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Master's thesis

Modelling the Dynamics of Bitcoin, Ethereum, Ripple Including COVID-19 Impact

Bitcoin, Ethereum, Ripple kriptovaliutų dinamikos modeliavimas įtraukiant COVID-19 įtaką

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Santrauka

Šiame darbe analizuojamos pasirinktų kriptovaliutų: Bitcoin, Ethereum ir Ripple dieninės grąžos bei gražų santykis su pasirinktais kintamaisiais. Darbe pateikiamos dvi pagrindinės analizės dalys. Pirmoje dalyje siekiama surasti pasikeitimo taškus dispersijoje, laikotarpyje nuo 2019.11.07 iki 2020.11.06 naudojant dieninius duomenis. Pasitelkiant pasikeitimo taškų dispersijoje algoritmus, nustatyta, jog Bitcoin pasikeitimo taškų datos yra: 2020.03.07, 2020.03.11, 2020.03.19. Ethereum: 2020.03.07, 2020.03.19, o Ripple: 2020.02.11, 2020.03.07, 2020.03.11 ir 2020.03.19. Antra analizės dalis tiria Granger kauzalumą tarp Bitcoin, Ethereum, Ripple kriptovaliutų bei pasirinktų socialinių, ekonominių, finansinių kintamųjų. Pirmiausiai, sudaromi VAR modeliai tarp kriptovaliutų ir kintamųjų ir tuomet atliekami Granger kauzalumo testai. Rezultatai atskleidė, jog tiriamame laikotarpyje nuo 2019.11.07 iki 2020.11.06 egzistuoja dvipusis Granger kauzalumo ryšys tarp kriptovaliutų dieninių logaritmuotų grąžų bei S&P500 logaritmuotų dieninių grąžų ir FSI indekso. Nustatyta, jog Grangerio kauzalumo vienpusis ryšys yra tarp aukso logaritmuotų grąžų bei kriptovaliutų dieninių logaritmuotų grąžų. Taip pat, Bitcoin ir Ethereum dieninės logaritmuotos grąžos turi Granger kauzalumo ryšį su USD/EUR dieninėm logaritmuotom grąžom. Visos nagrinėjamos kriptovaliutos Granger kauzaliai veikia USD/CHF dienines logaritmuotas grąžas, o pastaroji turi kauzalumo ryšį su Ripple dieninėm logaritmuotom grąžom. Taip pat, tarp kriptovaliutų dieninių logaritmuotų grąžų bei Wikipedia dieninių peržiūrų Bitcoin, Ethereum, Ripple tema, ryšys nenustatytas, taip pat, kaip ir su COVID-19 dieninėmis mirtimis pasaulyje.

Raktiniai žodžiai : Pasikeitimo taškas, koronavirusas, COVID-19, Granger kauzalumas, VAR, Bitcoin, Ethereum, Ripple, kriptovaliutos

Modelling the dynamics of Bitcoin, Ethereum, Ripple including COVID-19 impact

Abstract

In this thesis the daily returns of selected cryptocurrencies: Bitcoin, Ethereum and Ripple, as well as their returns relationship with the selected variables are analysed. The thesis consists of two main parts of the analysis. The first part aimed to find the points of change in the variance in the period from 2019.11.07 to 2020.11.06 using daily data. After implementing algorithms of changepoints in variance, it was detected that the dates of Bitcoin changepoints were: 2020.03.07, 2020.03.11, 2020.03.19. Ethereum: 2020.03.07, 2020.03.19, and Ripple: 2020.02.11, 2020.03.07, 2020.03.11 and 2020.03.19. The second part of the analysis examined the Granger causality between Bitcoin, Ethereum, Ripple cryptocurrencies and selected social, economic, financial variables. First, VAR models between cryptocurrencies and variables were constructed and then Granger causality tests performed. The results revealed that during selected period from 2019.11.07 to 2020.11.06, there was a bidirectional Granger causality relationship between cryptocurrency daily logarithmic returns and S&P500 logarithmic daily returns and FSI daily index. The one-sided relationship of Granger causality has been found between the logarithmic returns of gold and cryptocurrencies (Bitcoin, Ethereum, Ripple daily log returns). Also, the daily logarithmic returns of Bitcoin and Ethereum had a Granger causality relationship with USD/EUR daily logarithmic returns. All of the cryptocurrencies were found to Granger cause the daily logarithmic returns of the USD/CHF, and the latter had a causal relationship with the daily logarithmic returns of the Ripple. Also, there were no links between cryptocurrency daily logarithmic returns and Wikipedia daily reviews on Bitcoin, Ethereum, Ripple. Also no significant results were found when Granger causality test was paired between BTC, ETH, XRP daily log returns and COVID-19 daily deaths worldwide.

Key words : Changepoint, changepoint analysis, COVID-19, Granger Causality, VAR, Bitcoin, Ethereum, Ripple, cryptocurency

Contents

1 Introduction

Cryptocurrencies in nowadays world get people attention due to increasing popularity of it and most importantly their implementation in real life, in a way it can be used, for example, as a currency to pay for goods and services around the world. Also, uncertainty and price fluctuations of crypto market attracts scientists to investigate its movements, predict future value, model against other cryptocurrencies. As it is being used more in real life, researchers and people face the question whether it could sooner or later change the current fiat currencies.

The another approach of COVID-19 pandemic is undoubtedly one of the most discussed subject at the time of thesis. There is a need of researches regarding COVID-19 pandemic and its impact on various fields, such as Economic, Financial. In this thesis COVID-19 plays an important role in analysis as is helps to find abnormalities in data as well as helps checking the possible causality relationship between cryptocurrencies and COVID-19. Next, the thesis aim can be identified:
Thesis goal: Using daily data from Bitcoin, Ethereum, Ripple cryptocurrencies and selected variables, including COVID-19 to explain and model the dynamics of selected cryptocurrencies.

After noting the thesis goal it is important to define the thesis tasks that will lead to reaching the thesis goal. The tasks of this thesis are:
Thesis tasks:

1. To compare, explain differences and similarities between selected changepoint detection techniques;
2. To select and employ changepoints detection model for selected cryptocurrencies (Bitcoin, Ethereum, Ripple) daily data and explain if it could be related to COVID-19 pandemic;
3. To compare different modelling techniques used by researchers for cryptocurrencies and their chosen variables relationship;
4. To employ VAR and Granger causality tests model for relationships analysis between cryptocurrencies and selected variables;
5. To compare results with other authors‘ findings.

The understanding of cryptocurrencies volatility movements, interaction with financial, economical and social variables is important for investors, who seek to get information to choose the most appropriate investment portfolio and also to governments who could regulate cryptocurrency usage and implement it in banking sector, for example. The understanding of Bitcoin, Ethereum, Ripple and other cryptocurrencies would help to measure the risk of whether to invest in it or no.

Following the previous studies of cryptocurrencies, in this paper two approaches investigated. The first one is Changepoint detection analysis where using daily data from 2019-11-07 to 2020.11.06 the series of Bitcoin, Ethereum, Ripple daily log returns were investigated for structural breaks using PELT, BinSeg and AMOC techniques. It was found out that 2 techniques identify Bitcoin changepoints on 2020.03.07 and 2020.03.19 days, and another one on 2020.03.11. Ethereum first changepoint was detected on 2020.03.07 and second on 2020.03.19 by all used models. Lastly, Ripple analysis resulted in more changepoints detected if compared to Bitcoin and Ethereum. The first changpoint identified by 2 models was on 2020.02.11 day, the second on 2020.03.19. As the COVID-19 pandemic was announced as a worldwide on 2020.03.11 it can be assumed that it have influenced the volatility and caused changepoints in selected cryptocurrencies series.

The second part of econometric analysis focus on finding causal relationships between Bitcoin, Ethereum, Ripple logarithmical returns and selected economical, financial, social factors. Particularly we were trying to answer the questions: Can the knowledge of any following series: S&P 500 daily log returns, Gold daily log returns, FSI daily index, USD/EUR daily log returns, USD/CHF daily log returns, Wikipedia views, COVID-19 daily deaths help to predict future Bitcoin, Ethereum or Ripple log returns and vice versa?

To model the causal relationship firstly the Vector Autoregression (VAR) model was introduced. Then, the Granger Causality test for relationship between variables was applied. Granger causality test investigates if knowing past values of time series X together with past values of time series Y can be used together to make better predictions of time series Y as opposed to only using past values of time series Y. It was found out that there is a Granger causality relationship between Bitcoin, Ethereum, Ripple daily log returns and S&P500 daily log returns in both directions. The same result was found when pairing cryptocurrencies with FSI daily index. The one directional relationship was found in all cryptocurrencies in pairs with gold. Meaning that all cryptocurrencies log returns in this paper Granger cause gold log returns. Bitcoin, Ethereum daily log returns found to Granger cause USD/EUR daily log returns. In terms of BTC, ETH, XRP daily log returns and USD/CHF daily log returns relationship, bidirectional relationship was found between Ripple daily log returns and USD/CHF daily log returns. It was also found out that Bitcoin and Ethereum daily log returns Granger cause USD/CHF daily log returns in one directional relationship. No Granger cause relationships were found between cryptocurrency daily log returns and their wikipedia views and COVID-19 daily deaths.

2 Literature review

In this part of the research the main focus is put on the relevant literature regarding the research topic. In order to do the further analysis it is important to briefly address the findings of other researches.

2.1 Cryptocurrencies and Blockchain Technology

Cryptocurrencies are the first—and therefore most developed—application of blockchain technologies that allows secure and anonymous digital transactions without the involvement of central or commercial banks. Within a decade after a creation of first cryptocurrency it has become a multibillion-euro industry (Bank 2018).

Cryptocurrencies have many different definition approaches from the perspective of science and Andrulevicius et al. (2019) suggested two: as a social phenomenon and as a legal situation. The first approach indicates that cryptocurrency can be defined as a currency and has some facts that support it:

1) It can be easily exchanged for goods and services;

2) It can be withdrawn in small amounts throughout 6007 ATM's world-wide (Bitcoin.com 2019).

The second approach is supported by many scientists that cryptocurrency is not regulated by any institutions or legal intermediaries that results in some risks:

1) Lack of consumer protection (keeping value, theft prevention and arbitrage);

2) Anonymity brings criminal activities (tax avoidance, money laundering, financial terrorism) (Andrulevicius et al. 2019).

There are other definitions considered too. As suggested by Sovbetov (2018), a cryptocurrency is a digital or virtual currency that uses cryptography for security that is difficult to counterfeit because of the security features. Cryptocurrencies are decentralized digital currencies that use encryption to verify the transactions (Kjærland et al. 2018).

Cryptocurrency innovation is relied on the Blockchain. It is the technology which can be compared to a shared ledger on the peer-to-peer network. As reported by Milutinović (2018), the Blockchain records individual transactions and ownership of the cryptocurrencies. Those transactions are managed by miners. Their job is it update all the transactions that occurs and they must ensure the accuracy of the information. Miners are the only one who can confirm the blockchain transactions, then mark them as a legit and let them spread through the network (Milutinović 2018). This process is called mining and revolves around solving complex computational puzzles (Kjærland et al. 2018). Blocks are then added to the chain and miners get paid in cryptocurrency for their job. Abraham et al. (2018) indicates that the use of blockchains have a positive correlation with the use of cryptocurrencies. Many financial institutions have already started to use cryptocurrencies and blockchain technology because they want the transactions to go faster.

The following part of this paper will focus on analysing and comparing the most popular, attractive and most discussed about cryptocurrencies at the time of this thesis. The cryptocurrencies described below will be selected for further thesis analysis because of the popularity and different specifications and options it offers to customers.

2.1.1 Bitcoin (BTC)

Bitcoin is the most popular and famous cryptocurrency worldwide. On 2020.11.07 the total market capitalization of Bitcoin was 64,90 % (Tradingview.com 2020) of all the cryptocurrencies and the total market cap was equal to 274,97 billion US dollars (CoinMarketCap.com 2020). Bitcoin appeared in the market in 2008 but at that time did not gain much attention. The creator of Bitcoin is not know but it was represented by a person or group called Satoshi Nakamoto (Milutinović 2018). The white paper that started bitcoin in 2008 outlined a way to create and operate a decentralized electronic cash system where the payment system would not be controlled by any bank, therefore financial activities remains under a pseudonym (Nakamoto et al. 2008).

