerance (DBFT) was introduced by the NEO cryptocurrency platform in 2014[2]. Under this protocol, a group of nodes called backup nodes is selected via a voting system that prioritizes the vote of users based on their accumulation of cryptocurrencies. These backup nodes elect randomly a leader node that is responsible for generating a new block of transactions which is then broadcasted to them. The validity of transactions is performed by the backup nodes who must reach a consensus of at least 2/3 for the block to be appended in the blockchain. In the instance of less than 2/3 of the backup nodes reaches an agreement, a new leader node will be elected again.

Federated Byzantine Agreement (FBA) is another BFT algorithm that was proposed by Schwartz et al. (2014) to tackle the issue of communication overhead[3] between nodes while at the same time aims to sustain a decentralized way of selection of leader and backup nodes, in contrast to Practical Byzantine Fault Tolerance algorithm (PBFT) where the selection of nodes for the validation process is conducted by a central

---

[1] Info about Sawtooth Hyperledge Project can be found here: https://sawtooth.hyperledger.org/docs/core/releases/1.0/architecture/poet.html

[2] NEO White Paper. https://docs.neo.org/docs/en-us/basic/whitepaper.html

[3] Communication overhead refers to excessive data transferred between nodes in the network.

authority. In FBA, unlike PBFT, a higher approval ratio of 80 % is needed for a transaction to be validated by nodes. However, in this case, the increased network payload negatively affects its performance.

In Ripple blockchain, this issue is resolved by the implementation of a Unique Node List (UNL). When a transaction is broadcasted in the network, a Node of the UNL performs the task of validation and propagates the list of the candidate transactions to the other nodes of the UNL. The transaction is permanently registered in the ledger only if a consensus of 80% is achieved.

Chapter 2 Literature Review

Since the inception of Bitcoin in 2009, cryptocurrencies have generated tremendous interest from investors and the financial media, while often raising regulatory concerns by policymakers globally. Amid these current developments, Bitcoin and cryptocurrencies have also become a widespread topic of research in financial academic literature. In this context, Corbet, Lucey, Urquhart, & Yarovaya, (2019), carry out extensive analysis on the released research papers related to cryptocurrencies during the period from 2009 to 2018 and address several gaps in the literature.

Furthermore, because of their potential diversification benefits (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018) and their usability as hedging instruments (Bouri, Molnár, Azzi, Roubaud, and Hagfors, 2017), there has been an increased interest in studying the linkages between cryptocurrency markets as well as between cryptocurrencies and traditional assets like oil, gold, stock, and market indices. Although the empirical studies that focus on the price behavior of Bitcoin and its interrelationship with other traditional assets have been prolific, the strand of literature that focuses on cross-correlations among different cryptocurrency markets has recently begun to emerge.

2.1 Volatility relationships in the cryptocurrency markets

Fry & Cheah (2016) employ econophysics models to detect the contagion during bubbles between the two most prominent cryptocurrencies Bitcoin and Ripple. They investigated several notable developments (e.g. termination of the Silk Road illegal website by the FBI, discontinuation of trading activities on Mt.Gox exchange) presumed to exert influence on the Bitcoin market.

Their empirical observation suggests that a negative bubble between the two cryptocurrencies is evident on and after 2014 along with a spillover effect from Ripple to Bitcoin that adversely affects the price of Bitcoin. The implications of developments for the Bitcoin market were found to be either substantial or minor due to speculative bubbles in Bitcoin. However, the authors note that even though the disruptive effect on prices attributable to the Bitcoin bubble overshadows some of the related events, the bubble effectively bursts by a few of them in several instances.

Chan et al. (2017) used daily log-returns of the exchange rates of seven cryptocurrencies versus the U.S. Dollar from 2014 until 2017 to examine their statistical properties and parametric distributions. They employed five discrimination criteria to determine the best-fitted distribution for their specific set of cryptocurrencies by utilizing the maximum likelihood estimate.

Specifically, they observed that generalized hyperbolic distribution fits Bitcoin and Litecoin, while for the smaller cryptocurrencies the normal inverse Gaussian distribution, generalized t distribution, and Laplace distribution provide good fits. Moreover, their reviews are consistent with the work of Chu et al. (2015) who also showed that generalized hyperbolic distribution gives the best fit for Bitcoin, by examining fifteen of the most common distributions used in finance on their data, obtained for the period from 2011 until 2014.

Corbet et al. (2018) examined the volatility linkages among three cryptocurrencies and several financial assets. Their methodological approach was based on the paper of Diebold & Yilmaz (2012) to investigate the return and volatility spillover effect, as well as on the paper of Barunik & Krehlik (2015) to assess the time-varying degree of unconditional connectedness between markets. They found that although Bitcoin prices have an impact on the prices of both Ripple and Lite, the volatility spillover effect from Bitcoin has a mild influence on those two cryptocurrencies. Moreover, Lite has a dominant role in transmitting volatility shocks to Bitcoin and Ripple. These two findings indicate that Lite and Ripple are closely linked. On the other hand, the relationship between these three cryptocurrencies and the other markets is relatively sparse and time-dependent.

Further, the implementation of a frequency framework analysis provides the same results as far as connectedness between cryptocurrencies and other markets is concerned. In contrast, cryptocurrency markets affect each other at both long- and short-time intervals. Overall, their research underpins the diversification attributes that cryptocurrencies may offer when used with traditional assets in an investment portfolio.

Stocic et al. (2018) analyzed the cross-correlations between price changes of 119 publicly traded cryptocurrencies in the period from August 2016 until June 2018 by calculating the cross-correlation and partial cross-correlation matrices using normalized returns. Further, they employed concepts and methods from random matrix theory and minimum spanning trees to investigate the presence of hierarchical structures, which suggests collective behavior in the market of cryptocurrencies. Their findings support that the cross-correlation matrix of cryptocurrency price changes exhibits non-trivial hierarchical structures and groupings of cryptocurrency pairs.

However, for partial cross-correlations most of these structures are absent and anticorrelations seem to prevail in the matrix elements. Moreover, by exhibiting the correlations of the cryptocurrency market as an intricate network of interactions, they discovered distinct community structures in its minimum spanning tree which typically implies the existence of diverse collective behavior between cryptocurrencies. This comes as counterintuitive to the established doctrine that Bitcoin influences the entire market of cryptocurrencies due to its dominant position.

In their empirical study Ciaian et al. (2018) attempted to provide an insight into altcoin price formation dynamics by examining the short- and long-run price interlinkages between Bitcoin and six major altcoins, ten minor altcoins, and two altcoin price indices, on a sample consisting of daily data from 2013 until 2016. Their research was based on the empirical testing of two fundamental hypotheses. The first hypothesis states the prices of altcoins are guided by the change of Bitcoin prices while the second hypothesis states that similar price formation mechanisms between Bitcoin and altcoins intensify their market cointegration. The method of estimation they used to derive their findings is the Autoregressive Distributed Lag (ARDL) model proposed by Shin & Pesaran (1999).

In their model, the authors have taken into consideration the impact of global macroeconomic as well as demand and supply factors on the prices of cryptocurrencies. They applied the ARDL bounds test to examine the cointegrating relation among their model's variables by first performing the following three-unit root tests to determine the stationarity of time series: the augmented Dickey-Fuller test, the Dickey-Fuller GLS test, and the Zivot-Andrews test.

Their empirical results for the first testable hypothesis suggest that Bitcoin and altcoin prices are linked in the short- than in the long-run. For the second hypothesis, the results reveal that in the short-run Bitcoin transmits more profound shocks to altcoins that have similar price formation mechanisms including some altcoins that are heterogeneous to it. However, results fail to adequately explain the long-run relationship between Bitcoin and altcoin prices. Moreover, the supply and demand on cryptocurrency prices have a higher effect in the short run, whereas the effect of global macroeconomic factors on cryptocurrency prices is statistically significant in both short and long-run periods for most cryptocurrencies.

Yi, Xu, & Wang, (2018) assessed the volatility connectedness among eight cryptocurrencies from August 2013 until April 2018 by employing the spillover index approach and its variants proposed by Diebold and Yilmaz (2012, 2014) based on the groundwork of Koop, Pesaran, & Potter (1996) and Pesaran & Shin (1998). The authors also adopted the least absolute shrinkage and selection operator vector autoregression (LASSO-VAR) method developed by Nicholson et al. (2017) to enhance the predictability and comprehensibility of the statistical model through variable selection and regularization while they further extended their empirical analysis to fifty-two cryptocurrencies.

Furthermore, they used 100-day rolling-sample windows to properly account for cyclicity in their model and identified relevant events that may have caused volatility to fluctuate broadly. They found the fluctuation of total volatility connectedness among eight cryptocurrencies to be particularly susceptible to uncertain economic events affecting the market. Additionally, in consonance with the empirical findings of Ciaian et al. (2018), they observed that although cryptocurrencies with high capitalization such as Bitcoin and Litecoin are net transmitters of volatility shocks, market capitalization is not the dominant factor that influences volatility connectedness.

In a similar vein, Ji, Bouri, Lau, & Roubaud, (2018) evaluate the degree of connectedness among six leading cryptocurrencies by quantifying the spillover effects of both returns and volatilities in their respective markets. They develop their research on the methodological basis of Diebold and Yilmaz (2012, 2016) to establish connectedness networks of volatility, as well as networks of positive and negative returns. Further, they progress with regression analysis by constructing a model to estimate the factors affecting the level of integration in cryptocurrency markets. These factors are trading volume, global financial factors, US uncertainties, and major commodity markets. They utilize daily data ranging from August 2015 until February 2018 to calculate daily returns and daily range-based volatilities, while extending their analyses to positive and negative returns independently, to account for potential information asymmetries in the returns of the selected cryptocurrencies.

Moreover, the authors divided the sample into two subsample periods to mitigate the impact of the 2017 upward trend of the cryptocurrency market on their results for the full sample period. Their empirical findings demonstrate that Bitcoin and Litecoin are the two most influential currencies in terms of returns and volatility connectedness, while Ethereum, though it holds the second largest market share, it is the most receptive cryptocurrency to spillover effects emitted by other major or minor cryptocurrencies.

Their results confirm those obtained from Yi, Xu, & Wang, (2018), Corbet et al. (2018), and Ciaian et al. (2018) about significant interlinkages among leading cryptocurrencies who also highlighted the non-dominant position of Bitcoin as the largest emitter of volatility shocks in the cryptocurrency market.

In addition, the authors found that the amplitude of negative-return spillovers significantly exceeds that of positive-return spillovers, indicating that negative-return spillovers are insusceptible to the effects of positive-return spillovers. The significant role of key factors like global financial and commodity markets performance, trading volume, and economic uncertainties in the integration of the cryptocurrencies' markets, is emphasized by the findings of the regression analyses.

Katsiampa et al. (2019) implemented a Multivariate GARCH methodology to analyze the dynamic nature of volatility in eight cryptocurrencies including the conditional correlations among them as well as interlinkages within these cryptocurrency markets. The authors used data consisting of hourly closing prices for each cryptocurrency. They developed their approach by testing their time series for stationarity using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests and Engle's ARCH-LM test to detect the possible presence of ARCH effects in the residuals.

The authors proceeded further with their modeling process by utilizing the Diagonal and Asymmetric Diagonal BEKK-MGARCH models. Their empirical results produced by both the Diagonal and Asymmetric Diagonal BEKK-MGARCH models indicate that conditional covariances are influenced by cross products of past error terms and past conditional covariance terms, which implies that cryptocurrency markets are strongly interdependent. Further, cryptocurrencies' paired returns exhibit a high and positive correlation.

These conclusions are in line with the studies of Yi, Xu, and Wang, (2018) and Ciaian et al. (2018) who also examined the volatility connectedness among cryptocurrencies. Even though all the selected cryptocurrencies demonstrate continuous volatility in the long-term, shocks in OmiseGo fade sooner than shocks in Bitcoin. Finally, the effects of positive and negative shocks in the conditional variance of the returns are mixed.

In another study, Katsiampa (2019) examines the volatility interrelationship between Bitcoin and Ether, by also utilizing a bivariate Diagonal BEKK-GARCH model. The data collected covers a period from August 2015 until January 2018 and consists of daily closing prices. The author performs several tests before the modeling procedure is initiated to determine the stationarity of the time series and the presence of autocorrelation in the residuals.

The results demonstrate that the volatility of both cryptocurrencies exhibits high sensitivity to significant news and this effect persists through time. This was also found to be the case for conditional covariance and correlation. Furthermore, the author observed that although time-varying conditional correlations between the two cryptocurrencies manifest positive and negative oscillations, positive correlations are significantly dominant. These empirical findings are consistent with previous research on the interdependence of cryptocurrency markets while they also highlight the effectiveness of Ether as a hedging instrument against Bitcoin.

Omane-Adjepong & Alagidede, (2019) assess the level as well as the temporal fluctuations of connectedness among seven large cryptocurrencies to provide a ranking of these cryptocurrencies' susceptibility to market shocks, while at the same time examine the presence of any possible pairwise diversification benefits. The level of connectedness among the selected cryptocurrencies was estimated by using wavelet-based methods across different trading intervals for a specific period, while for the spillover effects of volatility among these cryptocurrencies, a VAR model and nonparametric test were employed. The dataset extends from May 2014 until February 2018 and contains historical daily closing prices.

The authors found that volatility spillovers intensify as the trading timeframe of each subsample expands, even though none of the cryptocurrency markets demonstrates a leading role in propagating or receiving volatility shocks. Moreover, they found that volatility shocks do not affect cryptocurrency market pairs uniformly, as volatility linkages are disseminated asymmetrically between several market pairs and throughout different trading periods. Akin to the empirical studies of Corbet et al. (2018); Yi, Xu, & Wang, (2018), leading cryptocurrencies are receptive to volatility shocks emitted by smaller cryptocurrencies despite their higher market share.