According to Sovbetov (2018) the Bitcoin characteristics make it different in comparison to a fiat currency, for example, Euro, Dollar, that are regulated by the nation's government and central bank. On the other hand, the author suggests that the value of Bitcoin is dependent on what people or investors are willing to pay at a point in time.

Payments in Bitcoin can be transferred between users without knowing the identity neither of sender nor receiver (Lee et al. 2019). The bitcoins exist only as tokens distributed in the database of all Bitcoin transactions called the Blockchain. A bitcoin transaction is simply done by entering the recipient's wallet number and the number of bitcoins willing to send. This transaction is done by announcing to public that these Bitcoin (that you own) now belong to the recipient (Bieliauskas et al. 2016). Every transaction and ownership of bitcoins is recorded in the Blockchain permanently.

As suggested by Bieliauskas et al. (2016), counterfeiting of Bitcoins in such system is not possible because if anyone would create any amount of Bitcoins for themselves, no one else would accept these Bitcoins for transactions as it would have no public history. These characteristics make it impossible to multiply, print the Bitcoin, different than the fiat currency.

As mentioned before, the miners are the ones who take a big part in blockchain technology and cryptocurrencies. Miner is a participant who use his computer power to solve a difficult puzzle. The first person who does that, can add a block of new transactions to the chain of the Blockchain and broadcast the new block to the network (Bank 2018). Although, as suggested by the previous author, the solution of the puzzle is easy to verify and the nodes in the Bitcoin network can easily determine if the newly created block is valid and can be added to the chain. The miner receives not only the newly created Bitcoins, but also the transaction fees of all Bitcoin transaction in that block which is voluntary and can range from 0 to any amount of bitcoins (Bieliauskas et al. 2016).

It is also worth to mention, that the total number of bitcoins in existence is based on geometrical progression and can never be higher than 21.000.000 (Nakamoto et al. 2008). As suggested by Sovbetov (2018), every four years the number of new coins per block gets halved, until the maximum number of 21 million bitcoins is reached.

2.1.2 Ethereum (ETH)

Ethereum is also a well known cryptocurrency worldwide as it has the second largest market capitalization and covers 11.27 % of all cryptocurrencies market which equalled 49.38 billion US dollars on 2020.11.07 (Tradingview.com 2020)

As suggested by Li et al. (2019), the Ethereum project was created in July 2015 to provide Smart Contract functionality on a blockchain. Smart contract transactions use this input data field to transmit messages: creating a transaction with input data to a Smart Contract is analogous to passing variables to a function. Rouhani et al. (2017) claim, that Ethereum includes two types of accounts: Externally Owned Accounts (EOA) where users directly send transactions using them and Contract accounts. Every account has two keys: public and private.

Some smart contracts implement mechanisms that allow trading or sharing digital assets, known as cryptotokens, on the blockchain. Bartoletti et al. (2019) indicates that contract has a permanent storage where to keep data, and a set of functions which can be invoked either by users or by other contracts. Users and contracts can own a cryptocurrency (called ether, or ETH in short), and send/receive ether to/from users or other contracts. Users can send transactions to the Ethereum network in order to:

1) create new contracts;

2) invoke a function of a contract;

3) transfer ETH to contracts or to other users.

The Ethereum transaction is like traditional blockchain transaction that launches with a genesis block and then other transactions process and create new blocks in the blockchain (Rouhani et al. 2017). The previous author also insists that ETH transaction is started by Externally Owned account holder who can directly transfer Ethereum digital currency, called – Ether to another account. Shorter, a token is traded publicly among blockchain nodes, and may have an associated euro value which is arbitrated by token demand and supply in the real world (Li et al. 2019). It is believed that as the supply of ETH is fixed, so his value is mostly determined by its demand.

Ethereum as well as Bitcoin and other cryptocurrencies store the public transaction data in the Blockchain. Upon receiving an external transaction, a contract can fire some internal transactions, which are not explicitly recorded on the blockchain, but still have effects on the balance of users and of other contracts (Bartoletti et al. 2019).

2.1.3 Ripple (XRP)

The Ripple cryptocurrency, known as XRP is the fourth largest cryptocurrency in the market in terms of the market cap. On 2020.11.07 its total market cap was 11,40 billion US dollars and covered 2.68% of all crypto market (CoinMarketCap.com 2020). The current deployment of Ripple is solely managed by Ripple Labs (Armknecht et al. 2015). This cryptocurrency was chosen for analysis because it offers two types of payment transactions that are analysed below.

Rosner et al. (2015) suggests that Ripple is an open-source Internet software that enables users to conduct payments across national boundaries in multiple currencies as seamlessly as sending an email. Other authors claim that decentralized I owe you (IOU) transaction network, which is used by Ripple is gaining prominence as a fast, low-cost and efficient method for performing same and cross currency payments as Ripple can offer not only its cryptocurrency XRP for a transfer but also other currencies (Moreno-Sanchez et al. 2016).

Rosner et al. (2015) insists that Ripple protocol uses a distributed ledger—a collection of financial accounts updated by numerous and dispersed entities—through which Ripple users can conduct cross-border payments in a way that is faster, less costly, and more efficient than traditional . That is the reason why Ripple payment system is attractive to various banks across the world as it offers fast and more efficient transfers. Banks such as Santander have claimed that adopting Ripple could save them $20 billion a year (Moreno-Sanchez et al. 2016) There can be found two payment types that Ripple offers:

1) Direct XRP payment. A direct payment involves a transfer of XRP between two wallets that do not require a credit path between them but needs to hold XRP for two reasons: the wallet is considered active only if it has a certain amount of XRP; moreover, the issuer of any transaction must pay a transaction fee in XRP (Moreno-Sanchez et al. 2016).

2) Path-based settlement transactions. Path-based settlement transactions transfer any type of credit (fiat currencies, cryptocurrencies and user-defined currencies) between two wallets having a suitable set of credit paths between them. Ripple network support 3 types of currencies and treats them evenly: fiat currencies (e.g, EUR), cryptocurrencies (e.g., bitcoins) and even user defined currencies (Moreno-Sanchez et al. 2016).

The Ripple network, at its core, is a replicated, public database (called the Ripple ledger) that tracks wallets and credit links extended between wallets along with their balances. Thus anyone could see the historical activity of transactions but all transactions are completely transparent up to pseudonyms. Armknecht et al. (2015) argues that user anonymity is ensured through the reliance on pseudonyms and users are also expected to have several accounts (corresponding to different pseudonyms) in order to prevent the leakage of their total account balance. Notice that, in Bitcoin, transactions can originate from different accounts. This is not the case in Ripple, in which payments typically have a single account as input. In order to make The Ripple protocol more secure, it requires each account to hold a small reserve of XRP in order to create ledger entries - transactions. Rosner et al. (2015) has claimed, that 20 XRP (reserve requirement) is a negligible transaction fee for normal users, so that if attackers would like to flood the network it would cost them too much by creating false transactions.

2.1.4 Cryptocurrencies comparison

In this section Bitcoin, Ethereum and Ripple will be compared and analysed while indicating the strengths and the weaknesses of each. As it can be seen from Table 1 below, Bitcoin is the oldest cryptocurrency in market, while Ripple (XRP) is the newest and was found in 2017. Ethereum has been in a market for 6 years.

Analysing the circulating supply it is noticeable that Bitcoin has the least circulating supply if compared to Ethereum or Ripple and that equals to about 18.5 million coins in the market at the moment of writing and can go up to 21 million maximum. It is worth to mention that Ripple is not a mineable cryptocurrency and 100 billion tokens of XRP have been initially pre-mined and now there are about 45.236 billion coins in the market and the rest is periodically released by Ripple labs. What is interesting about the Ethereum, unlike other analysed cryptocurrencies, Ethereum has opted not to set an upper limit on its total coin supply. Thus this has raised concerns about inflation in the Ethereum community for years on end.

Prices of crypto and the market cap are linked to each other because the total market cap value is equal to circulating supply multiplied by the price. Ripple has the lowest price between those 3 cryptocurrencies and is equal to $0.25, while Ethereum is second largest with $435.71. As it was mentioned before, Bitcoin has the highest Market cap with 64.90 % of all cryptocurrencies market. The second placed - Ethereum covers only 11.27 % of all market. It shows the clear difference that Bitcion is the most popular cryptocurrency at this time.

The interesting part is to analyse the 1 year change in the % of the total market cap. Clearly, the Ethereum yearly change is the highest with 142.19 %, Bitcoin had 64.52 %, while Ripple faced decrease of capitalization within a year. Ripple capitalization decreased by -10.58 %. All of those increases/decreases were the consequence of cryptocurrency price itself that have increased/decreased over the year.

Table 1. Cryptocurrencies comparison

	Bitcoin (BTC)	Ethereum (ETH)	Ripple (XRP)
Launch date	2009	2015	2017
Circulating supply	18 536 805	113 333 971	45 236 768 616
Price	$14833.75	$435.71	$0.25
Market Cap	$274 970 333 140	$49 380 744 878	$11 309 192 154
1 Year change %	64.52 %	142.19 %	-10.58 %
30-Day trade volume	$930 323 696 240	$441 338 006 970	$70 955 039 870
Maximum transactions per second	7	20	1500
Approximate transaction time	10-30 minutes	15 seconds	4 seconds
Proof type	PoW	PoW	Consensus
Anonymity	Low	Low	Low
Mineable	Yes	Yes	No
Strenght	Largest and most popular	Smart contracts	Fast and multi-currency transactions
Downside	Slow and expensive transactions	Slow and energy-hungry	Is not decentralized enough

Composed by author according to the data 2020.11.07 provided by (CoinMarketCap.com 2020; ig.com 2020)

Along with circulating supply, price, market capitalization, volume is one of the most prominent metrics in crypto. 30-day trade volume is the total volume of buys and sells during that time. Volume can infer the direction and movements of a coin. It is an essential metric for traders. This helps reveal if a coin's recent swings are an aberration or the norm. Generally, the biggest and most popular coins are traded the most. This pattern can be visible in Table 1 as Bitcoin has the highest trade volume, Ethereum has second and Ripple third. This order also applies to their popularity and market cap.

Transaction per second (TPS) is the number of transactions executed per second. Here, both Bitcoin and Ethereum are mostly criticized about. Their transaction speed, 7 and 20 respectively per second is relatively slow if compared to Ripple 1500 per second. Thus the transaction fees for BTC and ETH are higher so that the transaction does not take a day to complete. Many cryptocurrencies claim to have high TPS performance these days, but the transaction speed is often dependable and is generally hard to measure — especially with real-time traffic instead of test networks.

Approximate transaction time depends on two primary factors: the blockchain fee and the current load on the blockchain network. For example, for Bitcoin, the average time is 10-30 minutes. Though the higher the fee is paid, the fewer blocks are needed to use - thus reducing transaction time. The same applies to Ethereum. It is worth to mention, that if the person decides to send 2 transactions from his wallet to, for exmple, a friend, the second transaction will only be processed once the first one has been confirmed. Ripple has the fastest transaction time between the analysed cryptos. Transaction can take as fast as 4 seconds.

Proof of type is essential to all of the cryptocurrencies. PoW – Proof of Work is the most popular one and is used by Bitcoin and Ethereum in this case. Mining is the process in which Proof of Work is generated. The main purpose of mining is to verify the legitimacy of a transaction and prove that it is not a double spend. A double spend is when the same coins are spent more than once. Miners are rewarded on upon successful completion of mining a block. Ripple uses its consensus algorithm (RPCA), which is applied every few seconds by all nodes. Once consensus is reached, the current ledger is considered “closed” and becomes the last-closed ledger (Schwartz et al. 2014).