2.2 Efficiency of the cryptocurrency markets

Several studies examine the efficiency of cryptocurrencies in the sense of Fama's (1970) efficient market hypothesis (EMH) which is one of the fundamental principles considered when analyzing financial data. The efficient market hypothesis states that a market is efficient if prices reflect all available information. Weak form efficiency which is one of the three different degrees of the efficient market hypothesis (EMH) and implies that past information cannot be used by investors to predict future returns, has been widely studied in the literature for many cryptocurrencies.

Urquhart (2016) was the first to study the market efficiency of Bitcoin on a sample of daily closing prices from the 1st of August 2010 until the 31st of July 2016. He performed the following tests to inspect whether the weak form of market efficiency hypothesis is evident in Bitcoin returns: Ljung-Box test for the presence of autocorrelation, Runs test and Bartels test for dependencies, BDS test for serial dependence and identical distribution of returns, wild-bootstrapped automatic variance ratio test for the existence of random walk hypothesis. Although his findings indicate that Bitcoin is significantly inefficient in the entire sample period, by dividing the sample into two more brief periods the author found evidence that the Bitcoin market is strongly inefficient in the first period with a tendency of shifting into a less inefficient market in the second period of the halved sample.

Nadarajah and Chu (2017) conducted a follow-up study based on the research of Urquhart (2016). The authors also tested the weak form of the efficient market hypothesis on the returns of Bitcoin but instead of using normal returns, they computed Bitcoin returns powered to an odd integer. The full sample period, as well as the two subsample periods they examined, were the same as in Urquhart's study.

Besides the tests Urquhart carried out in his research, they further applied spectral shape tests for the random walk hypothesis, the portmanteau test to check for serial correlation, and the generalized spectral test to check whether the martingale difference hypothesis holds. Their findings in contrast to Urquhart's support that Bitcoin returns satisfy the weak form of the EMH over the full sample period as well as over its two equally divided shorter periods.

Consistent with Urquhart (2016) is also the study of Zhang et al. (2018) who tested the market efficiency of nine cryptocurrencies using a broad array of efficiency tests, rolling windows analysis, and inefficiency index analysis. Their empirical results support that all these cryptocurrencies can be regarded as inefficient markets.

Furthermore, they examined the cross-correlation of these cryptocurrencies with Dow Jones Industrial Average. To achieve that, they initially synthesized a value-weighted cryptocurrency composite index consisting precisely of these nine cryptocurrencies and then employed Multifractal Detrended Cross-Correlation analysis, which was first proposed by Zhou (2008), to conclude that cross-correlation between

Dow Jones Industrial Average and cryptocurrency composite index is persistent in the full sample period.

2.3 Impact of Covid-19 on the market of cryptocurrencies

Recently published papers investigated the effects of the COVID-19 pandemic on the volatility relationships between traditional financial and cryptocurrency markets. Corbet et al. (2020), follow a GARCH (1,1) methodology to study the dynamic conditional correlations (Engle, 2002) between Bitcoin, gold, and Chinese stock markets. The authors argue that Bitcoin's potential diversification benefits are not yet apparent amid the current pandemic crisis, considering its volatile behavior in the early months of the COVID-19 outbreak.

Conlon and McGee (2020), test whether Bitcoin can act as a store of value for investors of the S&P 500 throughout the COVID-19 pandemic. They employ VaR and CVaR measures to assess the potential decline in the value of the portfolio across diverse time intervals and asset allocations. Their empirical findings conclude that Bitcoin is riskier than the S&P 500 thus it may expose the portfolio to even greater risk.

Conlon, Corbet, and McGee (2020) extend their analysis even further by examining the safe-haven properties of three leading cryptocurrencies namely Bitcoin, Ethereum, and Tether at the onset of the COVID-19 pandemic, on a portfolio consisting of six major global stock market indices. Portfolio risk is quantified by using VaR and CVaR metrics through multiple time windows and asset allocations. The authors found that Bitcoin and Ethereum typically do not protect investors from the market downturn as portfolio risk increases even further with their inclusion. Furthermore, Tether was found to possess safe-haven characteristics during the current crisis, however, its peg with the US dollar makes it unattractive over the latter one due to its greater total risk exposure.

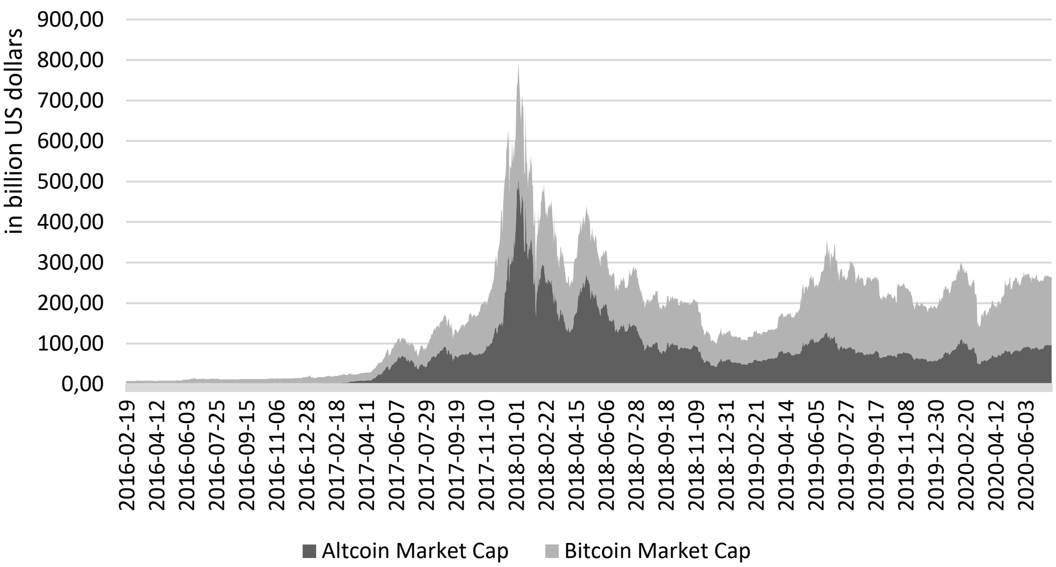
Chapter 3 Cryptocurrency markets

3.1 Bitcoin and altcoins

The significant expansion of cryptocurrencies can be attributed to the absence of governmental endorsement, their peer-to-peer design, and reduced transaction costs relative to traditional value transfer mechanisms. As a result, the prices of bitcoins and other cryptocurrencies have remained remarkably volatile over the last decade, with their total market capitalization jumping from US$18.8 billion to US$820 billion between January 2017 and January 2018, raising the interest of academics, governments, and policymakers, globally. Currently, there are more than 2752 cryptocurrencies available and their total market capitalization is about US$272 billion.[1] The historical market capitalization since February 2016 is displayed in Figure 4 below.

Figure 4

The market capitalization of cryptocurrencies



Source https://coinmarketcap.com/charts/

This section aims to provide a historical founding for each cryptocurrency used in this study, as well as information regarding their architecture and their market performance over their years of existence.

[1] Market capitalization data obtained from www.coinmarket.com. Data on number of cryptocurrencies as of 20 July 2020

3.1.1 Bitcoin

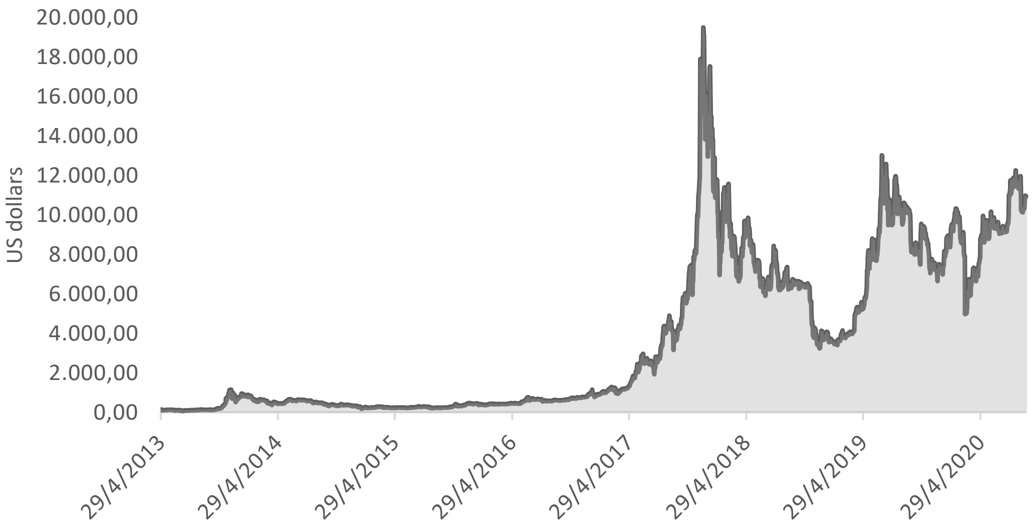
Launched in 2009, following the global financial crisis and based upon decades of notable advances in modern cryptography and distributed computer systems, bitcoin is the first decentralized digital currency that reasonably maintains the most sizeable share of the cryptocurrency market.

However, the price fluctuation of bitcoin has been quite erratic through its years of evolution. In December 2017, its value reached US$19,500 only to drop precipitously to US$10,200 one month later. Significant events associated with regulatory impositions and cybercrime had a negative impact on bitcoin's observed price. For example, in June 2011 a cyberattack launched at Mt. Gox, the first cryptocurrency exchange, removed about US$ 8.75 million in bitcoins through stolen credentials.

Ultimately, Mt. Gox terminated its trading activities in February 2014 after having lost a substantial number of bitcoins through a security breach that remained undetected for years. In October 2013, the FBI shut down the Silk Road website which provided a platform for users making illegal transactions paid in bitcoins. The same year, the People's Bank of China prohibited the Chinese financial institutions from using Bitcoin. In early 2018 government legislation in South Korea and China, led to a steep decline in the economic value of bitcoin by roughly 50%. The price evolution of bitcoin through the years is illustrated in the graph below.

Figure 5

The price evolution of bitcoin



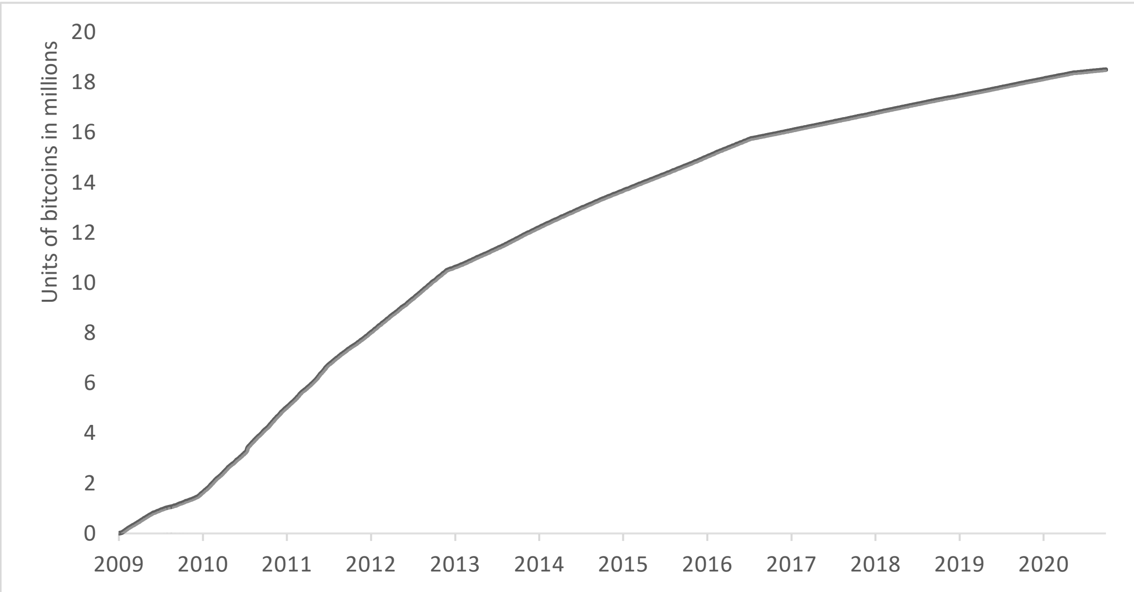
Source https://coinmarketcap.com/currencies/bitcoin/

The supply of bitcoins

As we mentioned in the first chapter Bitcoin relies on PoW consensus protocol to ensure the validity of transactions in the network while it also acts as an incentive mechanism by rewarding users with bitcoins for maintaining the integrity of the blockchain. The difficulty of the PoW mechanism adjusts as more users join the network to keep the average creation time of a new block by miners at 10 minutes. This achieves a metered supply of tokens through the course of Bitcoin's lifespan. When Bitcoin has first launched, the reward for generating a new block was 50 bitcoins. This amount has been programmed to gradually decrease every four years until it reaches zero. At that point, the total amount of bitcoins ever created will be twenty-one million[1]. The purpose of this downward trend in supply is to sustain the scarcity of issued digital coins. Currently, the reward is 6.25 coins per block with the next reduction event taking place in May 2024. The chart below displays the total number of bitcoins in circulation since they were first issued.

Figure 6

Total bitcoins in circulation



Source https://www.blockchain.com/charts/total-bitcoins

One of the major criticisms of Bitcoin mining is that it is a high energy expenditure activity that requires investing in equipment with particular technical specifications therefore, miners have to balance their costs to gain the most from their investment.

---

[1] This is expected to happen approximately in 2140.

Drivers of Bitcoin price

Bitcoin's price behavior has been studied widely by researchers driven by the huge media attention Bitcoin received rapidly in the first years of its deployment. Since Bitcoin is not endorsed by an issuing bank or government, and thus devoid of supply and demand characteristics present in fiat currencies, traditional economic theories cannot explain its price formation (Kristoufek, 2013). Moreover, because its supply is predetermined, its price was likely more susceptible to demand-driven events, such as queries on the web related to Bitcoin information and news in the early years after its launch. (Ciaian et al., 2016).

However, Bouoiyour et al. (2016), support that price formation, in the long run, can be partially explained by macro-financial developments in equity markets, exchange rates, and oil prices, while Ciaian et al., 2016 argue that determining factors of Bitcoin's demand side, such as market size and investor sentiment are more likely to be the drivers of the Bitcoin price in the long term. Speculative behavior by investors (Fry & Cheah, 2016; Ciaian et al., 2016) and global regulatory actions (Auer & Claessens, 2020) have also been found to be key drivers affecting Bitcoin's price.

3.1.2 Litecoin

Litecoin was launched in October 2011 by Charlee Lee a former Google employee as a digital coin that aimed to improve several inefficiencies in Bitcoin's blockchain while still maintaining its key innovations. For example, the transaction time in Litecoin is 2.5 minutes down from 10 minutes in Bitcoin, to facilitate the transfer of smaller amounts among merchants. Litecoin also uses a different Proof of Work algorithm than Bitcoin's SHA-256 called Scrypt. The reason for the adoption of this alternative hashing algorithm was to make the mining process more feasible for users with mainstream computer systems.

The supply of Litecoin is also predetermined as Bitcoin, with 84 million being the maximum number of digital coins that will ever be put into circulation. Moreover, Litecoin shares the same pattern of reward distribution with Bitcoin, as rewards per block tend to decrease every four years. The current reward is 12.5 litecoins per block which is expected to drop to 6.25 in 2023. The updates of Litecoin follow the same route as the updates of Bitcoin.

3.1.3 Ethereum

Ethereum was first proposed by programmer Vitalik Buterin in late 2013 and came into operation in July 2015 as an open-source blockchain platform that facilitates the utilization of decentralized applications and self-executing programs called smart contracts. The digital currency used in the Ethereum network is ether. Developers who wish to use the Ethereum network to deploy their applications have to pay in ether. This form of payment ensures that only quality programs are reposited on the Ethereum network. Moreover, Ether can be traded like any other cryptocurrency on a digital exchange.

Ethereum uses also the PoW protocol. Miners in the Ethereum network are rewarded in ether for verifying transactions related not only to the transfer of ether units between users but also to the broadcast of information between programs. The transaction time is significantly lower than Bitcoin as it takes approximately 12 seconds for a new block to be generated. The shifting towards a Proof of Stake protocol is expected to happen in the upcoming update of Ethereum to version 2.0.

Unlike Bitcoin, the supply of Ether is not subject to any limitation. The initial currency supply when the system became operational in 2015 was 72 million coins. The rate at which new coins are generated is constant contrary to Bitcoin which is halved every four years. As of July 2020, there are more than 111.5 digital coins in circulation[1].

A major event that led to the price of ether falling precipitously from US$ 21.52 to US$ 9.96 on 17th June 2016[2] was the cyberattack on DAO[3] digital decentralized venture capital fund that was established on the Ethereum platform in April 2016. The hack exploited imperfections in DAO's software design and resulted in the stealing of more than US$ 50 million funds that had been previously raised through crowdfunding. Eventually, the Ethereum blockchain was divided into two separate forks with one progressing over the initial blockchain after the hack had happened and the other progressing with the amount of theft restored. Proponents of the original blockchain created Ethereum Classic detached from the current Ethereum platform.

3.1.4 Ripple

Ripple was developed in 2012 by Ripple Labs as a distributed open-source network that enables money transfer, payments, and currency exchange in real-time as opposed to traditional interbank networks such as SWIFT. The accounts in Ripple are stored in a distributed database in which they can be credited with traditional as well as virtual currencies. The native currency of the Ripple network is XRP which is used to facilitate the transfer of funds among its participants. The transaction costs are minimal, and they exist to deter Distributed Denial of Service (DDoS)[4] attacks launched on the network. Moreover, the average time for a transaction to be confirmed is 5 seconds which is significantly lower than the average transaction time in Bitcoin.

The consensus algorithm of Ripple differs from the traditional Proof of Work implementations used in Bitcoin and other cryptocurrencies. In Ripple, each transaction among network participants is validated by trusted servers owned by a variety of financial entities such as banks and brokerage firms. As a consequence, the absence of a mining

[1] Source https://etherscan.io/chart/ethersupplygrowth
[2] Source: https://www.coindesk.com/classic-dao-drove-ether-prices-2016
[3] DAO stands for Decentralized autonomous organization.
[4] DDoS attack is a type of cyberattack aiming to disrupt the services of a network resource.

process meant that the initial supply of digital coins should be distributed by the company that developed Ripple. This amount was equal to 100 billion XRP units that were originally issued and held by Ripple Labs, whose purpose was to stimulate gradually the demand for these newly minted coins.

Ripple platform is being currently adopted by more than 300[1] financial institutions including major banks such as UBS, Santander, and Westpac.

3.1.5 Monero

Monero is an open-source cryptocurrency commenced in 2014 that aimed to achieve a higher level of privacy protection over other cryptocurrencies. Monero's privacy innovations stem from the implementation of ring signatures and stealth addresses. Ring signatures refer to the method under which the transactions are signed. In Monero the amount of a particular transaction is being signed by a group of users instead of the person who originally sent it. In this way, the identity of the sender cannot be verified since the receiver cannot trace the address back to a unique individual. Moreover, the system forces the creation of a new address by the sender dynamically each time a transaction takes place. Thus, an outside entity cannot link the transactions made to a receiver's public address with a specific address that belongs to a sender.

Another privacy feature of Monero is that its currency units are fungible since a unique identifier for each of those is nonexistent. Monero utilizes a Proof of Work algorithm different than that of Bitcoin. Its design allows users to join the mining process without the use of any specialized hardware. The difficulty of the mining process is adjusted so every new block can be generated in 2 minutes on average. The initial supply rate of monero units was 30 XMR per block every 2 minutes programmed to decline to 0.6 XMR by 2022. However, unlike Bitcoin and many other cryptocurrencies, Monero allows for a minimal supply rate to exist beyond its target cap of 18,4 million coins.

Monero's privacy traits made it a well-established cryptocurrency in darknet markets. The AlphaBay darknet market began to accept monero as a means of payment for illicit trade activities in July 2016. Eventually, in July 2017 the US law enforcement shut down AlphaBay. In May 2017, the masterminds behind the global ransomware attack WannaCry started to exchange the ransoms they have previously collected in bitcoins to moneros. In June 2017 Shadow Brokers, the hacker group which leaked the source code behind WannaCry ransomware announced that they will be accepting payments in moneros to provide leaked information to the highest bidder. The increased use of monero illegally led to its price skyrocketing in 2016, reaching close to a 2,760[2]% increase in growth over a year.

[1] https://ripple.com/customers

[2] Source https://www.investing.com/analysis/6-cryptocurrencies-putting-bitcoins-rally-to-shame-200273068

3.2. Cryptocurrencies and regulatory authorities

Since the introduction of Bitcoin in 2009, cryptocurrencies have been in the scope of many regulatory bodies around the world, with each approaching the subject in alternate ways.

The European Central Bank (2015) defines cryptocurrencies as "digital representations of value, not issued by a central bank, credit institution or e-money institution, which in some circumstances can be used as an alternative to money". The European Central Bank (2012) also stipulates in their report that cryptocurrencies do not pose a threat to financial stability as long as their traded volume is low and their attachment to the real economy remains limited. However, it mentions the potential risks that could occur at the user level while it also highlights the need to further monitor the overall developments in the cryptocurrency market and reassess the risks periodically.

The Committee on Payments and Market Infrastructures of the Bank of International Settlements (2015) classifies cryptocurrencies as digital currencies or digital currency schemes. Their classification is based on the following three criteria: 1) they are assets with zero intrinsic value that are not backed by any official authority. Consequently, their value stems from the perception that they can be exchanged eventually with commodities and services or even other traditional currencies, 2) they utilize distributed ledgers in peer-to-peer network formations, 3) they function outside traditional financial institutions. Furthermore, the report highlights the innovative technology behind cryptocurrencies which can have potential applications in financial market infrastructures if its adoption gradually increases and some risks and barriers could be eventually overcome. Lastly, according to the report, Central banks could explore the potential benefits of the distributed ledger technology and orient their policy actions accordingly.

The European Banking Authority ("EBA") (2014) labels cryptocurrencies as virtual currencies which are described as "a digital representation of value that is neither issued by a central bank or a public authority, nor necessarily attached to an FC, but is accepted by natural or legal persons as a means of payment and can be transferred, stored or traded electronically". EBA in its report lists more than 70 risks associated with cryptocurrencies ranging from user-level risks to macro-economic risks. According to EBA, the risks further exceed the potential benefits the distributed ledger technology could provide, while also stipulates that several legislative actions by the EU and national regulators must urgently take place to mitigate all these risks.

The International Monetary Fund ("IMF") (2016) places cryptocurrencies under the wider category of virtual currencies and it describes them as "digital representations of value, issued by private developers and denominated in their own unit of account". The IMF also identifies several financial, operational, and legal risks associated with the use of cryptocurrencies, although, the risks related to monetary policy implementation may fail to materialize in the short term as the public acceptance of cryptocurrencies is still narrow. However, as the landscape of virtual currencies evolves, IMF suggests that regulators should act accordingly to deter the risks in a way that technological innovation is preserved.

In contrast to the previous policy-making bodies, the World Bank (Natarajan et al.,2017) provides an alternative definition for cryptocurrencies. It defines cryptocurrencies as: “digital currencies that rely on cryptographic techniques to achieve consensus”. Moreover, it categorizes cryptocurrencies as a subcategory of digital currencies which characterizes them as “digital representations of value that are denominated in their own unit of account, distinct from e-money, which is simply a digital payment mechanism, representing and denominated in fiat money”. The World Bank acknowledges the potential improvements that Distributed Ledger Technology may offer in the financial infrastructure, however, due to its preliminary development, realistic implementations on a large-scale are unlikely to appear anytime soon. According to the World Bank, as the technology matures, several technological, legal, and regulatory challenges may emerge which can ultimately alter the traditional functions of the interested parties in the financial industry. Therefore, World Bank Group is currently unable to provide any guidelines for using Distributed Ledger Technology in the absence of a specific framework.

It can be inferred from the above standpoints that there is a lack of a widely accepted definition of cryptocurrencies, though most regulators share the common view that cryptocurrencies are a type of virtual or digital currencies. Moreover, the absence of regulatory orientation is evident at this current phase of the development of cryptocurrencies, while some regulators even abstain from providing a precise definition. Also, it can be further deduced that all the supervisory authorities highlight the technological innovation of the underlying technology of cryptocurrencies with most of them considering potential applications in the financial infrastructure in the long term. However, they place a great emphasis on the various types of risks the cryptocurrencies bear and advise caution to potential investors.

Chapter 4 Data and Methodology

This study aimed to investigate the price behavior of five cryptocurrencies *BTC, LTC, ETH, XMR*, and *XRP*. We investigated the fluctuations, potential peaks, minimums, and whether there is a link, co-movement in the price behavior of the cryptocurrencies.

The observations of the five cryptocurrencies were retrieved from coinmarketcap.com. The time frame was from 2013 until 2020. The available period of data for each cryptocurrency was the following: BTC (29/4/2013 – 18/9/2020), LTC (29/4/2013 – 18/9/2020), ETH (7/8/2015 – 18/9/2020), XRP (4/8/2013 – 18/9/2020), and XMR (22/5/2014 – 18/9/2020).

The data employed consists of daily closing prices for five leading cryptocurrencies: Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), Ripple (XRP), and Monero (XMR). Data availability was a key factor for selecting these digital currencies since there were fewer observations for the most recent cryptocurrencies. Furthermore, these five cryptocurrencies are well established in the cryptocurrency market and introduced noticeable innovations that have been adopted by other digital coin schemes launched in later years.

The daily historical closing prices of the five cryptocurrencies used in this study were obtained from coinmarketcap.com/currencies. Coinmarketcap.com lists important market data about each currency such as price, market capitalization, trading volume, and circulating supply. Moreover, it provides news related to cryptocurrency markets as well as general information about the design of each digital currency. Prices are calculated as a volume-weighted average of prices quoted in leading cryptocurrency exchanges. Additionally, certain mandatory requirements must be met for a digital currency to be listed on the website. Among others, cryptocurrencies must be publicly traded on an exchange, the total number of their units in circulation must be sufficient and displayed publicly in a URL. Cryptocurrencies that fail to meet these standards are subsequently delisted from the website.

The data for each cryptocurrency spans across different periods with Ethereum being the most recent. It should be noted that data for all cryptocurrencies on coinmarketcap.com was available from 29 April 2013 while the end date of our examination period is 18 September 2020. Bitcoin is the oldest cryptocurrency, and its data is comprised of 2700 observations starting from 29 April 2013. Litecoin also consists of the same number of observations as Bitcoin even though, as mentioned before, it was conceived afterward. The starting date of Ripple's data is the 4th of August 2013 and the number of its observations is 2603. Monero consists of 2312 observations starting from 22 May 2014. Lastly, the data of Ethereum covers 1870 observations starting from 7 August 2015.