Anonymity is undoubtedly one of the most important factors for cryptos users. Bitcoin, Ethereum and Ripple are all considered to be low anonymity even though no identity is revealed while sending/receiving the cryptocurrency. Low anonymity means that these cryptocurrencies records transactions that can be visible to the public where the sender and receiver wallet addresses are known as well as the transaction amount. Only the identity of each address is not known. Thus identifying of an address might come from network analysis, surveillance, searching the web.

Mineable indicates if the coin can be mined, in other words – if computers are required to solve the mathematical puzzle in order to confirm the transaction. As it can be seen from the table, all cryptocurrencies that have proof type of PoW, are mineable, while Ripple is pre-mined and does not use PoW proof type.

Strengths of all the analysed currencies differ. For instance, the greatest strength of BTC is the popularity around the world and the market cap it holds. Ethereum, as the second largest and popular cryptocurrency in the world has a built-in programming language that lets developers write computer programs, called smart contracts, that run on the blockchain. Most initial coin offerings (ICOs) so far have been based on Ethereum smart contracts. The strenght of Ripple has been discussed before and is the ability to transfer multi-currency transactions within seconds.

On the other hand, every cryptocurrency has its own drawbacks. In this case, both Bitcoin and Ethereum share very similar downsides that include low amount of transactions per second, as well as transaction time and of course they both require computer power that uses electricity, so it can be called energy-hungry cryptocurrencies. Ripple is considered as one of the fastest cryptocurrencies in the world with both great transaction per second and transaction time number, but since it is owned by a company and there is not much control over the systems, XRP is considered to be not decentralized enough.

To sum up, it can be seen that the Bitcoin might not have the greatest strengths, speeds of transactions, but its popularity and spreadiness around the globe make Bitcoin the most powerful crypto. Ripple, which seemed to bet almost a perfect currency with options to send the multi-currency as fast as within 4 seconds has suffered a -10.58 % decrease in the market cap. It suggests that cryptocurrency world is very diverse and unpredictable as well as unstable.

2.2 Authors' findings of factors that make impact on cryptocurrencies

Scientists have been analysing cryptocurrencies in different ways willing to find the factors, that make impact on their prices, volatility. Yet, the recent studies has shown that the same method of analysis performed for example, one month later, including new data, can show different results. That is because the cryptocurrency market is very unstable and unpredictable. It is notable that a great part of the articles focused on Bitcoin as a research object. Thus it gives an opportunity for new researches that would include other cryptocurrencies not only Bitcoin.

Table 2 is computed regarding the most common findings from studies by authors. The table is divided into 2 parts: internal factors and external factors that influence cryptocurrencies. It can be seen that there is only 1 internal factor, supply and demand, which is combined of sub-factors. Authors also claim, that there are 3 external factors: cryptomarket, macroeconomic and financial, social with their sub-factors that take a big part in cryptocurrency prices and their volatility.

Table 2. Factors that influence cryptocurrency prices and volatility

Internal factors	External factors		
Supply & Demand	**Cryptomarket**	**Macroeconomic and financial**	**Social**
Transaction volume	Popularity	Stock markets	Dark Web
Hashrate	Speculations	Exchange rate	COVID-19
Coins in circulation		Gold price	
		Oil price	
		FSI	

Note: composed by author.

2.2.1 Internal factors

Internal variables are directly derived from information of cryptos platforms. They have the main impact on cryptocurrencies prices mostly due to its supply and demand that includes transactions volume, hashrate, coins in circulation. Authors' findings regarding supply & demand sub-factors are described below.

Supply & Demand

Transaction volume. Poyser (2017) in his research included the daily USD exchange trade volume that represented the total USD value trading volume on major Bitcoin exchanges. The author in his study has not found any relevant effect on bitcoin price. Kjærland et al. (2018), on the other hand, has included not daily, but weekly transaction volume variable in his study. Unfortunately, he has not find any significant effect on bitcoin too. Moreover, Sovbetov (2018) found in his research that trading volume has significant long-run impact on Bitcoin at 1% significance level and on Ethereum, Litcoin, and Monero at 10% significance level. The result indicated that a unit increase in weekly trading volume causes 0.14, 0.13, 0.06, and 0.03 increases in Bitcoin, Ethereum, Litcoin, and Monero cryptocurrencies in long-run.

To sum up, researches have found that the total trading volume per day does not influence the cryptocurrency price neither in short nor long run. Though, the weekly trading volume data might have a significant positive long run impact. Transaction volume variable would need additional investigations especially in the long run as some authors found this variable to be influential.

Hashrate. The Hashrate is the speed at which a computer can complete an operation in the cryptocurrency code and is directly correlated to mining difficulty (Kjærland et al. 2018). In terms of hash rate, Poyser (2017) in his analysis used daily hash rate data and found out that hash rate had a very low non-zero probability of impact to the bitcoin price. Kjærland et al. (2018) found out that hashrate had a positive sign in both the estimated period and in-sample periods, but he insisted that it is irrelevant to include hashrate in the study as crypto price drives the hashrate. This outcome is consistent with economic theory since an increase in price will naturally result in the increased profitability of mining (Kjærland et al. 2018). Another authors, who found a positive relationship between hash rate and bitcoin were Georgoula et al. (2015) and Hayes (2017) who used daily data. Hayes also claimed that additional hashing power added to the global mining network will tend to increase the mining difficulty.

In conclusion, all the analysed authors above have insisted that daily hash rate positively influence crypto prices, but some authors claim that the has rate should not be included in the model because crypto price drives the hash rate. It means that increased price of cryptocurrency will naturally increase the profitability of mining that is a goal for miners.

Coins in circulation. Georgoula et al. (2015) in his analysis revealed that the stock of Bitcoins has a positive long-run impact on their price. Though, Kjærland et al. (2018) in his studies claimed that not the coins in circulation are dependent on price, but the supply of coins are given by the code (Bitcoin in particular) and is solely dependent on time.

Authors, regarding coins in circulation had different views. One revealed that stock of Bitcoin has a positive long run impact, another insisted that supply of coins is dependent on price. This particular variable was not analysed by many authors thus it needs additional studies to support or deny the researchers views.

To sum up the internal factors that could influence cryptocurrency prices it can be seen that more researches and studies would help to make more precise conclusions. The hash rate variable was the most analysed in comparison to coins in circulation and transaction volume. The 2 latter lacks more researches.

2.2.2 External factors

Besides the pure demand and supply variables, many researches put their attention to external factors that make an impact on cryptos prices. The most discussed are described below.

Cryptomarket

Popularity. Popularity in this case is described as the cryptocurrency popularity on the internet regarding its tweet or search volume, social media. For instance, Abraham et al. (2018) has shown in his study that both Google trends and Twitter tweet search volume index is highly correlated with cryptocurrency prices both when they rise and fall. Though, another researcher claimed that there is no statistical significance of Twitter signals impact as a predictor of Bitcoin with regard to the close price (Kaminski 2014). Moreover, Phillips et al. (2018) in his studies also included Google trends, Wikipedia views and Reddit subscriber growth and found out that in the short term relationship between online factors and cryptocurrency prices are erratic and generally weak. Online factors exhibit stronger relationships in the long term and the influence on prices were positive. Wikipedia views as a significant and positive factor on Bitcoin price increase was also identified by the Georgoula et al. (2015). Another interesting finding was suggested by Jerdack et al. (2018) who found out in her study that Google Trends volume positively correlates with Bitcoin trading volume. Sovbetov (2018) claimed that Google search term frequency also derives significant coefficients for Bitcoin and Ethereum at 1% significance level and for Litecoin and Monero at 10% significance level. Smuts (2019) in his research also included Telegram messaging platform analysis as well as Google trends and found Telegram data can predict the direction of short-term cryptocurrency price movements. Research suggested that Telegram better predicts Bitcoin price movements, while Google Trends the Ethereum price movements.

Similarly, Yelowitz et al. (2015) collected Google Trends data of Bitcoin to examine the reasons of people interest in Bitcoin. The research results indicated that unobserved illegal activities drive interest of Bitcoin.

Finally, another approach was done by Kim et al. (2016) who analysed user comments in online cryptocurrencies communities and constructed a sentiment analysis index in order to explain if those variables affect Bitcoin, Ethereum, and Ripple cryptocurrencies price, finding that the proposed approach predicted variability in the price of low-cost cryptocurrencies. Moreover, Kim insisted that community sizes online may have direct effects on fluctuations in the price of cryptocurrencies and provided Ripple example which had a relatively small community and active users, thus the predicted result was least precise in Ripple.

To sum up, there are many different researches regarding popularity variable on the internet and it seemed to have a great impact on cryptocurrencies prices. All the variables described above, for example, Google Trends, Twitter tweet, Wikipedia views had a impact on prices both on short time and long time thus it would be obvious to include these variables in the following researches as they were significant in almost every research that was analysed.

Speculations. Often, the cryptocurrencies are being called as speculative vehicles. To support this statement, there are some researches done. First of all, Cheah et al. (2015) has found that as with other asset classes, Bitcoin prices are prone to speculative bubbles. Secondly, the bubble component contained within Bitcoin prices is substantial. Moreover, Baek et al. (2015) indicated that speculations made by buyers and sellers of cryptocurrencies are the drivers of its prices and not the fundamental economy factors. Though, Baek expects cryptocurrencies to become more stable in the future as their importance is growing.

Talking about speculations, it is natural that as cryptocurrencies are not very stable and their rate can change dramatically within an hour, day, week, it attracts people who seek to gain fast money by simply buying and selling cryptos when the rate increases especially when the popularity and uncertainty are very common. Thus the researches that were analysed provided different approach. The one claimed that Bitcoin prices are pro to speculative bubbles and another one insisted that buyers and sellers (speculators) are the ones who drives the cryptocurrency prices.

Macroeconomic and financial factors

Macroeconomic and financial variables are widely analysed and discussed by the authors. It is notable that the main factors include the stock markets, particularly S&P 500 index, while exchange rate varies as it depends on the author and there can be found USD/EUR, USD/CNY rates included in studies. Gold price index is often followed by Silver price index, but Gold was chosen by more researchers.

It is worth to mention, that Pieczulis et al. (2019) using her study data revealed that the higher the price of cryptocurrencies is, the greater interest and more money invested in the cryptocurrencies can be. Moreover, the results of households investment in cryptocurrencies forecast shown that investment volumes are likely to continue to grow in the near future. It means that people interest in cryptocurrencies are growing so is the market and its potential to develop further on.

Stock markets. The empirical findings indicate that the price of cryptocurrencies can be affected by returns on the S&P 500. S&P 500 also shows how the financial markets are perfoming. Kjærland et al. (2018) in his study found a positive link between the S&P 500 index and Bitcoin price at the 5% level meaning that when the S&P 500 increases by 1%, the price of Bitcoins increases by 1.77%. Sovbetov (2018) has found out that S&P 500 index had a weak positive long-run impact on Bitcoin, Ethereum, and Litecoin price at 10% level indicating that when the S&P 500 index increases by 1%, the price of Bitcoins increase by 0.8%, Ethereum by 0.2% and Litcoin by 0.04 %. Though, in the short-run there can be seen a decrease in Bitcoin by -0.2 % when S&P index increases by 1%. Baek et al. (2015) has also included S&P variable in his research, but no significant evidence has been found. The negative impact in the long-run on Bitcoin price by Standard and Poor's 500 stock market index was also found by Georgoula et al. (2015) at the level of significance 5%. It meant that an increase of 1% in S&P price index results in -4.21 % Bitcoin price drop implying that stocks and Bitcoins are treated as substitutes by investors.

Summing up the stock markets influence, it can be seen that S&P 500 index was found to be significant at various levels of trust. It was also seen that influence on price found by authors was focused on Bitcoin and authors found both positive and negative impact on prices. Thus it suggests that different data set might cause different results, so it is important to include the newest data to get the best and updated results.

Exchange rate. Researchers choose exchange rate as a variable in their studies for numerous reasons. Ones insists that if the data of cryptocurrency price is denominated in the US dollars thus if the US dollar would appreciate against Euro, most likely it would also appreciate against the crypto price.