Statistical Analysis

Initially, each cryptocurrency was investigated graphically with the use of the daily closing prices. In this way, the researcher observed when there was a decreased or increased trend in the development of prices. Afterward, the closing prices of the cryptocurrencies were transformed with the use of the logarithmic function. Then, all the cryptocurrencies were graphically represented on the same almost scale. The observation of similar patterns was easier this way.

The second stage of the analysis included the calculation of the logarithmic returns of each cryptocurrency (the difference between the logarithmic value of the current closing price and the logarithmic value of the previous closing price). The returns of the cryptocurrencies were investigated for a potential relationship with the use of correlation analysis. For this reason, the Pearson index was used.

Furthermore, this kind of analysis was applied not only on the entire timeframe of the cryptocurrencies but also on a moving window of 100 days. More precisely a rolling window of 100 days period was calculated for each pair of cryptocurrencies, BTC - LTC, BTC - ETH, BTC - XMR, BTC - XRP, LTC - ETH, LTC - XMR, LTC - XRP, ETH - XMR, ETH - XRP, and XMR – XRP. The use of a rolling window among time series/cryptocurrencies in our case helped the researcher to investigate the consistency of the correlation across time, whether a stable correlation between time series is evident or not.

For example, the case of a stable correlation line depicted in a graph indicates a possible co-movement between the time series. On the other hand, a line with lots of ups and downs depicts an unstable relationship or no relationship at all between the time series even though the correlation index for the entire timespan could be very high (Schittenkopf & Dorffner, 2002).

Finally, a cointegration analysis was conducted with the use of the Johansen test. The reason for this choice over the simple regression method is that the latter may be inadequate to identify the potential relationship between two time-series, which could ultimately lead to spurious regression (false regression), as explicated by Granger and Newbold (1974). Thus, it is possible to result in a false relationship between two time-series caused by short-term fluctuations.

The concept of cointegration can help overcome the phenomenon of spurious relationships among time series. According to the concept of cointegration two or more, nonstationary time series can have a long-term relationship which means that they share a co-movement pattern across time. To test for the existence of cointegration among time series, the researcher must test first whether the time-series are stationary (constant mean and volatility). The stationarity assumption was tested with the Augmented Dickey-Fuller test.

The most common method of testing cointegration is the Johansen test (1988). This method is based on the vector self-regression model (VAR) and the technique of maximum probability to conclude the existence of integration. The VAR method is a system of autoregression models, with each variable being affected by its previous values but also by the values of all other variables in the system. The Johansen method identifies the maximum number of integration relations that connect the variables since it allows for testing many equations simultaneously. In contrast, in the Engle and Granger method one equation is checked at a time. This is mainly the reason the Johansen method has prevailed in integration tests between variables.

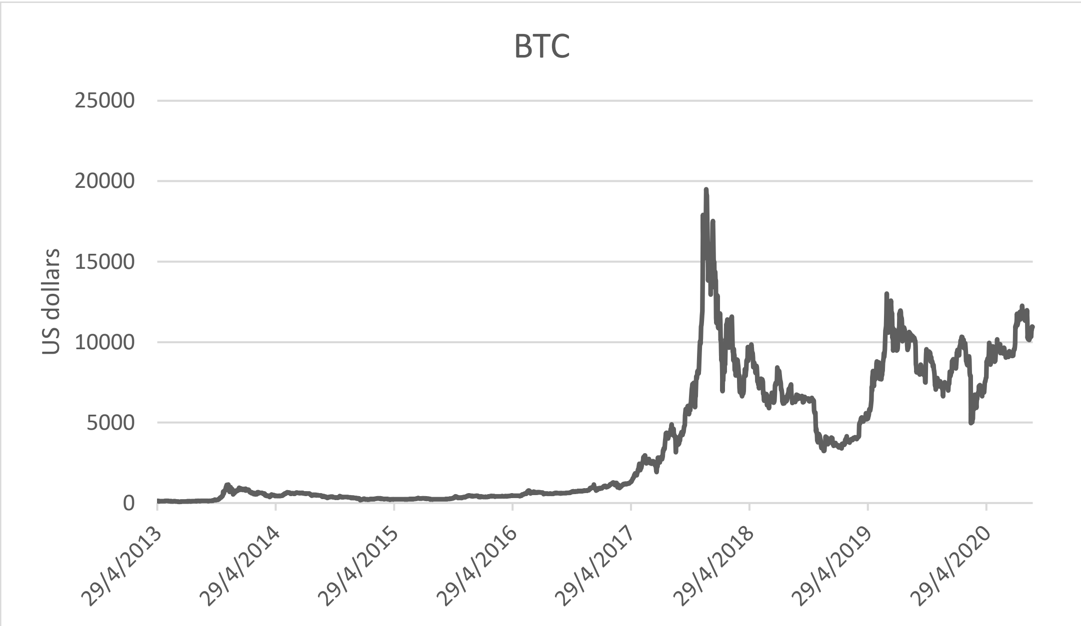
The statistical analysis was conducted with the use of R studio and Microsoft Excel 365 software. More specifically, R studio was used for the test of stationarity as well as cointegration hypotheses while Microsoft Excel was used firstly to import data from coinmarketcap.com, secondly to perform graphically a rolling correlation analysis with a rolling window of 100 days, and lastly to calculate the static correlation of the studied cryptocurrencies for the entire timeframe.

Chapter 5 Results

In figure 7, the BTC cryptocurrency depicts a stable trend from April 2013 until April of 2017. From May 2017 there is a rapid increase until the end of the same year. The BTC cryptocurrency reaches a peak and afterward, it follows a decreased trend until April 2019. After that, it follows again an increased trend with intense fluctuations until April 2020.

Figure 7

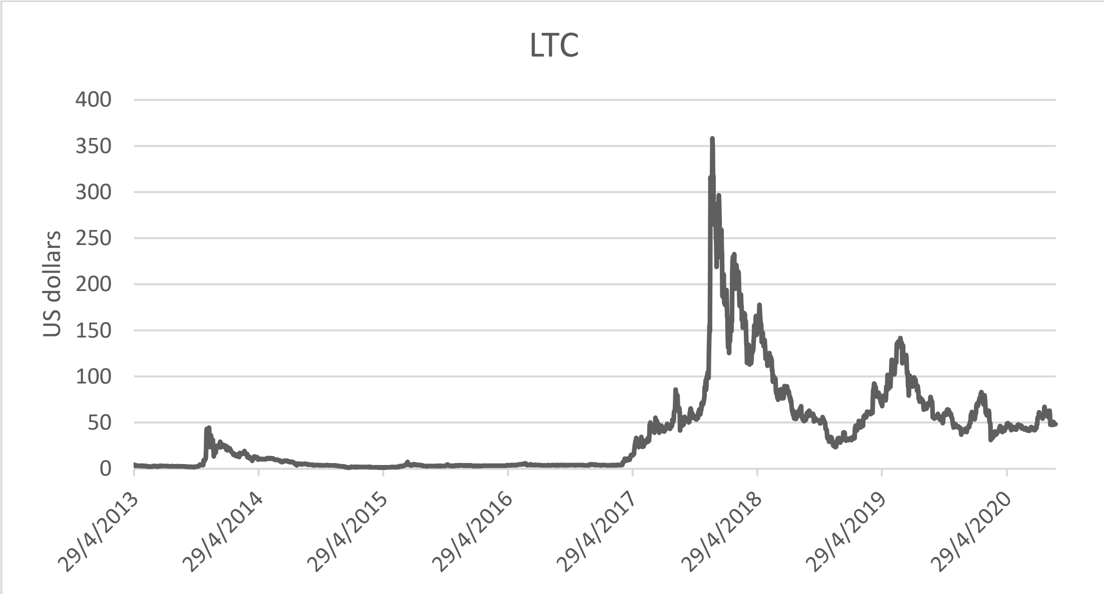
BTC cryptocurrency closing prices, 29/4/2013 – 18/9/2020.



In figure 8, the LTC cryptocurrency depicts a stable trend from April 2013 until April of 2017. From, May 2017 there is a rapid increase until the end of 2017. The LTC cryptocurrency reaches a peak and afterward, it follows a decreased trend until April 2019. After that, it presents medium-level fluctuations until April 2020. It seems that the LTC cryptocurrency follows almost the same pattern as the BTC cryptocurrency except for the last period, April of 2019 until April of 2020.

Figure 8

LTC cryptocurrency closing prices, 29/4/2013 – 18/9/2020.



In figure 9, the XRP cryptocurrency depicts a stable trend from August 2013 until April of 2017. From May of 2017, there is a rapid increase until the end of 2017. The XRP cryptocurrency reaches a peak and afterward, it follows a decreased trend until April of 2019. After that, it presents a stable trend until April of 2020. It seems that the XRP cryptocurrency follows almost the same pattern as the BTC and LTC cryptocurrencies from August of 2013 until the April of 2018, after the April of 2018 until the April of 2020 the XRP cryptocurrency follows a more stable trend compared with the other two cryptocurrencies.

Figure 9

XRP cryptocurrency closing prices, 4/8/2013 – 18/9/2020.

In figure 10, the XMR cryptocurrency depicts a stable trend from May of 2014 until April of 2017. From May of 2017, there is a rapid increase until the end of 2017. The XRP cryptocurrency reaches a peak and afterward, it follows a decreased trend until April of 2019. After that, it presents a stable trend until April of 2020. It seems that the XMR cryptocurrency follows almost the same pattern as the XRP cryptocurrency from May of 2014 until April of 2020.

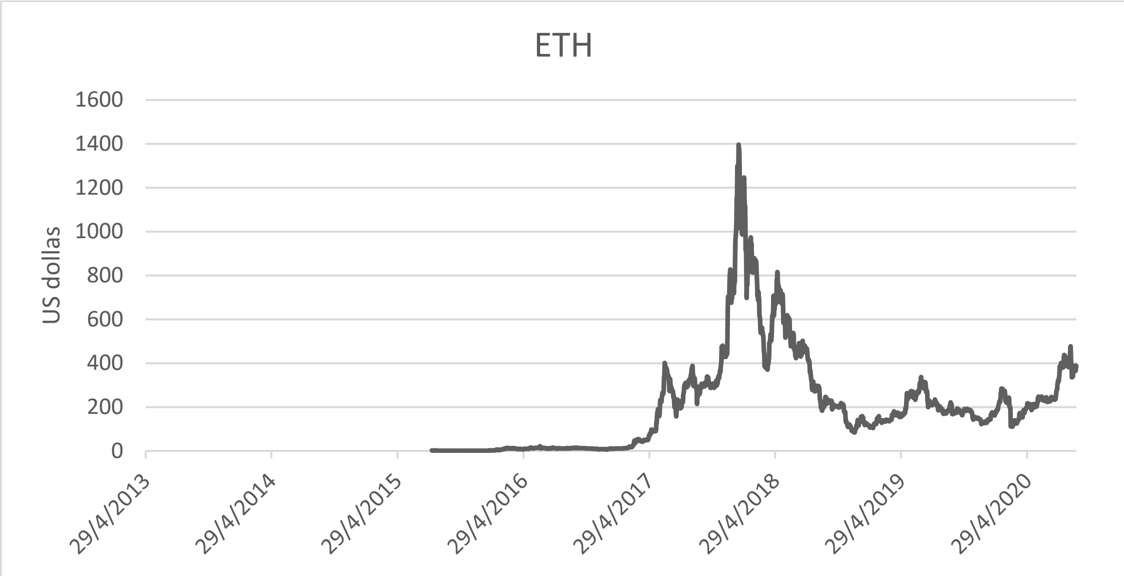
Figure 10

XMR cryptocurrency closing prices, 21/5/2014– 18/9/2020.

In figure 11, the ETH cryptocurrency depicts a stable trend from August of 2015 until April of 2017. From May of 2017, there is a rapid increase until the end of 2017. The ETH cryptocurrency reaches a peak and afterward, it follows a decreased trend until April of 2019. After that, it presents a slowly increasing trend with fluctuations until April of 2020. It seems that the ETH cryptocurrency follows almost the same pattern as the BTC cryptocurrency.

Figure 11

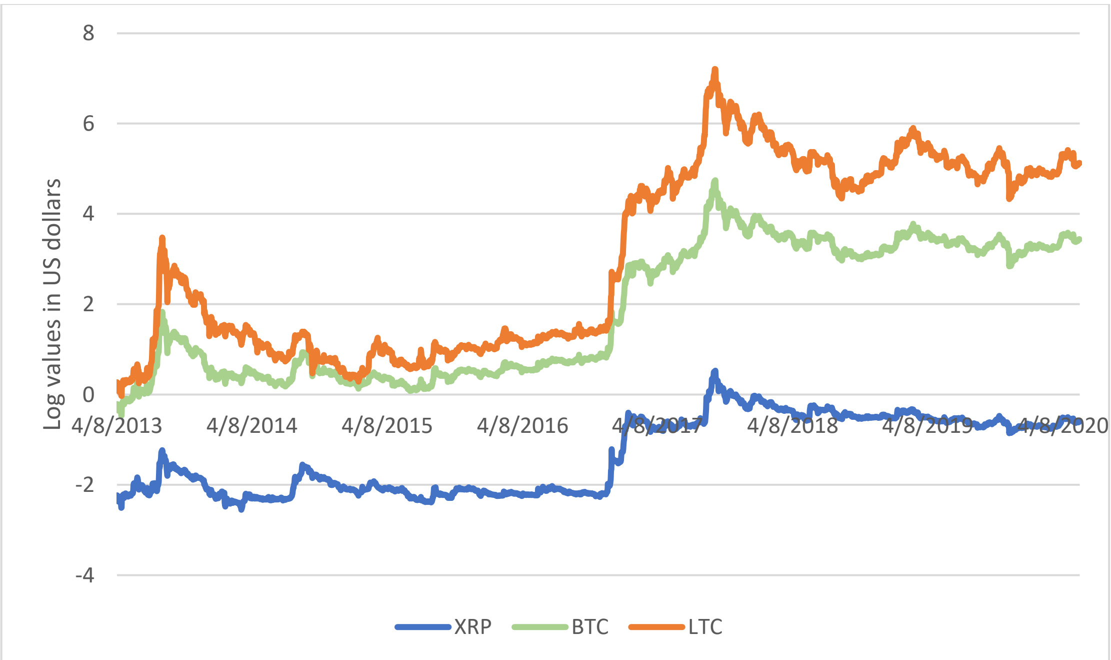
ETH cryptocurrency closing prices, 7/8/2015 – 18/9/2020.



In figure 12, the log price values of three of the five cryptocurrencies can be seen, LTC, BTC, and XRP covering a period from 4/8/2013 until 18/9/2020. It seems that the three cryptocurrencies follow the same pattern for the whole time frame. The LTC and BTC cryptocurrencies present patterns that are less different compared to the pattern of the XRP cryptocurrency. This similarity between the patterns of the LTC and BTC cryptocurrencies is more intense after the end of 2017.

Figure 12

Logarithmic closing prices of LTC, BTC, XRP cryptocurrencies, 4/8/2013 – 18/9/2020.



In figure 13, the log price values of the five cryptocurrencies can be seen, LTC, BTC, XMR, ETH, and XRP ranging from 7/8/2015 until 18/9/2020. It seems that the LTC, BTC, XMR, and ETH cryptocurrencies follow the same pattern for the whole timeframe. This similarity between the movement pattern of the LTC, XMR, BTC, and ETH cryptocurrencies is more intense after the end of 2017.

Figure 13

Logarithmic closing prices of LTC, BTC, XRP, XMR, ETH cryptocurrencies, 7/8/2015 – 18/9/2020.

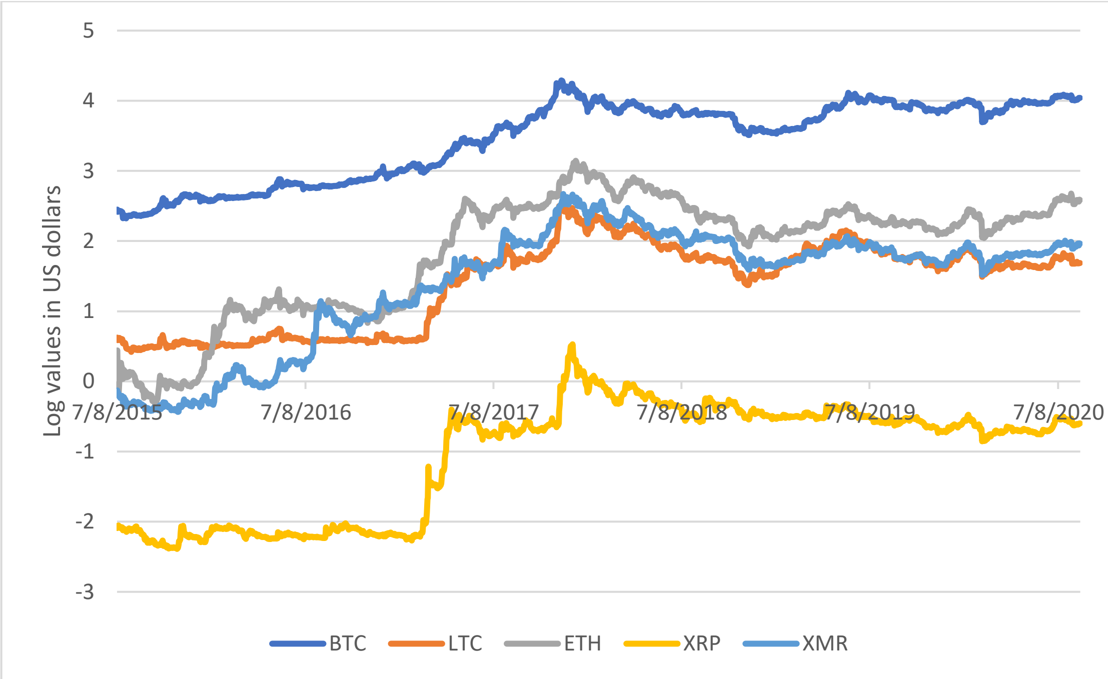


Table 1

Correlations of BTC, LTC, and XRP cryptocurrencies, 5/8/2013-18/9/2020.

	BTC	*LTC*	*XRP*
BTC	1,00	0,68	0,40
LTC	0,68	1,00	0,39
XRP	0,40	0,39	1,00

In table 1 there is a positive correlation of medium intensity between the BTC and LTC cryptocurrencies. Further, it can be noticed that there is a low positive correlation between the XRP, LTC, and BTC cryptocurrencies.

Table 2

Correlations of BTC, LTC, ETH, XMR, and XRP cryptocurrencies, 8/8/2015-18/9/2020.

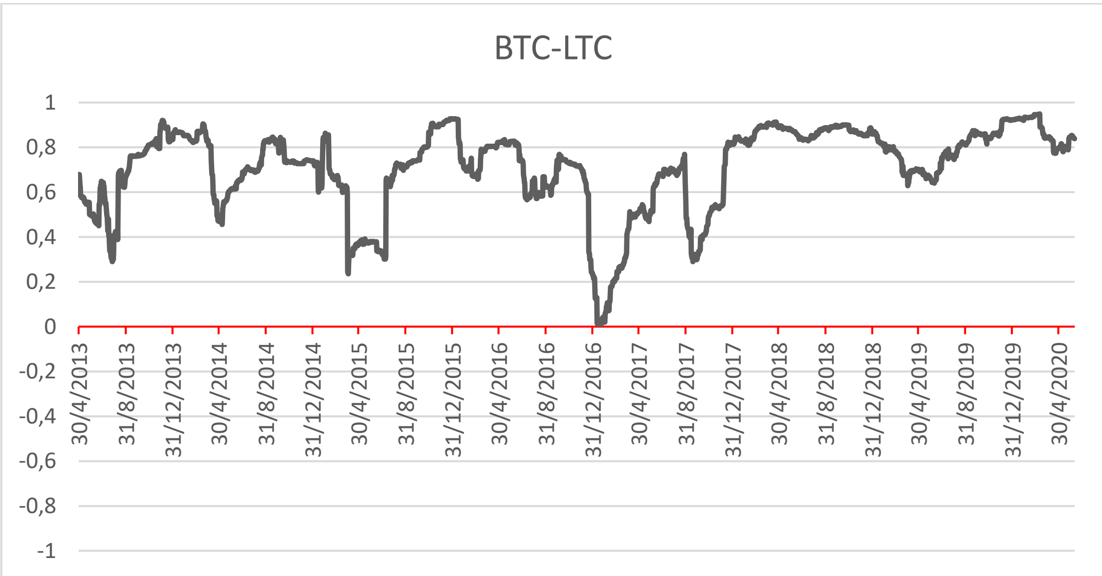
	BTC	*LTC*	*ETH*	*XRP*	*XMR*
BTC	1,00	0,67	0,48	0,39	0,57
LTC	0,67	1,00	0,46	0,44	0,51
ETH	0,48	0,46	1,00	0,31	0,43
XRP	0,39	0,44	0,31	1,00	0,36
XMR	0,57	0,51	0,43	0,36	1,00

In table 2 the correlations among the three cryptocurrencies, BTC, LTC, and XRP are the same as those that were presented in table 1. Furthermore, the ETH and XMR cryptocurrencies are weakly positively correlated with the LTC, BTC, and XRP cryptocurrencies.

In figure 14 the intensity of the correlation between BTC and LTC exhibits extreme fluctuations from April of 2013 until the end of 2017 on a rolling window of 100 days. Specifically, correlation jumps from almost zero at the beginning of 2017 to 0.82 at the end of the same year. After 2017 the correlation remains more stable ranging from 0.6 to 0.9.

Figure 14

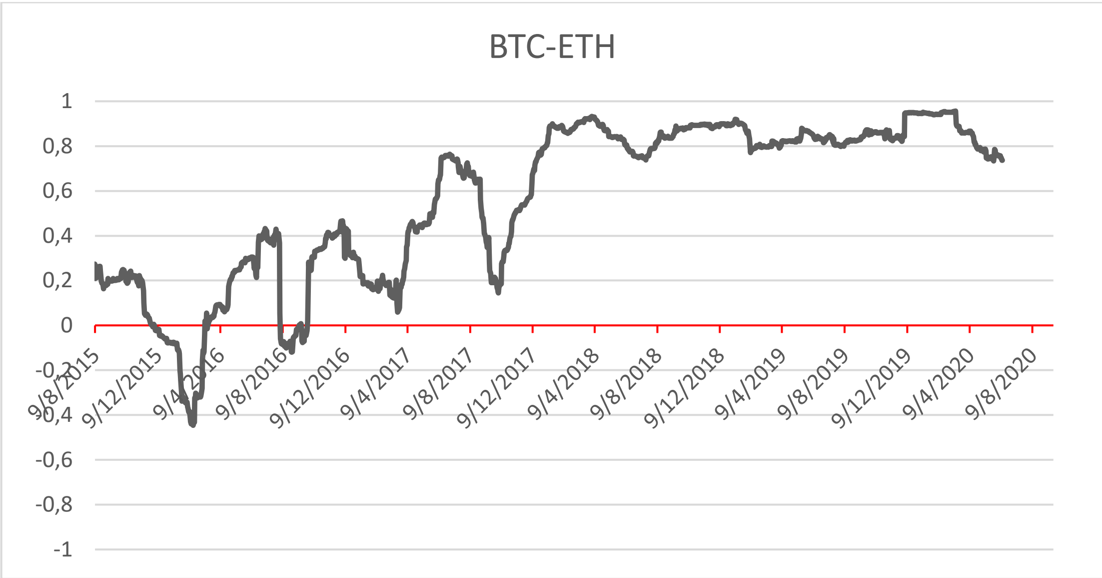
Rolling correlation between the BTC and LTC cryptocurrencies.



In figure 15 the intensity of the correlation between BTC and ETH cryptocurrencies exhibits extreme fluctuations from August of 2015 until the end of 2017 on a rolling window of 100 days, with values oscillating in the range from -0.4 to 0.9. After 2017 the correlation presents a more stable and positive trend with its values ranging from 0.7 to 0.9.

Figure 15

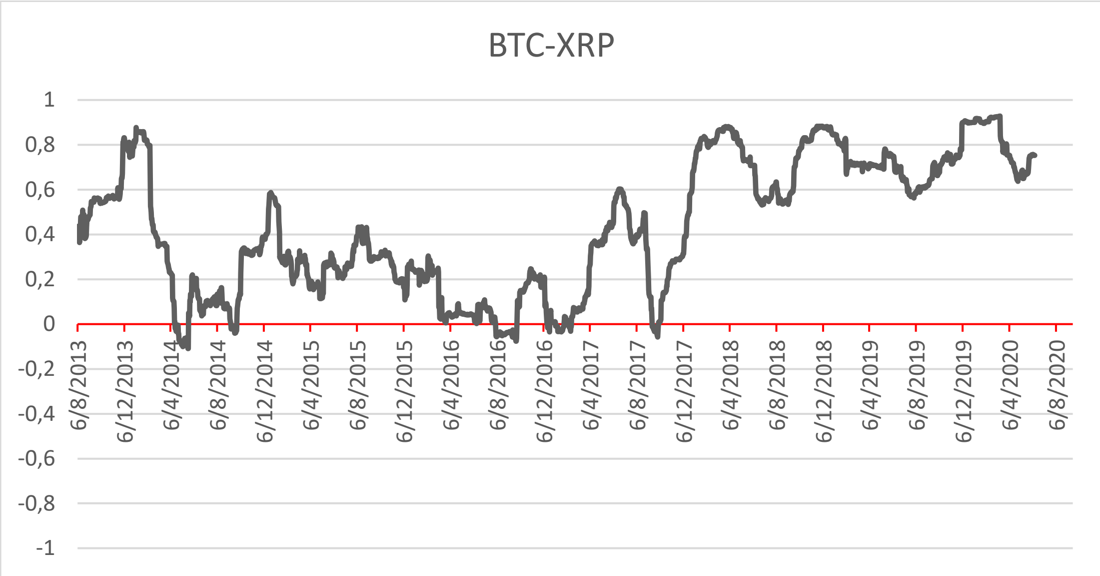
Rolling correlation between the BTC and ETH cryptocurrencies.



In figure 16 the intensity of the correlation between BTC and XRP exhibits extreme fluctuations from August of 2013 until the end of 2017 on a rolling window of 100 days. More specifically, the value of correlation jumped from almost zero at the end of the third quarter of 2017 to 0.67 at the end of 2017. From the end of 2017 onwards, the correlation follows a more stable trend, nevertheless, with fluctuations ranging from 0.53 to 0.92.