Moreover, Poyser (2017) has claimed, that Chinese Yuan (CNY) might have an impact on Bitcoin's price due to capital controls that China have been introducing in order to control speculation. That was the reason why the author included the CNY/USD exchange rate as well as USD/EUR in his studies. The results shown that the Bitcoin price is negatively associated with Yuan to USD exchange rate, while positively related to USD to EUR exchange. Opposite insight was found by Georgoula et al. (2015) and Ciaian et al. (2016) who found out that the value of Bitcoins is negatively affected by the exchange rate between the USD and Euro in the short-run and there was no impact in the long-run. Baek et al. (2015) in his study included a monthly change in euro exchange rate but no significant evidence was found.

An interesting approach was made by Pakenaite et al. (2019). In her research author inspected if the increased number of Bitcoin in the circulation do any impact on USD/EUR exchange rates. The results indicated that if the number of BTC in the circulation of the market increases, exchange rates of USD/EUR should slightly decrease. Moreover, if the inflation rate of BTC drops, the exchange rates of USD/EUR should slightly rise.

To sum the exchange rates, it can be seen that the short run impact on Bitcoin price was identified by researches while the impact of long run was not found. Moreover, none of the authors have included for example USD/CHF exchange rate. It would be worth to investigate the impact of that rate because the Switzerland Franc is identified as one of the stablest currencies.

Gold price. The gold price variable significance in studies varied. Kristoufek (2015) in his research used gold prices for a troy ounce in Swiss francs (CHF) currency because gold is usually considered to provide the long-term storage of value and the Swiss franc as mentioned before is considered to be a very stable currency. Results indicated that the Bitcoin is not connected to the dynamics of gold and thus no significant impact has been found. Kjærland et al. (2018) and Sovbetov (2018) have also found the gold price to be insignificant variable in their studies.

Poyser (2017) is the only author whose results revealed that the Bitcoin price is negatively associated with the gold price, and indicated that if gold price increase by 1 %, the Bitcoin price will decrease by -0.6 %.

Talking about the gold price impact on cryptocurrency, most of the researchers results show that gold price does not influence the price change of cryptocurrency, though there was only study that identified the negative impact. Taking into the consideration that the gold was not included into the study by many researches, this variable might not be important for the future studies and analysis.

Oil price. Kjærland et al. (2018) insist that WTI Oil is considered to be important global commodities whose prices have impacts on almost all economies around the world. Unfortunately, oil was found to be insignificant in the estimated regression period in the research. Giudici et al. (2019) has also included oil in his model but no significant results were found.

The only positive approach was identified by Ciaian et al. (2016) who claimed that oil price can make impact on cryptocurrency price only in the short run. In contrast, in the long run it has no effect.

To sum up the Oil price influence, most of the researches who included this variable in their studies have not found any significant outcome, but there was one author who found a short run effect on cryptocurrencies prices. As the oil is considered to be an important factor that influence all the worldwide economy it might be worth to analyse and include this variable in future studies and possibly focus on short term impact.

Financial stress index (FSI). Financial stress is another financial variable that was included in researchers analysis. Bouri et al. (2018) found out that financial stress strongly Granger-caused Bitcoin returns at the left tail (deficient performance), the middle (average performance) but not the right tail (superior performance). FSI index was also found to have influence on Bitcoin price, but only in one period of time Kristoufek (2015).

Summing up the financial stress index it can be said that FSI might have impact on Bitcoin but the shortage of articles limits this statement.

Social

Social as an external factor is identified by some researches too. They mainly focus on how social life, social media influence people choice. Pakenaite et al. (2019) insist that cryptocurrencies have some limitations: anonymity encourages to use virtual money for illegal purchases, "Black market", money laundering. Thus, he most discussed about and most influential subfactor is the Dark Web where people can find "black markets" these days. Even though none of the authors made a research regarding the Dark Web or black market influence on Bitcoin or any other cryptocurrency prices, there might be some theoretical hypothesis and insights towards it. For example, as Dark Web is getting more popular, the demand of cryptocurrencies increase so might the prices. However, there are many cryptocurrencies that are entering the market and so we could see competition between them which would not let the prices to rise. As there are only theoretical insights at this time it is rather more rational to focus on the Dark Web itself and to understand what problems and challenges it provides.

Dark web. Anonymity is a double-edged sword. It can protect people privacy, their freedom of speech but on the other hand it is misused to conduct illegal behaviours and co-called cyberterrorism. This problem is getting more common due to the advances in technologies and the way they are used in combination Lee et al. (2019). As claimed by DiPiero (2017), government agencies have been slow to adapt to evolving technologies and the increasing use of decentralized, digital currencies for illegal acts. The Dark Web was first proposed to support the freedom of the press and guarantee the open discussions without political pressure, but eventually it was misused for malicious purposes, such as buying and selling drugs, guns, credit cards. Lee et al. (2019) in his research discovered that more than 80 % of Bitcoin wallet addresses on the Dark Web were used for malicious intent and the volume was around 180 million USD.

The web people are using everyday for their needs and which can be easily accessed via various search engines like Google, Yahoo is called the surface web. The dark web can only be accessed by using a special software/browser called Tor (Lee et al. 2019). The Onion Router ("Tor") was created to ensure secure government communications for the U.S. Navy and thus Tor encrypts and sends the information through random nodes located around the globe (DiPiero 2017). It means that the path between user and his final destination in browsing is blurred and protected thus it makes difficult or nearly impossible for government to identify the user. This makes all the websites on the Deep(Dark) Web nearly completely anonymous. It is also worth to note that the FBI insisted that The United States are capable of ”cracking Tor” and eventually identifying the users of Dark Web markets (DiPiero 2017).

Controversial insights were claimed by Greenberg (2014) who insisted that anonymous purchasing and receiving of drugs has the potential to reduce violence related by drug crimes by 50%. As one of the reason he identified the eye to eye meeting absence while conducting a drug transaction. It would reduce the chance for violence when, for example, the drug deals go bad.

The buying process in the dark market does not require any special requirements. Firstly, a buyer confer with a seller about the shipping method, price and payment method. Payment type can be without a third-party mediator which mean a buyer has to send the money for a product directly to the seller. Another transaction type can be done using third-party mediator, for exmple, Escrow which provides an automated payment system to buyers and charge service fees to the sellers (Lee et al. 2019).

Lee et al. (2019) in his research has found out that Bitcoin, Ethereum and Monero are the most popular cryptocurrencies used in the black market. The author has obtained 5440 Bitcoin, 50 Ethereum and 61 Monero addresses. It shows the Bitcoin is without a doubt the most popular crypto on the dark market. It was also found that the total of 43000 BTC was used for purchasing goods and which equalled around 180 million dollars at that time. It thus lead to the conclusion that market volume is so high this indeed is a concern for the world.

Summing up the dark web, it has been discovered that no actual researches were done to measure the dark web influence on cryptocurrencies prices. It is clear that the cryptocurrencies run the dark web and thus the markets expands even though there were findings that legitimate institutions are aware of that but as the technology improves day by day, it becomes more secure and more anonymous thus it could require a lot to do to close all the roads to the dark web.

COVID-19. Newly occurred pandemic of coronavirus, known as COVID-19 has become the recent researches object as scientists started to measure its impact on financial markets, stocks and cryptocurrencies too. Some scientists decided to model cryptocurrencies behaviour during COVID-19 pandemic to check if can act like safe haven others investigated if COVID-19 made an impact on crypto prices or volatility. Conlon et al. (2020) and Chen et al. (2020) in their researches investigated if Bitcoin during the COVID-10 was a safe haven or risky hazard and found out that Bitcoin did not act as a safe haven, instead decreased in price in lock-step with the S&P 500 as the crisis developed. Opposite results were obtained by Mariana et al. (2020) who found out that Bitcoin and Ethereum are suitable as short-term safe-havens and insisted that Ethereum is possibly a better safe-haven than Bitcoin.

Others focused on finding the possible coronavirus impact on cryptocurrencies price dynamics. Chen et al. (2020) in his research implemented sentiment analysis of hourly Google search queries on coronavirus-related words and found out that that negative Bitcoin returns and high trading volume could be explained by fear sentiment regarding the coronavirus. Interesting results were presented by Pano et al. (2020) who investigated if sentiment scores of Twitter text can make impact on Bitcoin prices during the COVID-19 pandemic. His findings suggests that the Bitcoin prices only correlate well with sentiment scores over shorter timespan. Another approach was suggested by Goodell et al. (2020) who used wavelet coherence analysis of daily deaths from COVID-19 and Bitcoin daily prices. Author has found out that especially for the period from 5th April 2020 to 29th April 2020, the death levels from COVID-19 caused a rise in Bitcoin prices.

Summing up the COVID-19 object, it can be seen that it became a widely analysed among the researchers and the results they get differs. It suggests that more different approaches are needed including new models and techniques in order to analyse the COVID-19 impact towards the cryptocurrencies.

2.3 Methods and tests used by authors for analysis

There are many various techniques, methods or test to analyse different data, datasets meaning that for example daily data, monthly data, yearly data can be analysed using different methods to get the best results. Thus, researchers that are analysed in this paper used great variety of methods and tests to check their hypothesis and implemented models efficiency. The Table 3 illustrates the most popular methods and tests that were used by authors in order to study the volatility changes of the cryptocurrencies and what factors influence their price or financial returns.

Table 3. Most popular methods and tests used by the researchers

Researcher	Methodologies and tests used by authors											
	GARCH/ARIMA	Changepoint	Linear regression	Multiple linear regression	Structual time series	Vader	Wavelet analysis	Johansen-Cointegration test	ADF test	Granger Causality test	AIC test	ARDL, VEC/VECM or VAR
Georgoula et al. (2015)				+				+	+			VECM
Abraham et al. (2018)			+			+						
Smuts (2019)						+						
Kim et al. (2016)						+				+		
Kristoufek (2015)							+					
Phillips et al. (2018)							+					
Hageman(2018)									+	+		VAR
Kaminski (2014)									+	+		
Jerdack et al. (2018)				+								
Pakenaite et al. (2019)				+								
Kjærland et al. (2018)	+								+		+	ARDL
Sovbetov (2018)									+			ARDL
Ciaian et al. (2016)								+	+		+	VEC
Poyser (2017)					+							
Hayes (2017)				+								
Yelowitz et al. (2015)				+								
Cheah et al. (2015)							+					
Baek et al. (2015)				+								
Pieczulis et al. (2019)	+											
Giudici et al (2019)												VAR
Catania et al. (2018)	+											
Bouri et al. (2018)	+									+		
Pano et al. (2020)						+						
Chen et al. (2020)									+	+		VAR
Conlon et al (2020)												VAR
Mariana et al. (2020)	+											
Goodell et al. (2020)							+					
Thies et al. (2018)		+										
James et al. (2020)		+										

Note: composed by author.

Most of the methods and tests were used to identify the factors that influence the cryptocurrency prices and some researchers did analysis of price data and checked if it was stationary or had causal relationships between different price series. The most popular and significant methods and tests used by researchers are described below.

GARCH

GARCH model can predict unconditional variance and requires fewer parameters. The most recent observations have greater impacts on the predicted volatility (Kjærland et al. 2018).

Three authors Kjærland et al. (2018), Catania et al. (2018), Bouri et al. (2018), and Mariana et al. (2020) included GARCH method in their studies. It is worth to mention that Catania et al. (2018) included this GARCH method to compare it with various Score Driven models with conditional Generalized Hyperbolic Skew Student's t (GHSKT) innovations because the GARCH model did not perform accurately. (Catania et al. 2018) included GARCH and GHSKT along with its 3 extensions: 1) leverage, 2) time-varying skewness, and 3) fractional integration the volatility process. The results of his study indicated that his beliefs were right as GHSKT models with extensions improved the volatility forecast horizons from 1% to 6% compared to GARCH. Moreover, Kjærland et al. (2018) compared GARCH results with ARDL model and found out that they perform approximately the same. Bouri et al. (2018) used ARMA (1,1)-tGARCH(1,1) model on Bitcoin daily returns and investigated it dependence on global financial stress index. This model was selected because data contained a serial correlation, data did not have heteroscedasticity and there were many outliers in the data. Mariana et al. (2020) used another approach of GARCH called DCC-GARCH (1,1) as it was the most appropriate for the data used.