Figure 16

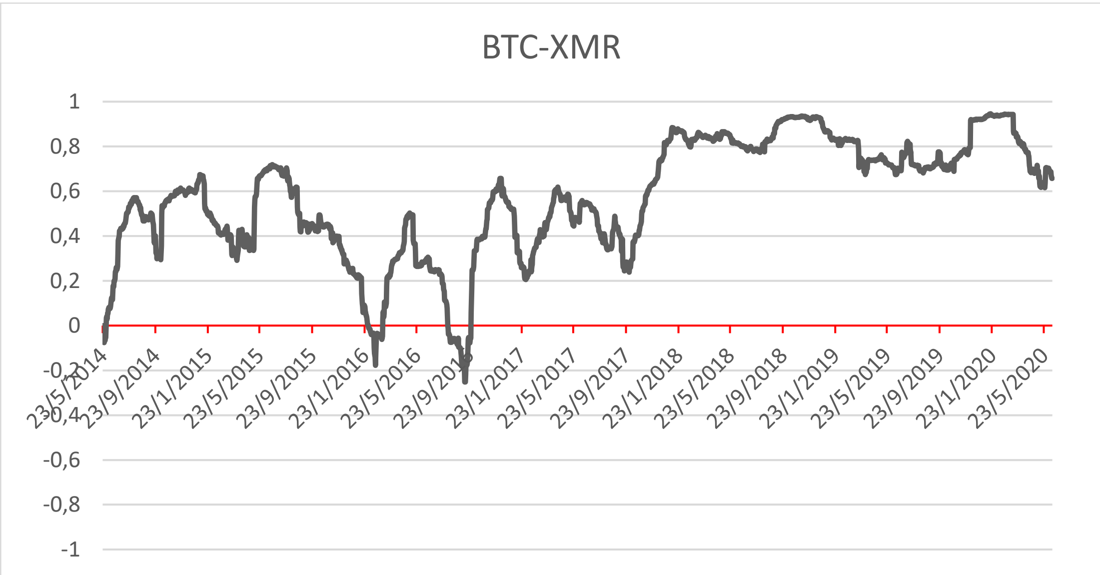
Rolling correlation between the BTC and ETH cryptocurrencies.



In figure 17 the intensity of the correlation between BTC and XMR cryptocurrencies exhibits extreme fluctuations from May of 2014 until the end of 2017 on a rolling window of 100 days, with a range from as low as -0.21 to as high as 0.82. From 2018 onwards, the correlation stabilizes with fluctuations ranging positively from 0.62 to 0.93.

Figure 17

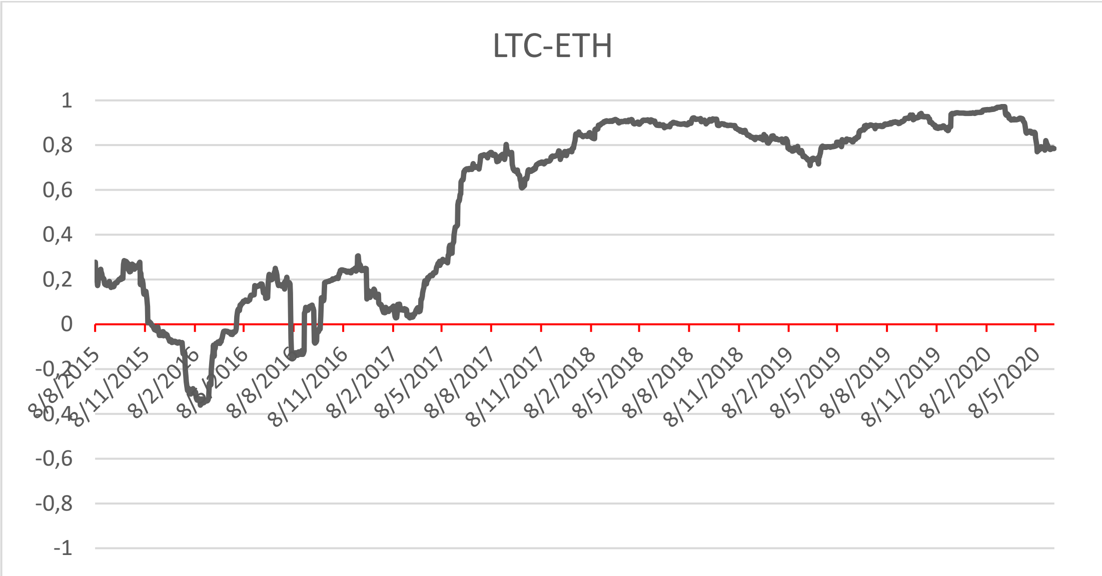
Rolling correlation between the BTC and XMR cryptocurrencies.



In figure 18 the intensity of the correlation between LTC and ETH cryptocurrencies exhibits extreme fluctuations from August of 2015 until the end of 2017 on a rolling window of 100 days, with its values reaching as low as -0.36 in February 2016 to as high as 0.76 in September 2017. After 2017 the correlation is stabilized within the positive range of 0.73 to 0.97.

Figure 18

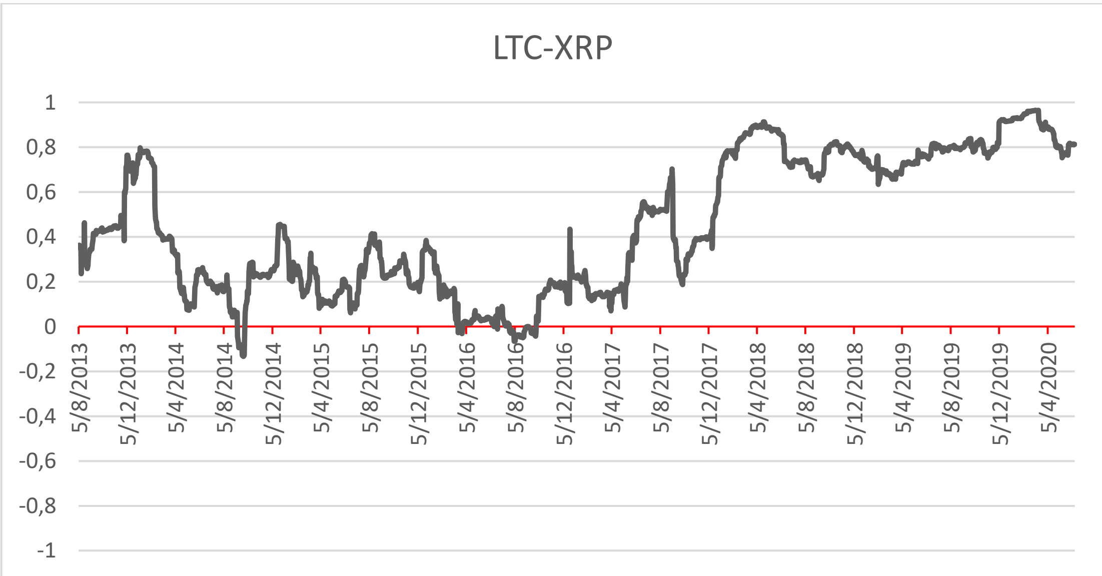
Rolling correlation between the LTC and ETH cryptocurrencies.



In figure 19 the intensity of the correlation between LTC and XRP cryptocurrencies presents extreme fluctuations from August of 2013 until the end of 2017 on a rolling window of 100 days, ranging from -0.1 to 0.7. After 2017 the correlation stabilizes within the positive range of 0.65 to almost 1.0 in March 2020.

Figure 19

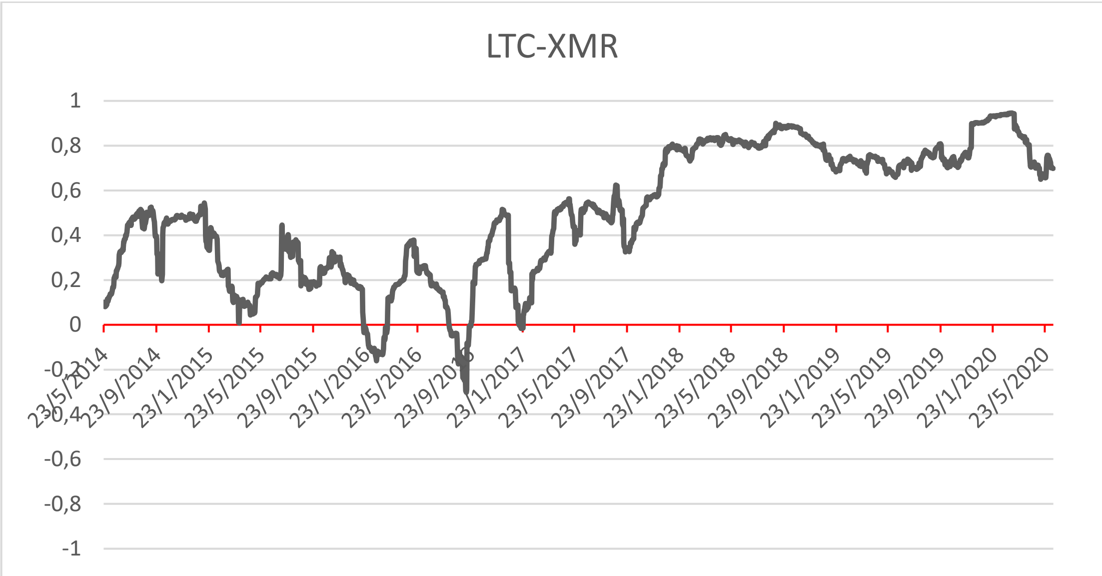
Rolling correlation between the LTC and XRP cryptocurrencies.



In figure 20 the intensity of the correlation between LTC and XMR cryptocurrencies exhibits extreme fluctuations from May of 2014 until the end of 2017 within the range of -0.30 to 0.77 on a rolling window of 100 days. From the beginning of 2018 onwards, the correlation follows a more stable path with fluctuations in the positive range of 0.65 to as high as 0.95 in March of 2020.

Figure 20

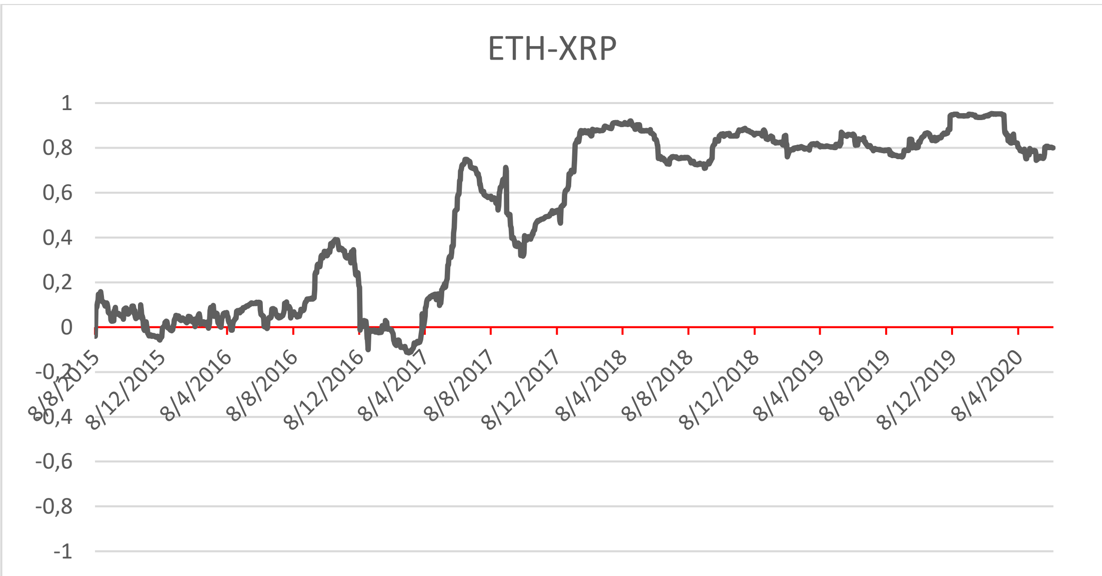
Rolling correlation between the LTC and XMR cryptocurrencies.



In figure 21 the intensity of the correlation between the ETH and XRP cryptocurrencies exhibits extreme fluctuations from August of 2015 until the end of 2017 on a rolling window of 100 days, ranging from -0.11 to 0.68. After 2017 the correlation is more stable with its values ranging within the positive range of 0.68 to 0.95 in March 2020.

Figure 21

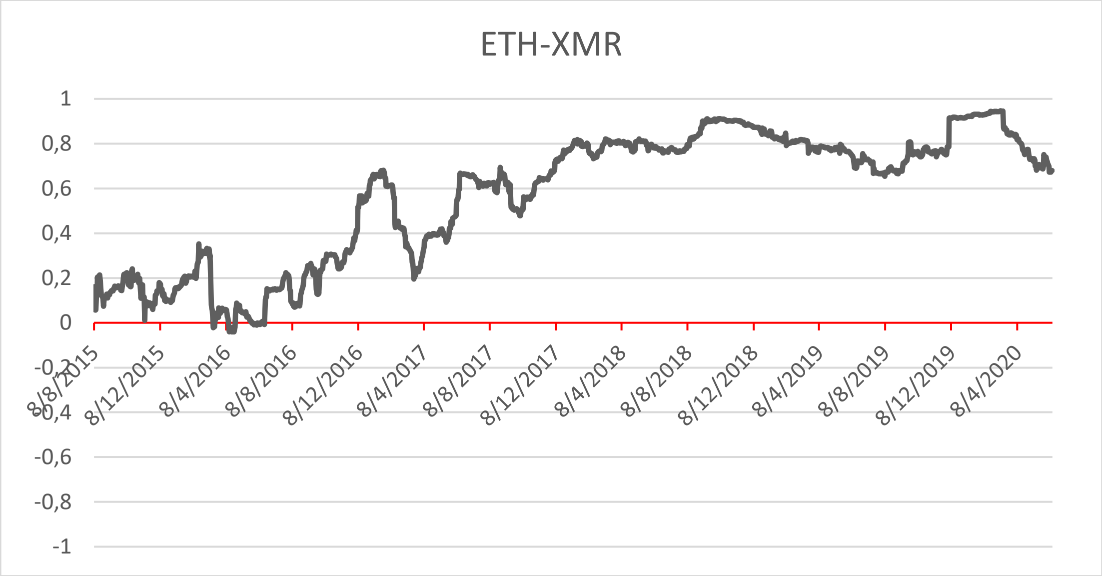
Rolling correlation between the ETH and XRP cryptocurrencies.