All described authors above had different approaches to GARCH modelling. To some researchers the GARCH model shown uncertainty, other used it because it fit the data. Thus it can be concluded that in order to use GARCH, the data must be appropriate for that model.

ARIMA

ARIMA forecast model was used by Pieczulis et al. (2019). The author chose ARIMA (2,1,0) as a forecasting model for her study. Model had one degree of non-seasonal differentiating and two AR lags. The implicated model resulted in the outcome - forecast of household investment in cryptocurrencies for a year ahead.

To sum up, it would be worth to analyse the prediction results after a year to check if the forecast was correct.

Changepoint analysis

At the time of this thesis writing, there is not a lot of studies regarding changepoint analysis on cryptocurrencies. Changepoint detection is the name given to the problem of estimating the point at which the statistical properties of a sequence of observations change. With increased collection of time series and signal streams there is a growing need to be able to efficiently and accurately estimate the location of multiple changepoints.

The most recent paper that implemented changepoint analysis on cryptocurrencies was written by James et al. (2020). In his study author implemented two-phase change point detection algorithm to obtain a set of structural breaks known as changepoints. It was found out that during COVID-19 pandemic the cryptomarket variance was disrupted if compared to the period before COVID-19.

Another scientist in his research implemented Bayesian Changepoint Model algorithm of Bitcoin returns and analysed structural breaks in the average return and volatility of the Bitcoin price. Author found out that structural breaks in average returns and volatility of Bitcoin are very frequent and higher volatility is associated with higher average returns (Thies et al. 2018).

Changepoint analysis suggest that it can be widely used for abnormalities detection, thus it might be worth to start implementing this technique in the future researches.

Linear regression

Linear regression is one of the most popular approaches to modelling the relationship between dependent and one independent variable. The Ordinary least squares technique (OLS) is probably the most common for linear regression analysis. Notable, that using the linear regression it is only possible to identify one independent variable impact on dependent. Thus, many researches use multiple linear regression where they can include many independent variables.

Abraham et al. (2018) chose linear model to find Twitter tweet volume impact on cryptocurrency price. In this case he only used one dependent and one independent variable thus author completed linear regression model using OLS technique.

Talking about linear regression, it is clear that it has limitations especially as it can show one independent variable impact on depended. Thus is it more useful and wise to use, for example, multiple linear regression when including more independent variables.

Multiple linear regression

The multiple linear regression model and its estimation using ordinary least squares (OLS) is probably the most widely used tool in econometrics. That can be seen from 3 table. A great number of researchers used multiple linear regression. It allows to estimate the relation between a dependent variable and a set of explanatory(independent) variables.

Two researchers Jerdack et al. (2018) and Pakenaite et al. (2019) in their studies formulated hypothesis of how their independent variables influence dependent variable and used multiple linear regression method.

Yelowitz et al. (2015) and Hayes (2017) used OLS technique for their multiple linear regression analysis. The former researcher used cross-sectional data from 66 of the most widely used and actively traded altcoins. Yelowitz et al. (2015) created model to determine the reason for Bitcoin search interest on Google.

One more multiple linear regression method technique, widely used by scientists was Newey–West standard errors for coefficients estimated by OLS regression. The estimator is used to try to overcome autocorrelation, and heteroskedasticity in the error terms in the models. Georgoula et al. (2015) and Baek et al. (2015) in their research included this technique to test independent variables impact on Bitcoin price in short term.

Summarizing the multiple linear regression it is clear why researches often use it as it has many techniques, for example OLS, Newey-West standart erros thus it is easier for researchers to compare various methods by results and find the best working as some has its limits and others do not.

Structural time series

Structural Time Series (STS) framework provides the possibility to expand the information to explain the observed data by adding explanatory variables as a separate component (Poyser 2017). For example, state space model (SSM) is equivalent to a dynamic system composed by a seasonal and trend elements and perturbed by random disturbances. SSM allow the treatment of missing observations, inclusion of stochastic explanatory variables can be permitted to vary stochastically over time (Poyser 2017). SSM the key task is to generate predict future observations in the unobserved states.

Poyser (2017) explored in his research the association between Bitcoin's market price and a set of internal and external factors using Bayesian Structural Time Series Approach.

To sum up, Structural Time Series framework has a lot to offer. Firstly, the ability to incorporate uncertainty into forecasts thus it is possible to predict future risk. Model also offers transparency which helps to understand how the model works. All these features help to merely maximize chances of successful forecast.

VADER

VADER (Valence Aware Dictionary and sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool. Sentiment analysis is the act of extracting and measuring the subjective emotions or opinions that are expressed in text, typically VADER normalizes positive and negative sentiments from -1 to 1. The end goal of this analysis is to apply sentiment analysis to collected tweets so that it can be determined if the tweets are generally positive or negative and what impact they can do on selected variable.

Authors Abraham et al. (2018), Smuts (2019), Kim et al. (2016), and Pano et al. (2020) have used VADER for their sentiment analysis to inspect their influence on cryptocurrency prices. The only difference was that they all used data from various sources. For example, Abraham et al. (2018) used data from Twitter and Google Trends, Smuts (2019) collected data from Google Trends and Telegram messaging platform while Kim et al. (2016) extracted data from Bitcoin, Ripple, Ethereum forums. Pano et al. (2020) in his analysis used data from Twitter text during COVID-19 pandemic.

Summarazing the VADER methodology it can be concluded that in the future this methodology could break the ice even more and provide significant results. This is because the amount of data available in the world is increasing everyday, some scientists claim that 90% of data of the world has been created in the last few years. Thus discussions about cryptocurrencies between people could definitely increase on the internet forums even more. It is likely to be much more sentiment analysis done in the future.

Wavelet analysis

Wavelet coherence in this particular cryptocurrecy analysis is used to study co-movement between a cryptocurrency price and its related factors. It can localize correlations between series and evolution in time and across scales. Wavelet analysis including cryptocurrency data is a new approach and only a few researches has already completed the investigation. Wavelet coherence is used alongside a well-known test for financial asset bubbles.

Phillips et al. (2018), Kristoufek (2015), and Goodell et al. (2020) used Wavelet coherence analysis in their studies. Their goal was to check if especially Google search volume, Wikipedia views does influence on cryptocurrency prices. Phillips et al. (2018) has included a few cryptos in his studies, for example Bitcoin, Monero, Litecoin, Ethereum while Kristoufek (2015) investigated only Bitcoin. In addition, Cheah et al. (2015) indicated that Firstly, Bitcoin prices are prone to speculative bubbles. Different analysis was performed by Goodell et al. (2020) who examined if COVID-19 daily death number can influence Bitcoin price.

To sum up wavelet coherence analysis, as claimed by researchers it is a new method especially for implementing the analysis of the cryptocurrencies, thus it might attract future scientists to apply this method as it provide significant results. Moreover, the variables used by authors included social media, for example Google Search volume, Wikipedia views. Interestingly, researchers that used VADER method also included similar variables, though their analysis was based on sentiment.

Johansen-cointegration test

Johansen's co-integration test method is used to identify the long-term relationship between the price series in this case and to specify the number of co-integrating vectors in time series. Ciaian et al. (2016) explains that the number of cointegrating vectors is determined by the maximum eigenvalue test and the trace test. Both tests use eigenvalues to compute the associated test statistics. Moreover, Johansen co-integration test helps to decide which model to use: VAR (no co-integration), ARDL (one cointegration relatioship among $I(0)$ and $I(1)$) or VEC (more than one co-integration relationships).

Authors Ciaian et al. (2016) and Georgoula et al. (2015) both used Johansen co-integration tests to find if their econometric models have co-integrating vectors. After that, depending on the results they implicated new models: VAR, ARDL or VEC to check the long-run relationship between the co-integrated series

Summarazing the Johansen co-integration test it can be said that this test is very useful for selecting the appropriate method for long-term model selection to investigate the long-run relationship.

ADF test

Augmented Dickley-Fuller (ADF) test was one of the most popular among the researchers. Test is used to determine the presence of unit root in the series, and hence helps in understand if the series is stationary or not. Stationarity in series means that statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. Such series are easy to predict.

Georgoula et al. (2015), Hagemann (2018), Kaminski (2014), Kjærland et al. (2018), Sovbetov (2018), Ciaian et al. (2016), and Chen et al. (2020) all included ADF test in their analysis. To make the data stationary if it is not, researchers therefore use first differences of the data.

To sum up, ADF test is without a doubt is useful for checking unit roots and then implementing the new methods in further studies, for example using Granger causality test, where the data must be stationary but it is suggested to employ Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test or Phillips (PP) tests for testing stationarity instead of ADF test.

Granger causality test

Granger causality is a statistical concept of causality that is used to predict how one time series can forecast another. A scalar Y is said to Granger-cause scalar X if X is better predicted by using the past values of Y than by solely relying on past values of X (Kaminski 2014). As mentioned before, in order to do the Granger causality test, the series has to be stationary, so KPSS test, for example, should be run.

Hagemann (2018) in his studies checked how one cryptocurrency Granger-cause another one. While Kaminski (2014) and Kim et al. (2016) investigated how people reactions, replies, comments in social online forums about cryptocurrencies and Twitter influence their prices. Chen et al. (2020) used Google Trends data of COVID-19 and checked how fear sentiment influenced Bitcoin returns. Another approach was done by Bouri et al. (2018) who investigated the Granger-cause relationship between Bitcoin returns and global financial stress index.

Granger causality test could be very helpful when trying to model causal relationships between variables and what impact they do on each other using, for example different time series data. It might also be useful for future researchers to select the appropriate explanatory variables by checking their causality relationship against the dependent variable.

AIC test

To find the appropriate lag length for each of the underlying variables in, for example VEC or ARDL modes, one of the option is to use the modified Akaike information criteria (AIC).The model with the lowest AIC and highest R-squared is considered the best. Akaike information criteria was included in Kjærland et al. (2018) and Ciaian et al. (2016) methodology where researches tried to find the best selection of lags to ARDL and VEC models respectively.

AIC is essential to use in order to select the appropriate number of lags for models otherwise the results might not be significant and correct.

ARDL

ARDL is the model which estimate the short and long-term effects of selected independent variables on dependent. The ARDL model is estimated using ordinary least squares (OLS), where the only difference is the inclusion of lags (Kjærland et al. 2018).

Two authors used ARDL model in their analysis. Kjærland et al. (2018) examined the factors influencing the prices of Bitcoin and then compared the model results with GARCH model, while Sovbetov (2018) included additional cryptocurrencies in his analysis: Ethereum, Dash, Litecoin, and Monero and tried to identify the factors that influence the price change in short and long-run.

ARDL model advantage is that it can be used for finding both short and long-run impact. Though, in order to use this method the data must be stationary on $I(0)$ and $I(1)$ or both and finally the error terms should have no autocorrelation with each other.

VEC or VECM

VEC(can be noted as VECM) model is just a special case of the VAR for variables that are stationary in their differences. The model can be applied when time series are considered to be co-integrated, implying that there exists a long-run equilibrium relationship between them. In this case, the Vector Error Correction (VEC) model is suitable for estimation.

Researchers Ciaian et al. (2016) and Georgoula et al. (2015) selected VEC models as for analysis. It means that both have found their time series to be co-integrated and stationary in their differences.

VAR

The vector autoregressive (VAR) model is a general multivariate time series framework used to describe the dynamic interrelationship among stationary variables. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and for forecasting.

VAR model has been used in Hagemann (2018), Giudici et al. (2019), Chen et al. (2020), and Conlon et al. (2020) studies. The first researcher used this method to test whether the Bitcoin, Etereum and Monero cryptocurrency prices and their lagged prices of each variable impact one another, thereby implying a form of causality. While Giudici et al. (2019) proposed the VAR to find out the correlation structure between Bitcoin prices in different exchange markets and traditional assets. Moreover, the model was able to improve the Bitcoin price prediction. Chen et al. (2020) used VAR model and found out that an increase in fear sentiment will lead to lower Bitcoin returns and higher Bitcoin trading volume. Conlon et al. (2020) implemented VAR model to examine the Bitcoin if it act as a safe haven during COVID-19 pandemic.

To sum up, VAR model is chosen for multivariate time series when variables are stationary to examine the linear interdependence among multiple time series. Moreover, VAR models can be used for forecasting, predictions as one of the authors did, who was analysed before.

Summarizing all the models and tests described above, the multiple linear regression and ARDL, VEC, VAR models were used by the most of the researchers. Different models need to fulfill the required conditions for the model to be valid. Thus the authors before applying, for example, ARDL, VEC or VAR models may have to run the Johansen co-integration, ADF, AIC tests.

Moreover, sentiment analysis approach using VADER analysis tool offers new possibilities for analysis using people comments, replies on the social networks impact on dependent variable, in this analysed case, impact on cryptocurrency prices.

Wavelet analysis methodology included similar variables that authors used in sentiment analysis, though be methodology of wavelet analysis is to characterize intermittent cross-correlations between two time series at multiple time scales.

The least popular analysis methods used by researches were GARCH, ARIMA, Linear regression and Structural Time series models.

3 Data Collection and Manipulation

This section consists of 2 subsections for 2 different econometric analyses. The first part will focus on changepoint detection analysis in variance. Changepoint analysis in this research plays an important role as the main idea of employing this model is to find the calendar dates, as a changepoints and check if they have any relation to COVID-19 pandemic dates. This changepoint model is applied on Bitcoin, Ethereum, Ripple time series.

Second analysis will also be performed on Bitcoin, Ethereum and Ripple time series. Here the main focus is put on finding whether there is a causality relationship between cryptocurrencies and selected variables.

3.1 Changepoint detection in variance

As suggested by Killick and Eckley (2014), changepoint detection is the name given to the problem of estimating the point at which the statistical properties of a sequence of observations change. Detecting such changes is important in many different application areas. Recent examples include climatology, bioinformatic applications, finance, oceanography and medical imaging. With increased collection of time series and signal streams there is a growing need to be able to efficiently and accurately estimate the location of multiple changepoints.

In other words, assume an ordered sequence of data, $y_{1:n} = (y_1, \ldots, y_n)$. The model will have a number of changepoints, m, together with their positions, $\tau_{1:m} = (\tau_1, \ldots, \tau_m)$. Each changepoint position is an integer between 1 and $n-1$ inclusive. We define $\tau_0 = 0$ and $\tau_{m+1} = n$ and assume that the changepoints are ordered such that $\tau_i < \tau_j$ if, and only if, $i < j$. Consequently the m changepoints will split the data into $m+1$ segments, with the i th segment containing $y_{(\tau_{i-1}+1):\tau_i}$ (Killick, Fearnhead, et al. 2012).

Nowadays, the most common approach to identify multiple changepoints described in researches is to minimize:

$$\sum_{i=1}^{m+1} \left[\mathcal{C}\left(y_{(\tau_{i-1}+1):\tau_i}\right)\right] + \beta f(m), \tag{1}$$

where C is a cost function for a segment e.g., negative log-likelihood and $\beta f(m)$ is a penalty to guard against over fitting.

Changepoint analysis can be applied on mean, variance and mean-variance. In this research the analysis on variance is selected as it is the most appropriate on the selected data. The daily data of the log returns of cryptocurrency price during the period from 2019-11-07 to 2020.11.06 is used in this research for changepoint analysis.

The usage of the log returns is well documented by the empirical finance literature because prices are believed to be non-stationary thus log returns solves this problem. Another advantage of using log returns is that the data is normalized and normally distributed. The log returns are defined as the first difference of the natural logarithm.

3.1.1 Data and Descriptive Statistics

As mentioned before, in this thesis for analysis we use daily log returns for cryptocurrencies from period 2019-11-07 to 2020.11.06. There are many ways of calculating returns, but one of the most popular ways when analysing financial data is through continuous compounding (Ruppert 2014). The equation 2 indicates the model used for each cryptocurrency daily price conversion to logarithmic returns. The general assumption of independent and identically distributed (i.i.d) and log-normally distributed returns is followed in this research as suggested by Ruppert (2014).
Let

$$r_t = \ln(P_t) - \ln(P_{t-1}), \tag{2}$$

here:
r_t = log returns at time t,
P_t = price of cryptocurrency in USD at time t.

Logarithmical returns time series of Bitcoin, Ethereum, Ripple cryptocurrency can be seen in Figure 1. From the figure it can be seen that all three graphs do not differ a lot, has similar patterns and from the first sight it is noticeable that all have a spike in the beginning of 2020 March. Ethereum and Ripple also seem to have more movement over period from 2020.07.01 to 2020.10.01 while Bitcoin returns have shown more stability. The occurred spike in March, when the COVID-19 pandemic was announced suggests that there might be significant results after implementing change-point analysis on this data.

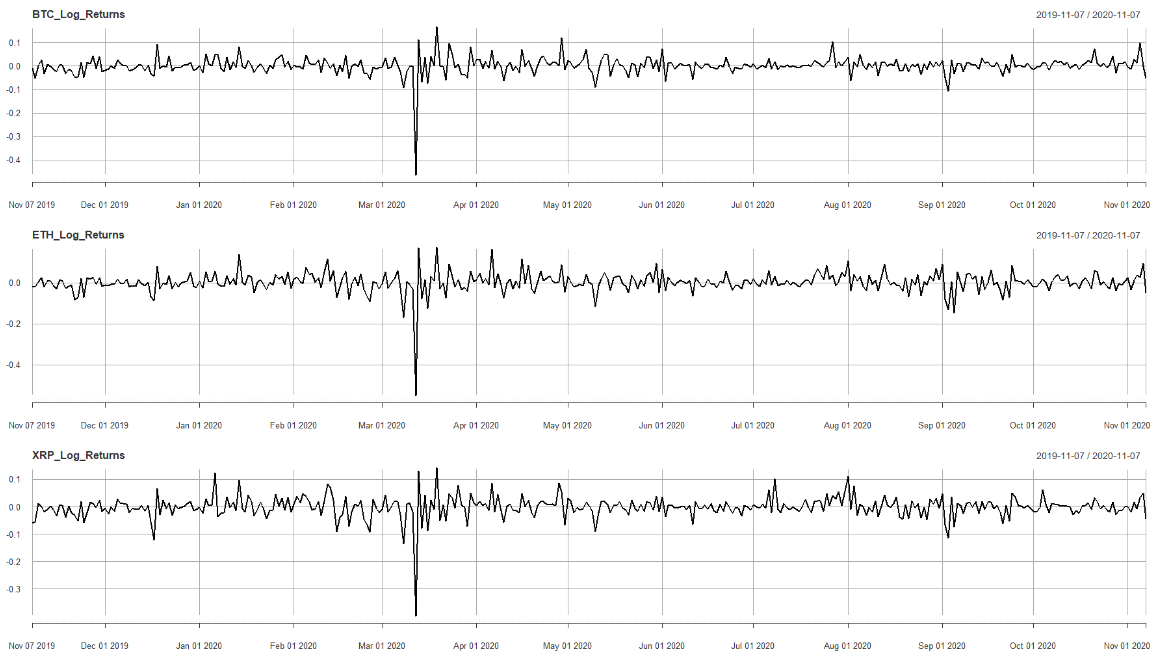

Figure 1. Daily log returns of Bitcoin, Ethereum, Ripple prices

All three cryptocurrency times series of log return, plotted on one graph can be seen in Appendix Figure A1. From the Figure A1 it can be seen that Ethereum logarithmic returns fluctuates more over the period than BTC and XRP but all cryptocurrencies show similar pattern.

The descriptive statistics of these cryptocurrencies log returns can be seen in Table 4 below. It can be seen that Ethereum reached the largest minimum value of -0.550732 and the greatest maximum value of 0.173452 over the period, as well as its mean and median was highest if compared to Bitcoin and Ripple. Also, only Ripple mean value of the period was negative and equal to -0.006183 that is close to 0.

Table 4. Cryptocurrency log returns summary statistics

Cryptocurrency	Min.	Median	Mean	Max
Bitcoin (BTC)	-0.464730	0.001224	0.001247	0.167104
Ethereum (ETH)	-0.550732	0.002664	0.002218	0.173452
Ripple (XRP)	-0.3989676	0.0013153	-0.0006183	0.1426260

Note: composed by author.

Summarizing the descriptive statistics of the analysed cryptocurrencies it can clearly be seen that there were abnormalities in the data, especially during March of 2020 where all the analysed cryptocurrencies faced minimum values. Thus changepoint analysis would help to check if this assumption of abnormality is correct and if it can be related to COVID-19 pandemic.

3.1.2 Model and Methodology

For changepoint detection, each of Bitcoin, Ethereum, Ripple daily log returns time series data was randomly divided into 2 time series. The 1st data set now contains returns data from 2019-11-07 to 2020.05.23, while 2nd data set contains data from 2020.05.24 to 2020.11.06. The changepoint detection methods will be applied on both series.

In this research PELT (Pruned Exact Linear Time), BinSeg (Binary segmentation) and AMOC (At most on changepoint) methods will be used for changepoint detection. Their specifications, assumptions, equations are described below.

PELT

The PELT method for changepoint detection considers the data sequentially and searches the solution space exhaustively. Computational efficiency is achieved by removing solution paths that are known not to lead to optimality. The essence of pruning in this context is to remove those values of τ which can never be minima from the minimisation performed at each iteration in (1) equation. The detection of multiple changepoints by PELT algorithm is first applied to the whole data set and iteratively and independently to each partition until no further changepoints are detected. The main assumption of the PELT algorithm is that the numbers of changepoints increases linearly with the increase of data set, that is, the changepoints are spread throughout the data and are not restricted to one portion of the data (Wambui et al. 2015). As indicated by Wambui et al. (2015), the PELT method modifies the optimal partitioning method by pruning. It combines optimal partitioning and pruning to achieve exact and efficient computational cost which is linear in n. The optimal segmentation is $F(n)$ where:

$$F(n)=\min_{\tau}\left\{\sum_{i=1}^{m+1}\left[C\left(y_{\tau_{i-1}+1},\ldots,y_{\tau_i}\right)+\beta\right]\right\}. \tag{3}$$

Conditioning on the last changepoint, τ_m and calculating the optimal segmentation of the data up to that changepoint gives:

$$F(n)=\min_{\tau_m}\left\{\min_{\tau|\tau_m}\sum_{i=1}^{m}\left[C\left(y_{\tau_{i-1}+1},\ldots,y_{\tau_i}\right)+\beta\right]+C\left(y_{\tau_m+1},\ldots,y_n\right)\right\}. \tag{4}$$

This model can repeated for the second to last, third to last and etc. changepoints detection. The inner minimisation is equal to $F(\tau_m)$ and thus (3) equation can be written as:

$$F(n)=\min_{\tau_m}\left\{F\left(\tau_m\right)+C\left(y_{\tau_m+1},\ldots,y_n\right)\right\}. \tag{5}$$

As suggested by Wambui et al. (2015), model is started by calculating $F(1)$ then $F(2)$ until $F(n)$. At each step the optimal segmentation up to τ_{m+1} is stored. When model reaches $F(n)$ the optimal segmentation for the entire data is set to be completed and the number and location of changepoints are recorded and every step of minimisation over τ_m covers all previous values. For instance if calculating $F(4)$ it covers τ_m = 0, 1, 2, 3. The computational efficiency of the PELT method is achieved by removing candidate values of τ_m from the minimisation at each step.