In figure 22 the intensity of the correlation between ETH and XMR cryptocurrencies exhibits extreme fluctuations from August of 2015 until the end of 2017 on a rolling window of 100 days. The values of correlation are ranging from -0.02 to 0.77. From January 2018 onwards, the correlation is more stable with smaller fluctuations within the positive range of 0.77 to 0.94 in March 2020.

Figure 22

Rolling correlation between the ETH and XMR cryptocurrencies.



In figure 23 the intensity of the correlation between XRP and XMR cryptocurrencies exhibits extreme fluctuations from May 2014 until the end of 2017 on a rolling window of 100 days. The values of correlation are ranging from as low as -0.10 to as high as 0.72. After 2017 the correlation stabilizes with fluctuations in the positive range from 0.67 to 0.93 in March 2020.

Figure 23

Rolling correlation between the XRP and XMR cryptocurrencies.

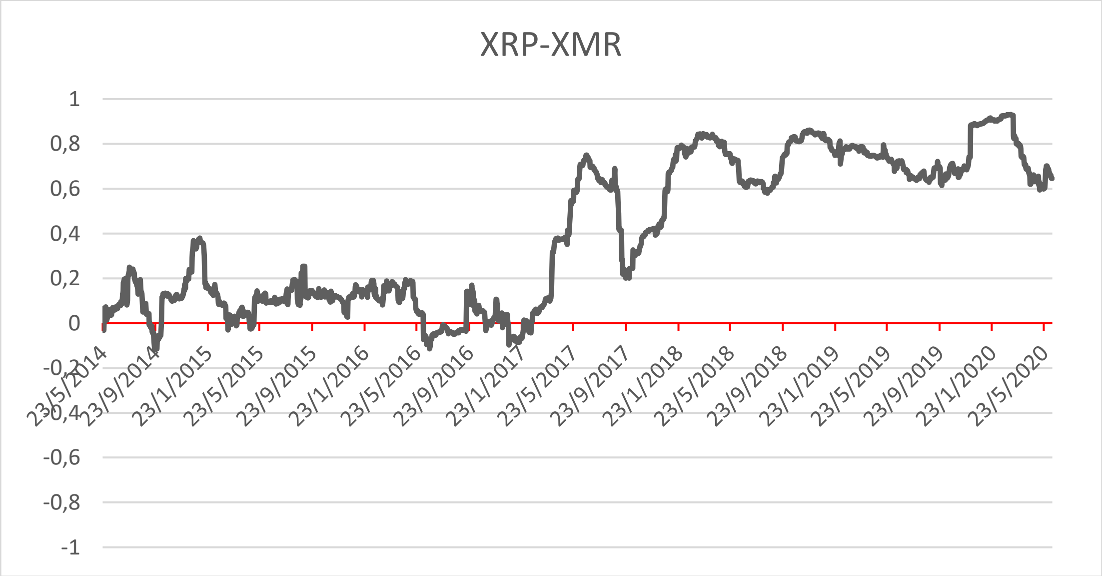


Table 3

Augmented Dickey-Fuller Test

	Dickey-Fuller	Lag order	p-value
BTC	-1,97	13	0,593
LTC	-1,82	13	0,653
ETH	-1,33	13	0,842
XRP	-1,91	13	0,616
XMR	-1,43	13	0,818

The Augmented Dickey-Fuller Test investigates whether the null hypothesis that a unit root is present vs the alternative that the time-series are stationary. In this case, the null hypothesis cannot be rejected since all p – values are above the threshold of 0.05, which is the selected significance level. Therefore, we conclude that the returns of all five cryptocurrencies are non-stationary time – series.

Table 4

Cointegration Johansen test, *BTC, LTC, and XRP cryptocurrencies, 5/8/2013-18/9/2020.*

	test	10pct	5pct	1pct
r <= 2	1.64	6.50	8.18	11.65
r <= 1	8.46	15.66	17.95	23.52
r = 0	18.50	28.71	31.52	37.22

Note: 10pct, 5pct, 1pct represent the critical values at 10%, 5% and 1% respectively.

Table 4 presents the results of Johansen's cointegration test carried out for BTC, LTC, and XRP cryptocurrencies from a period starting from 5/8/2013 until 18/9/2020. The results table displays the trace test statistic value as well as the corresponding critical values at certain levels of confidence: 10%, 5%, and 1% for each of the three hypotheses r=0, r <= 1, and r <= 2 tested. In the first case, r = 0, the hypothesis of whether there is a cointegrating relationship between the three time-series is investigated. The null hypothesis of no cointegration cannot be rejected since the trace value 18.50 is lower compared to all the critical values. Thus, we conclude that there is no cointegrating relationship among these three cryptocurrencies for the examined period.

Table 5

Cointegration Johansen test, *LTC, BTC, XRP, XMR, ETH cryptocurrencies, 7/8/2015 – 18/9/2020.*

	test	10pct	5pct	1pct
r <= 4	3.42	6.50	8.18	11.65
r <= 3	9.56	15.66	17.95	23.52
r <= 2	19.09	28.71	31.52	37.22
r <= 1	34.60	45.23	48.28	55.43
r = 0	58.58	66.49	70.60	78.87

Note: 10pct, 5pct, 1pct represent the critical values at 10%, 5% and 1% respectively.

Table 5 presents the results of Johansen's cointegration test conducted for the LTC, BTC, XRP, XMR, and ETH cryptocurrencies, from a period starting from 7/8/2015 until 18/9/2020. Similarly, as the previous table, the first column of the table displays the trace test statistic value as well as the corresponding critical values for each level of confidence: 10%, 5%, and 1% for all the five hypotheses r=0, r <= 1, r <= 2, r <= 3, and r <= 4 tested. In the first case, r = 0, the hypothesis of whether there is a cointegrating relationship between the five time-series is investigated. The null hypothesis of no cointegration cannot be rejected since the trace value 58.58 is lower compared to all the critical values. Therefore, we conclude that no cointegrating relationship between all five cryptocurrencies is evident for the examined period.

Table 6

Cointegration Johansen test, *LTC, BTC, XRP, XMR, ETH cryptocurrencies, 3/2/2017 – 18/9/2020.*

	test	10pct	5pct	1pct
r <= 4	3.62	6.50	8.18	11.65
r <= 3	10.51	15.66	17.95	23.52
r <= 2	18.82	28.71	31.52	37.22
r <= 1	40.66	45.23	48.28	55.43
r = 0	70.86	66.49	70.60	78.87

Note: 10pct, 5pct, 1pct represent the critical values at 10%, 5% and 1% respectively

Table 6 presents the results of Johansen's cointegration test conducted for the LTC, BTC, XRP, XMR, and ETH cryptocurrencies, from a period starting from 3/2/2017 to 18/9/2020. The researcher observed through price and rolling correlation graphs that there might be a cointegrating relationship between some of the cryptocurrencies for the selected period. The previous observation is supported by the results of Table 6. At first, we observe that the trace statistic of the rank = 0 hypothesis exceeds the critical value of

70.60 at a 5% significance level. Therefore, the null hypothesis of no cointegration relationship between the five time-series can be rejected. Also, the trace statistic of the second hypothesis (rank <= 1), is lower than the critical value of 48.28 at a 5% significance level. Therefore, the null hypothesis of at least one cointegration equation cannot be rejected. Thus, we conclude that a cointegrating relationship exists between the LTC, BTC, XRP, XMR, and ETH cryptocurrencies for the date span of 3/2/2017-18/9/2020. The linear combination of all five time-series which is a stationary series can be expressed with the following equation:

$LC = 1.000000 * BTC - 1.060256 * LTC + 1.197342 * ETH + 1.444403 * XRP - 1.738968 * XMR$ **Equation 1**

The coefficients above were obtained from the eigenvector that corresponds to the largest eigenvalue which is 0.022584110 (see Appendix p.58).

Conclusion

The analysis of descriptive statistics revealed that all five cryptocurrencies reached their peak values at the end of 2017. Before this year, all five cryptocurrencies presented lower values and a low level of volatility. After the peak of 2017, the values of the cryptocurrencies decreased but they remained significantly higher compared to their previous levels before 2017. Also, volatility was more intense after 2017 compared to the previous period. But the price level all the cryptocurrencies reached and maintained after 2017 “aided” them to have more similar patterns compared to the period before 2017. It seems that the year 2017 was a boom period for the five cryptocurrencies under investigation.

The above outcome was also confirmed from the rolling correlation analysis. The rolling correlation analysis resulted that all five cryptocurrencies before the year 2017 presented an unstable pattern. On the other hand, after 2017 the correlation level was higher than 0.6 for all five cryptocurrencies which is a sign of a more stable and similar pattern among them. Of course, they were some differences among the cryptocurrencies since the BTC, LTC, and ETH presented more similar patterns after 2017 compared to the remaining cryptocurrencies, XMR and XRP.

An additional argument that there is a link among the five cryptocurrencies, LTC, BTC, XRP, XMR, and ETH was the result of the Johansen test/cointegration analysis. Even though there was no cointegrating relationship for the period starting from 2013 until 2020 and from 2015 until 2020, there was a cointegration equation for the time of 2017 until 2020 between all five cryptocurrencies. This result is consistent with the results of descriptive statistics and rolling correlation analysis.

Appendix

Below we present all the command lines run in R studio. We begin our script by installing and enabling all the necessary libraries.

install.packages("readxl")

library(readxl,dplyr);library(tseries)

options(scipen = 999)   #remove scientific notation

Log_prices<-read_excel("CRYPTO_DATA (5).xlsx", sheet = 3)

library(urca)

The above command lines perform the Augmented Dickey-Fuller Test to each time series.

#Augmented Dickey-Fuller Test

adf.test(na.remove(Log_prices$BTC))

Output

Augmented Dickey-Fuller Test

data: na.remove(Log_prices$BTC)

Dickey-Fuller = -1.9653, Lag order = 13, p-value = 0.593

alternative hypothesis: stationary

adf.test(na.remove(Log_prices$LTC))

Output

Augmented Dickey-Fuller Test

data: na.remove(Log_prices$LTC)

Dickey-Fuller = -1.824, Lag order = 13, p-value = 0.6528 alternative hypothesis: stationary

adf.test(na.remove(Log_prices$ETH))

Output

Augmented Dickey-Fuller Test

data: na.remove(Log_prices$ETH)

Dickey-Fuller = -1.3772, Lag order = 12, p-value = 0.842

alternative hypothesis: stationary

adf.test(na.remove(Log_prices$XRP))

Output

Augmented Dickey-Fuller Test

data: na.remove(Log_prices$XRP)

Dickey-Fuller = -1.9103, Lag order = 13, p-value = 0.6163

alternative hypothesis: stationary

adf.test(na.remove(Log_prices$XMR))

Output

Augmented Dickey-Fuller Test

data: na.remove(Log_prices$XMR)

Dickey-Fuller = -1.4331, Lag order = 13, p-value = 0.8183

alternative hypothesis: stationary

#Johansen's cointegration Test (trace)

summary(ca.jo(Log_prices[98:2700,c(2,3,5)],type = "trace")) #BTC, LTC, XRP data from 4/8/2013-18/9/2020

Output

```
######################

# Johansen-Procedure #

######################


Test type: trace statistic , with linear trend


Eigenvalues (lambda):

[1] 0.0038515917 0.0026199493 0.0006300837


Values of teststatistic and critical values of test:


          test 10pct  5pct  1pct

r <= 2 |  1.64  6.50  8.18 11.65

r <= 1 |  8.46 15.66 17.95 23.52

r = 0  | 18.50 28.71 31.52 37.22



Eigenvectors, normalised to first column:
```

(These are the cointegration relations)

```
         BTC.l2     LTC.l2    XRP.l2
BTC.l2  1.000000  1.0000000 1.0000000
LTC.l2  3.263712 -0.8083674 0.4524709
XRP.l2 -3.266719 -0.1438934 0.7392056
```

Weights W:

(This is the loading matrix)

```
            BTC.l2       LTC.l2        XRP.l2
BTC.d -0.0002094206 9.620432e-05 -0.0003012632
LTC.d -0.0007497901 4.713872e-03 -0.0002782231
XRP.d  0.0013516564 3.983761e-03 -0.0002619593
```

summary(ca.jo(Log_prices[831:2700,c(2:6)],type = "trace")) #all five cryptocurrencies 7/8/2015-18/9/2020

Output

```
######################
# Johansen-Procedure #
######################
```

Test type: trace statistic , with linear trend

Eigenvalues (lambda):

[1] 0.012756387 0.008265078 0.005088558 0.003284832 0.001827039

Values of teststatistic and critical values of test:

	test	10pct	5pct	1pct
r <= 4 |	3.42	6.50	8.18	11.65
r <= 3 |	9.56	15.66	17.95	23.52
r <= 2 |	19.09	28.71	31.52	37.22
r <= 1 |	34.60	45.23	48.28	55.43
r = 0 |	58.58	66.49	70.60	78.87

Eigenvectors, normalised to first column:

(These are the cointegration relations)