BinSeg

Binary Segmentation or BinSeg method for changepoint detection in essence extends a single changepoint method to multiple. Firstly, model applies a single changepoint test statistic to the entire data, if a changepoint is identified the data is split into two at the changepoint location. The single changepoint procedure is repeated on the two new data sets, before and after the change until no changepoints are found in any part of the data (Killick and Eckley 2014). Binary segmentation is considered to be an approximate algorithm but fast. Moreover, BinSeg is arguably the most popular changepoint detection method used in the changepoint detection papers (Killick, Fearnhead, et al. 2012). Rohrbeck (2013) insists that formally, in the context of (1) equation, the single changepoint method tests whether there exist an integer $\tau \in \{1, \ldots, n-1\}$ that satisfies :

$$C\left(y_{1:\tau}\right)+C\left(y_{(\tau+1):n}\right)+\beta<C\left(y_{1:n}\right), \tag{6}$$

where:

$y_{1:\tau}$ = first segment of splitted data,
$y_{\tau+1:n}$ = another segment of splitted data,
$y_{1:n}$ = entire dataset with sequence of observations of length n,
β = penalty.

If the result of (6) equation is false, then no changepoint is found and algorithm stops. If the result is not false, then data splits again into two segments consisting of the sequence before and after identified changepoint (Killick, Fearnhead, et al. 2012). The equations for changepoint detection to each new segments are:

$$\begin{aligned}&\mathcal{C}\left(y_{1:\tau}\right)+\mathcal{C}\left(y_{(\tau+1):\tau_a}\right)+\beta<\mathcal{C}\left(y_{1:\tau_a}\right),\\&\mathcal{C}\left(y_{\tau_a:\tau}\right)+\mathcal{C}\left(y_{(\tau+1):n}\right)+\beta<\mathcal{C}\left(y_{\tau_a:n}\right).\end{aligned} \tag{7}$$

Now, if at least one test is true, further splitting of segments at the newly identified changepoint(s) are implemented and the detection method to each new segment is applied (Killick, Fearnhead, et al. 2012). This procedure is repeated until no further changepointsare detected. It is worth to mention that BinSeg algorithm does not automatically lead to the global minimum of equation (1) and is thus only approximative (Rohrbeck 2013). In other words, this process is an approximate minimisation of equation (1) with $f(m) = m$, as any changepoint locations are dependent on changepoints identified previously.

AMOC

At most one changepoint - AMOC is a technique used to detect a hypothesised single changepoint. As suggested by Wambui et al. (2015), the null hypothesis refers to no changepoint, and its maximum log likelihood is given by $\log p\left(y_{1:n} \mid \hat{\theta}_1\right)$, where $p(\cdot)$ is the probability density function associated with the distribution of the data and $\hat{\theta}$ is the maximum likelihood estimate of the parameters. Alternative hypothesis considers changepoint at τ_1 with $\tau_1 \in \{1, 2, \ldots, n-1\}$. The expression for the maximum log likelihood for a given τ_1 is $\mathrm{ML}\left(\tau_1\right)=\log p\left(y_{1:\tau_1} \mid \hat{\theta_1}\right)+\log p\left(y_{(\tau_1+1):n} \mid \hat{\theta_2}\right)$.

It is assumed that $\max \tau_1 \mathrm{ML}\left(\tau_1\right)$ is the maximum log-likelihood value under the alternative hypothesis, where the maximum is taken over all possible changepoint locations due to the fact that changepoint location is discrete in nature. Consequently, the test statistic is $\lambda = 2\left[\max \tau_1 \mathrm{ML}\left(\tau_1\right)-\log p\left(y_{1:n} \mid \hat{\theta}\right)\right]$. The null hypothesis is rejected if $\lambda > C$, where C is a threshold of our choice. When detecting a changepoint, its position is estimated as $\hat{\tau_1}$, which is the value of $\hat{\tau}_1$ that maximises $\mathrm{ML}\left(\tau_1\right)$.

3.1.3 Results

In this subsection the results of implemented changepoint detection techniques on variance including AMOC, BinSeg, PELT on selected data will be presented, compared and analysed. The results of all three implemented changepoint methods for each cryptocurrency is presented separately. For all the changepoint detection methods below the default model penalty was used as well as assumption of normally distributed data.

Bitcoin

In the beginning the changepoint detection models are implemented on 1st period of data. As mentioned before, 1st period of data consists of daily log returns cryptocurrency data from 2019-11-07 to 2020.05.23, while 2nd data set contains data from 2020.05.24 to 2020.11.06. The results of changepoint detection of Bitcoin 1st period can be seen in Figure 2.

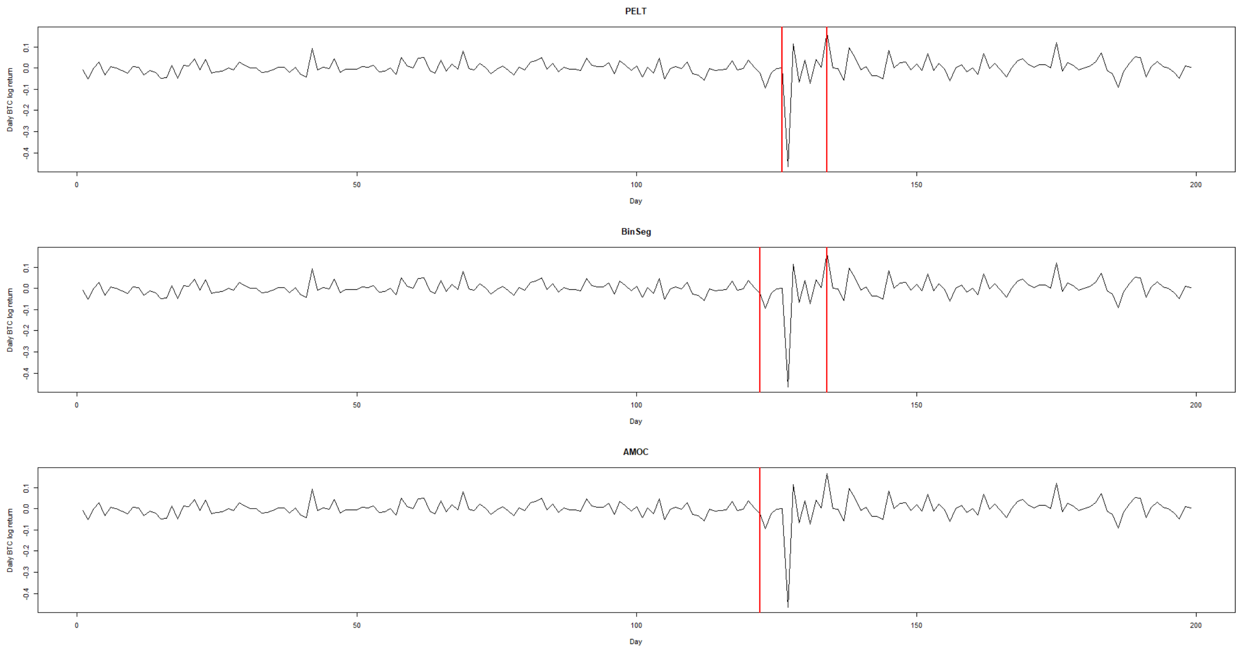

Figure 2. Bitcoin changepoint detection for 1st period using PELT, BinSeg, AMOC methods

From the Figure 2 it is possible to see that different methods resulted in different results but multiple changepoint detection techniques (PELT, BinSeg) both found 2 changepoints while single changepoint method (AMOC) found 1. It is worth to mention, that the 2nd changepoint detected by PELT method is the same as 2nd detected by BinSeg and the 1st detected by BinSeg is the same as detected by AMOC. The exact dates detected by the methods are described in Table 5 below.

Table 5. Bitcoin changepoint detection results from 1st period

Changepoint method	Changepoint on a day	Day on calendar
PELT	126	2020.03.11
	134	2020.03.19
BinSeg	122	2020.03.07
	134	2020.03.19
AMOC	122	2020.03.07

Note: composed by author.

As it can be seen from the Table 5, 2020.03.07 and 2020.03.19 were detected as changepoint dates most of the time.

After completing the changepoint analysis on the first data set, the same procedure was applied on the second data set. This time, no changepoints were detected. It can be seen from Figure A2 in the Appendix A.

Ethereum

The same changepoint detection procedure is now applied on Ethereum. Similarly as for Bitcoin, PELT, BinSeg methods resulted in 2 changepoints detected while AMOC, as expected resulted in 1. Interestingly, this time the changepoints detected by PELT and BinSeg methods were exactly the same as well as 1st changepoint of those methods were the same as found by AMOC. The results can be seen in Figure 3.

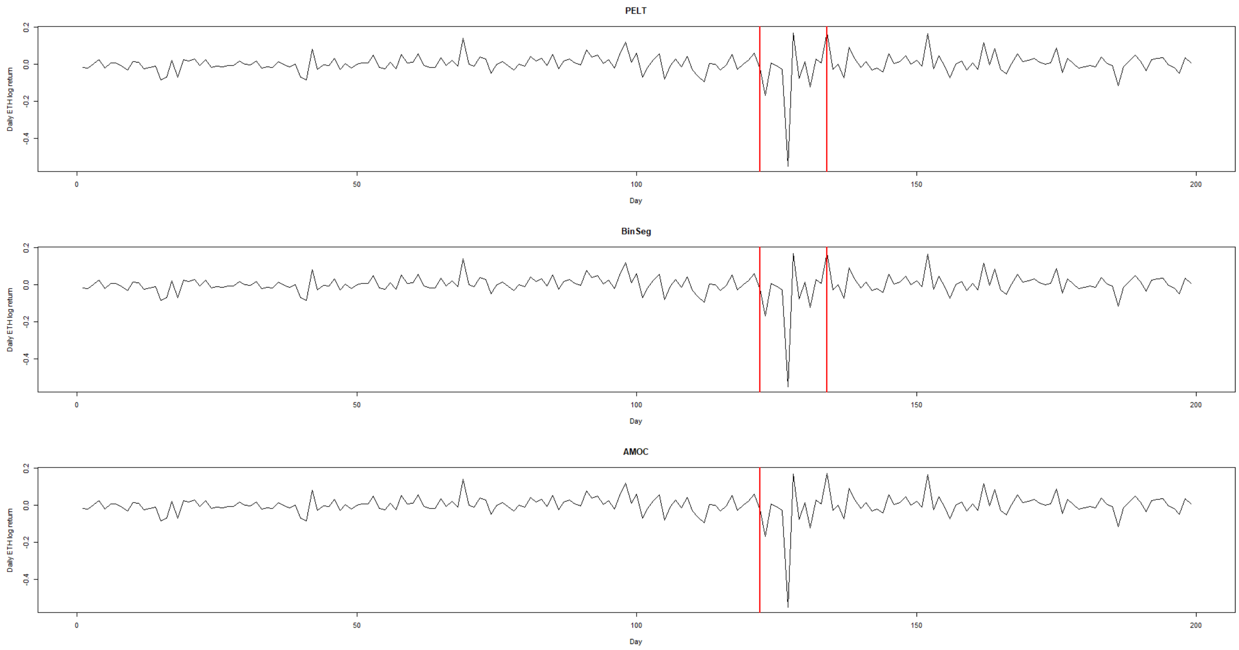

Figure 3. Ethereum changepoint detection for 1st period using PELT, BinSeg, AMOC methods

From Table 6 it can be seen that 2020.03.07 day was detected most of the time and by all the methods. If compared to Bitcoin results, it is clear that changepoint dates are almost the same as only PELT method on Bitcoin indicated first changepoint on day 126, while Ethereum 1st period dataset did not have changepoint detected on this date.

Table 6. Ethereum changepoint detection results from 1st period

Changepoint method	Changepoint on a day	Day on calendar
PELT	122	2020.03.07
	134	2020.03.19
BinSeg	122	2020.03.07
	134	2020.03.19
AMOC	122	2020.03.07

Note: composed by author.

After applying changepoint detection methods on Ethereum 2nd data set, no changepoints were detected as well. The graphical result can be seen in Appendix A from Figure A3.

Ripple

Lastly, the same changepoint detection procedure was applied on Ripple. Interestingly, but this time the result was different if compared to Bitcoin and Ethereum. PELT method found 2 changepoints, while BinSeg resulted in 3. Not surprisingly, AMOC found 1 changepoint. All the changepoints found for 1st dataset can be seen in Figure 4.