	BTC.l2	LTC.l2	ETH.l2	XRP.l2	XMR.l2
BTC.l2	1.0000000	1.0000000	1.00000000	1.0000000	1.000000000
LTC.l2	-3.5203364	-2.7744776	0.50982490	-2.4406113	-0.276391565
ETH.l2	-0.7093486	2.1405482	0.09877362	-1.6978244	-0.208692076

XRP.l2 3.0281674 0.3906601 -0.40360246 -0.2066912 -0.129296743

XMR.l2 -0.3043864 -1.1997327 -0.95504265 2.3976907 0.001224763

Weights W:

(This is the loading matrix)

	BTC.l2	LTC.l2	ETH.l2	XRP.l2	XMR.l2
BTC.d	-0.0007761977	0.0001284331	7.680187e-05	0.0002778584	-0.0038261267
LTC.d	-0.0003103409	0.0019837096	-1.892080e-03	0.0009383813	-0.0029366961
ETH.d	0.0005547802	-0.0005250416	2.302103e-03	0.0015132204	-0.0021931281
XRP.d	-0.0050071962	-0.0004383498	-1.145203e-03	0.0009856923	-0.0007007721
XMR.d	-0.0023075639	0.0027396913	3.253931e-03	0.0005058199	-0.0026171131

summary(ca.jo(Log_prices[1377:2700,c(2:6)],type = "trace")) #all five cryptocurrencies 3/2/2017-18/9/2020

Output

######################

Johansen-Procedure

######################

Test type: trace statistic , with linear trend

Eigenvalues (lambda):

[1] 0.022584110 0.016390135 0.006264960 0.005196781 0.002735317

Values of teststatistic and critical values of test:

```
          test 10pct  5pct  1pct
r <= 4 |  3.62  6.50  8.18 11.65
r <= 3 | 10.51 15.66 17.95 23.52
r <= 2 | 18.82 28.71 31.52 37.22
r <= 1 | 40.66 45.23 48.28 55.43
r = 0  | 70.86 66.49 70.60 78.87
```

Eigenvectors, normalised to first column:

(These are the cointegration relations)

```
          BTC.l2     LTC.l2     ETH.l2    XRP.l2      XMR.l2
BTC.l2  1.000000  1.0000000   1.000000  1.000000  1.00000000
LTC.l2 -1.060256 -4.2598112   6.116499 -2.616880 -0.14561548
ETH.l2  1.197342 -0.9965434 -11.463155  4.584368  0.06329482
XRP.l2  1.444403  1.7552783  -1.098115 -3.005838 -0.23319298
```

XMR.l2	-1.738968	2.7021057	9.874414	2.680463	-0.52692744

Weights W:

(This is the loading matrix)

	BTC.l2	LTC.l2	ETH.l2	XRP.l2	XMR.l2
BTC.d	-0.002279556	-0.0021923836	-4.674202e-04	-6.486268e-04	-0.0011091222
LTC.d	-0.004619821	0.0006160652	-9.309700e-04	8.980302e-05	-0.0005069364
ETH.d	-0.005561779	0.0006287830	-3.989200e-04	-8.989884e-04	0.0020256213
XRP.d	-0.008972819	-0.0037942124	-2.774741e-05	4.602980e-04	-0.0002176815
XMR.d	-0.003038569	-0.0031023594	-6.667740e-04	-3.125364e-04	0.0039329844

References

Auer, R., & Claessens, S. (2020). Cryptocurrency market reactions to regulatory news. *Federal Reserve Bank of Dallas, Globalization Institute Working Papers, 2020*(381). doi:10.24149/gwp381

Bank, E. C. (2012). Virtual Currency Schemes. *EC Bank, Virtual Currency Schemes* (h. 13-14). Frankfurt: European Central Bank. https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemes201210en.pdf

Bank, E. C. (2015). Virtual currency schemes-a further analysis. Tech. rep., *European Central Bank*, Frankfurt am Main, Germany. https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemesen.pdf

Bouoiyour, J., Selmi, R., Tiwari, A. K., &Olayeni, O. R. (2016). What drives Bitcoin price. *Economics Bulletin*, *36*(2), 843-850.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192-198. doi:10.1016/j.frl.2016.09.025

Casino, F., Dasaklis, T. K., & Patsakis, C. (2018). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and Informatics*, *36*, 55-81. doi:10.1016/j.tele.2018.11.006

Chan, S., Chu, J., Nadarajah, S., &Osterrieder, J. (2017). A statistical analysis of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(2), 12.

Chohan, U. W. (2017). The double spending problem and cryptocurrencies. *SSRN Electronic Journal*. doi:10.2139/ssrn.3090174

Ciaian, P., Rajcaniova, M., & Kancs, D. (2016). The economics of bitcoin price formation. *Applied Economics*, *48*(19), 1799-1815. doi:10.1080/00036846.2015.1109038

Ciaian, P., Rajcaniova, M., & Kancs, D. (2018). Virtual relationships: Short- and long-run evidence from Bitcoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money, 52*, 173-195. doi:10.1016/j.intfin.2017.11.001

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the covid-19 bear market. *SSRN Electronic Journal*. doi:10.2139/ssrn.3560361

Corbet, S., Larkin, C. J., & Lucey, B. M. (2020). The contagion effects of the COVID-19 Pandemic: Evidence from gold and cryptocurrencies. *SSRN Electronic Journal*. doi:10.2139/ssrn.3564443

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis, 62*, 182-199. doi:10.1016/j.irfa.2018.09.003

Corbet, S., Meegan, A., Larkin, C. J., Lucey, B. M., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *SSRN Electronic Journal*. doi:10.2139/ssrn.3070288

CPMI (2015). Digital currencies https://www.bis.org/cpmi/publ/d137.pdf

Crosby, M., Pattanayak, P., Verma, S. and Kalyanaraman, V. (2016) 'Blockchain technology: Beyond Bitcoin'. *Applied Innovation Review* Vol.2 pp. 6–10.

Dziembowski, S., Faust, S., Kolmogorov, V., & Pietrzak, K. (2015). Proofs of space. *Lecture Notes in Computer Science*, 585-605. doi:10.1007/978-3-662-48000-7_29

EBA (2014). EBA opinion on virtual currencies. https://www.eba.europa.eu/documents/10180/657547/eba-op-2014-08+opinion+on+virtual+currencies.pdf

Fry, J., & Cheah, E. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis, 47*, 343-352. doi:10.1016/j.irfa.2016.02.008

Granger, C., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2*(2), 111-120. doi:10.1016/0304-4076(74)90034-7

He, D., Habermeier, K., Leckow, R., Haksar, V., Almeida, Y., Kashima, M., . . . Verdugo Yepes, C. (2016). Virtual currencies and beyond: Initial considerations. *Staff Discussion Notes, 16*(03), 1. doi:10.5089/9781498363273.006

Ismail, L., & Materwala, H. (2019). A review of blockchain architecture and consensus protocols: Use cases, challenges, and solutions. doi:10.20944/preprints201908.0311.v1

Janze, Ch. (2017) 'Are Cryptocurrencies Criminals Best Friends? Examining the Co-Evolution of Bitcoin and Darknet Markets'*23rd Americas Conference on Information Systems* Boston, MA, USA, 2017

Ji, Q., Bouri, E., Lau, C. K., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis, 63*, 257-272. doi:10.1016/j.irfa.2018.12.002

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2-3), 231-254. doi:10.1016/0165-1889(88)90041-3

Karame, G. O., Androulaki, E., Roeschlin, M., Gervais, A., & Čapkun, S. (2015). Misbehavior in Bitcoin: A study of double-spending and accountability. *ACM Transactions on Information and System Security, 18*(1), 1-32. doi:10.1145/2732196

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and ether. *Finance Research Letters, 30*, 221-227. doi:10.1016/j.frl.2018.10.005

Katsiampa, P., Corbet, S., & Lucey, B. M. (2019). High frequency volatility co-movements in cryptocurrency markets. *SSRN Electronic Journal*. doi:10.2139/ssrn.3454217

Kim, S., & Deka, G. C. (Eds.). (2020). Advanced applications of blockchain technology. *Studies in Big Data*. doi:10.1007/978-981-13-8775-3

Kristoufek, L. (2013). BitCoin meets Google trends and Wikipedia: Quantifying the relationship between phenomena of the internet era. *Scientific Reports, 3*(1). doi:10.1038/srep03415

Lai, R., & LEE Kuo Chuen, D. (2018). Blockchain – from public to private. *Handbook of Blockchain, Digital Finance, and Inclusion, Volume 2,* 145-177. doi:10.1016/b978-0-12-812282-2.00007-3

Lamport, L., Shostak, R., & Pease, M. (1982). The byzantine generals problem. *ACM Transactions on Programming Languages and Systems*, *4*(3), 382-401. doi:10.1145/357172.357176

Miraz, M. H., & Ali, M. (2018). Applications of blockchain technology beyond cryptocurrency. *Annals of Emerging Technologies in Computing, 2*(1), 1-6. doi:10.33166/aetic.2018.01.001

Nakamoto, S. (2008) *'Bitcoin: A Peer-to-Peer Electronic Cash System'*, https://bitcoin.org/bitcoin.pdf

Natarajan, H., Krause, S., & Gradstein, H. (2017). Distributed ledger technology and blockchain. doi:10.1596/29053

Omane-Adjepong, M., & Alagidede, I. P. (2019). Multiresolution analysis and spillovers of major Cryptocurrency markets. *Research in International Business and Finance, 49*, 191-206. doi:10.1016/j.ribaf.2019.03.003

Osterrieder, J., Chan, S., Chu, J., & Nadarajah, S. (2017). A statistical analysis of cryptocurrencies. *SSRN Electronic Journal*. doi:10.2139/ssrn.2948315

Peters, G. W., Panayi, E., & Chapelle, A. (2015). Trends in crypto-currencies and blockchain Technologies: A monetary theory and Regulation perspective. *SSRN Electronic Journal*. doi:10.2139/ssrn.2646618

Pilkington, M. (2016). Blockchain technology: Principles and applications. *Research Handbook on Digital Transformations,* 225-253. doi:10.4337/9781784717766.00019

Pinzón, C., & Rocha, C. (2016). Double-spend attack models with time advantage for bitcoin. *Electronic Notes in Theoretical Computer Science*, *329*, 79-103.

Schittenkopf, C., Tiňo, P., & Dorffner, G. (2002). The benefit of information reduction for trading strategies. *Applied Economics, 34*(7), 917-930. doi:10.1080/00036840110061938

Stosic, D., Stosic, D., Ludermir, T. B., & Stosic, T. (2018). Collective behavior of cryptocurrency price changes. *Physica A: Statistical Mechanics and Its Applications, 507*, 499-509. doi:10.1016/j.physa.2018.05.050

Urquhart, A. (2016). The inefficiency of bitcoin. *SSRN Electronic Journal*. doi:10.2139/ssrn.2828745

Yaga, D., Mell, P., Roby, N., & Scarfone, K. (2018). Blockchain technology overview. doi:10.6028/nist.ir.8202

Yang, R., Wakefield, R., Lyu, S., Jayasuriya, S., Han, F., Yi, X., . . . Chen, S. (2020). Public and private blockchain in construction business process and information integration. *Automation in Construction, 118*, 103276. doi:10.1016/j.autcon.2020.103276

Yi, S., Xu, Z., & Wang, G. (2018). Volatility connectedness in the cryptocurrency market: Is bitcoin a dominant cryptocurrency? *International Review of Financial Analysis, 60*, 98-114. doi:10.1016/j.irfa.2018.08.012

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). The inefficiency of cryptocurrency and its cross-correlation with dow jones industrial average. *Physica A: Statistical Mechanics and Its Applications, 510*, 658-670. doi:10.1016/j.physa.2018.07.032

Zheng, Z., Xie, S., Dai, H., Chen, X., & Wang, H. (2017). An overview of blockchain technology: Architecture, consensus, and future trends. *2017 IEEE International Congress on Big Data (BigData Congress)*. doi:10.1109/bigdatacongress.2017.85

Websites

[1] https://medium.com/@marcomanoppo/delegated-byzantine-fault-tolerance-consensus-mechanism-502f9586c358
[2] https://www.bitcoinblockhalf.com/
[3] https://www.investopedia.com/terms/e/ethereum.asp
[4] https://en.wikipedia.org/wiki/Ethereum
[5] https://cointelegraph.com/ethereum-for-beginners/what-is-ethereum
[6] https://en.wikipedia.org/wiki/Litecoin#cite_note-4
[7] https://www.coingecko.com/en/coins/litecoin
[8] https://arstechnica.com/information-technology/2013/05/wary-of-bitcoin-a-guide-to-some-other-cryptocurrencies/
[9] https://cointelegraph.com/tags/litecoin
[10] https://bitcointalk.org/index.php?topic=47417.0
[11] https://cointelegraph.com/ripple-101/what-is-ripple
[12] https://www.gsb.stanford.edu/insights/chris-larsen-money-without-borders
[13] https://en.wikipedia.org/wiki/Ripple_(payment_protocol)
[14] https://cointelegraph.com/ripple-101/ripple-vs-bitcoin-key-differences
[15] https://cointelegraph.com/tags/monero
[16] https://www.kraken.com/learn/what-is-monero-xmr
[17] https://www.investopedia.com/tech/introduction-monero-xmr/
[18] https://en.wikipedia.org/wiki/Monero_(cryptocurrency)#cite_note-ArsWanna-3
[19] https://www.wired.com/2017/01/monero-drug-dealers-cryptocurrency-choice-fire/
[20] https://hbr.org/2017/01/the-truth-about-blockchain