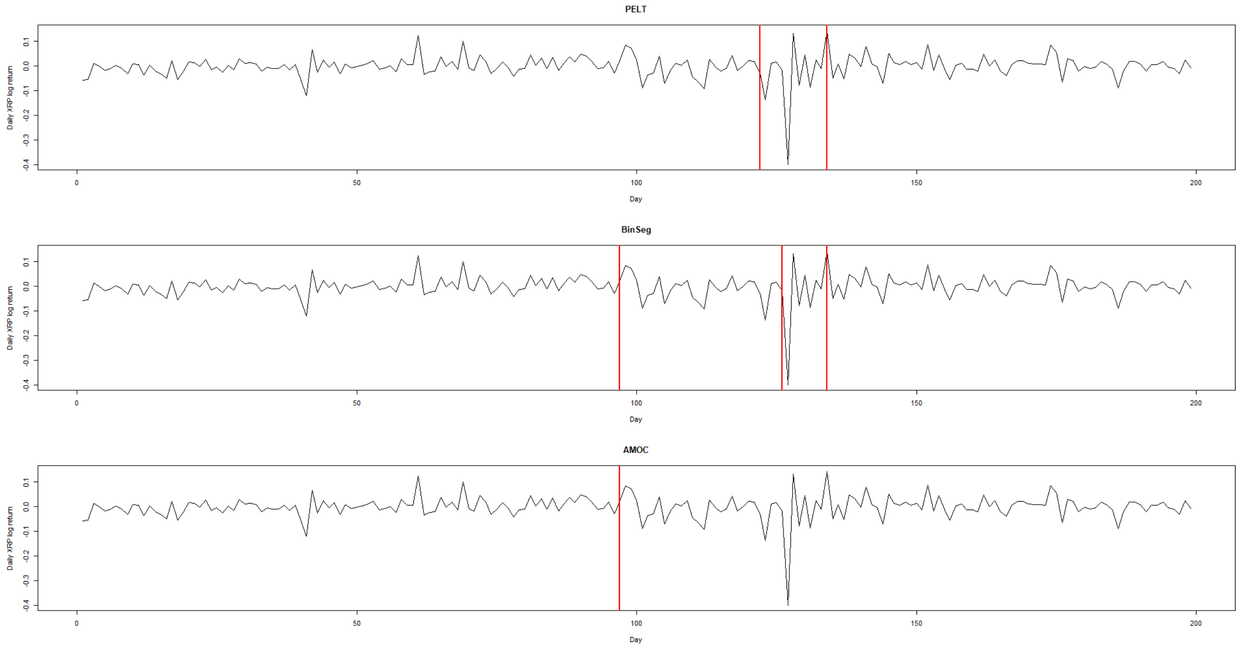

Figure 4. Ripple changepoint detection for 1st period using PELT, BinSeg, AMOC methods

After compiling the Table 7 for the changepoint analysis results from 1st period it can be seen that AMOC and BinSeg methodologies found a changepoint which was not found on Bitcoin or Ethereum 1st dataset. It is 2020.02.11 date. But it is worth to mention that the rest of the found changepoints were the same ones as found on Bitcoin or Ethereum.

Table 7. Ripple changepoint detection results from 1st period

Changepoint method	Changepoint on a day	Day on calendar
PELT	122	2020.03.07
	134	2020.03.19
BinSeg	97	2020.02.11
	126	2020.03.11
	134	2020.03.19
AMOC	97	2020.02.11

Note: composed by author.

Lastly, models were applied on 2nd period data, but once again no significant changepoints were found by any changepoint method. The graphical result can be found in Appendix A Figure A4.

Once the analysis of changepoint was done and changepoint location were identified, the analysis of change in variance of cryptocurrency log return prices was performed. First of all, from tables 5,6,7 it can be seen that the most common locations of changepoints of all the models were 122 and 134. Thus, the period from 122 to 134 was excluded from the variance analysis in order to check the variance difference before and after this excluded period. The results are presented in Table 8 below.

Table 8. Variance before and after changepoints location

Cryptocurrency	Variance until 2020.03.07	Variance after 2020.03.19	Variance on full data-set
Bitcoin(BTC)	0.0006876113	0.0008422556	0.001530179
Ethereum(ETH)	0.001394254	0.001590449	0.002611924
Ripple(XRP)	0.001211657	0.009059806	0.001612214

Note: composed by author.

It can be seen from Table 8 that the variances of all cryptocurrencies log returns in period 2019-11.07-2020.03.07 and from 2020.03.19-2020.11.06 were smaller if compared to variance of the full data-set in period 2019.11.07-2020.11.06.

For example, the variance of Bitcoin log return prices until 2020.03.07 was 0.0006876133 and after 2020.03.19 0.0008422556, while the variance on full date set was noticeably higher of 0.001530179. It means that the period which was excluded from this variance analysis (2020.03.07-2020.03.19) had a great impact on variance increase as if it is included in the analysis, variance increase, if excluded, variance decrease. It means that this excluded period can be significant in change point detection analysis as larger variance indicates that numbers in the set are far from the mean and far from each other.

COVID-19 influence

One of the main goals of this thesis was to investigate the COVID-19 influence on cryptocurrencies. That was the reason why the dataset of 2019-11.07 - 2020.11.06 was selected as it covers COVID-19 period. The first COVID-19 case was identified in December 2019 in Wuhan, China and was declared as a worldwide pandemic on 2020.03.11 by World Health Organization (WHO 2020).

By implementing the changepoint analysis the objective was to find out if the worldwide pandemic of COVID-19 could have any influence on cryptocurrencies? Particularly Bitcoin, Ethereum and Ripple daily log returns prices.

After investigating the changepoint detection results it can be seen that the location dates of changepoints were as follows: 2020.02.11, 2020.03.07, 2020.03.11 and 2020.03.19. The most often dates were 2020.03.07 and 2020.03.19.

Changepoint dates indicates that in the beginning and in the middle of March the analysed cryptocurrencies logarithimcal returns had a significant change in variance that was detected by multiple methods. This is the reason why it can possibly be assumed that the announcement of COVID-19 pandemic had an impact on this change and occurrence of changepoints.

Summing up the methods of changepoint analysis and the results it can be concluded that all three methods: AMOC, PELT and BinSeg methods performed very similarly and detected the same changepoints most of the time. The first changepoint location was often different between the models, but the last changepoint location matched between the methods. Though, it is worth to mention that AMOC method is for single changepoint detection and BinSeg, PELT can detect multiple changepoints.

The first changepoint location on Bitcoin data found by BinSeg and AMOC were the same on 2020.03.07 date, while the second changepoint detected on 2020.03.19 was indicated by PELT and BinSeg methods.

Analysis of changepoints on Ethereum data was the most precise because all models indicated the same first Changepoint which was on 2020.03.07. The second changepoint location was also found by PELT and BinSeg methods and was the same on 2020.03.19.

Ripple in this analysis resulted in slighly different results as it was the only cryptocurrency which had 3 changepoints indicated by BinSeg method. The first changepoint detected matched between BinSeg and AMOC methods and was on 2020.02.11, while the second changepoint matched between PELT and BinSeg and was on 2020.03.19.

Lastly, after changepoint detection analysis it was worth checking the variance of the data. After comparing the variance before the first changepoint location and after the last, which were identified the most times, it was found out that the variance before and after changepoint locations was smaller in comparison to full data-set. It means that the detected changepoints were likely identified correctly as the period of 2020.03.07 to 2020.03.19 increases the variance of all analysed cryptocurrencies significantly.

3.2 Granger causality test modeling

First part of the econometric analysis have shown that there were changepoints on all cryptocurrencies data on 2020 February and March months. Thus, in this subsection the further analysis of cryptocurrencies daily logarithmical returns drivers will be performed.

Regarding previous authors researches about cryptocurrency price drivers, economical, social, financial explanatory variables were chosen by authors. The main goal of this part is to choose and define the variables that will be used to model Granger causality tests in order to inspect if there is any relationship between cryptocurrencies daily log returns and chosen variables and vice-versa.

With the Granger causality test we are testing whether knowing past values of time series X together with past values of time series Y can be used together to make better predictions of time series Y as opposed to only using past values of time series Y.

3.2.1 Data and Descriptive Statistics

Cryptocurrencies variables

The main variables in this analysis are Bitcoin, Ethereum, Ripple daily log returns from period 2019-11-07 to 2019-11-06. Data is supposed to be normalized and normally distributed. From Table 4 in the previous subsection the log returns summary statistics of analysed cryptocurrencies can be seen. The initial data of cryptocurrency prices was obtained from Yahoo Finance (Yahoo.com 2020). Further, the relationship between cryptocurrencies daily log returns and selected variables will be analysed.

Chosen variables for Granger Causality test

The selection of the following variables in this Granger causality test modelling is based on previous authors researches. The selected variables come from cryptomarket, macroeconomic, financial and social factors groups and are described below.

It is very important to note that the initial data collected of S&P500 daily closing price, Gold daily closing price per ounce, FSI daily index, USD/EUR, USD/CHF exchange rates had missing values due to the fact that financial markets do not work on weekends and public holidays. To fill the missing values the linear interpolation function na.approx was used from zoo package in R. Linear interpolation calculates values that lie on a line between two known data points. As the obtained data is fairly linear data, this method fits it well.

Cryptomarket.

Wikipedia daily views of Bitcoin, Ethereum or Ripple is included in Granger causality test. This variable was selected due to significant findings of internet search volume by scientists as described in 2.2 section of this thesis. The daily amount of searches in Wikipedia for Bitcoin, Ethereum and Ripple keywords are obtained from Wikishark webpage (Wikishark.com 2020). In the Table 9 below the descriptive statistics can be found.

Table 9. Wikipedia views descriptive statistics

Wikiviews on Cryptocurrency	Min	Median	Mean	Max
Bitcoin(BTC)	3876	6157	6623	16533
Ethereum(ETH)	929	1835	2434	24682
Ripple(XRP)	366	647	836	6783

Note: composed by author.

From the Table 9 it is visible that Bitcoin was the most popular during the analysed period of 2019.11.07-2020.11.06 as its mean was the highest. Interestingly, Ethereum during the analysed period reached the maximum views of 24682 per day and it was the highest number among the cryptocurrencies in this research. The least times per day searched in Wikipedia was Ripple. Someday its search volume only reached 366 views.

Macroeconomic and financial factors. Macroeconomic and financial variables play a very important role in this research as 5 factors from this section are included in the analysis. Variables were chosen again regarding analysed authors studies. The first variable is S&P500 daily log returns. The initial data of daily price was taken from Yahoo Finance Yahoo.com (2020). In the table below the summary statistics can be seen.

Table 10. S&P500 daily log returns summary statistics

Variable	Min	Median	Mean	Max
S&P500 log returns	-0.0999449	0.0016175	0.0003627	0.089683

Note: composed by author.

Table 10 indicates that there were fluctuations over the period as the minimum and maximum values of the series differs significantly but the mean of the series is close to 0.

Next variable included is Financial Stress daily index. The index data is obtained from OFR webpage FSI (2020). The OFR Financial Stress Index (OFR FSI) is a daily market-based snapshot of stress in global financial markets. It is constructed from 33 financial market variables, such as yield spreads, valuation measures, and interest rates. The index is positive if the (weighted) average stress contribution of the indicators is positive. The index is zero if the average is zero, and negative if the average is negative.

Table 11. FSI index summary statistics

Variable	Min	Median	Mean	Max
FSI index	-4.2420	-1.5500	-0.4740	10.2660

Note: composed by author.

From Table 11 it can be noticeable that FSI index during the period was not stable because the minimum value at some point reached -4.2420 and the maximum was 10.2660. It can be said that as during the analysed period the average stress contribution of the indicators was negative because the mean of FSI index was negative and equal to -0.4740.

Another important variable included in this section is Gold daily log returns. The initial Gold daily price was obtained from Gold hub (GoldHub.com 2020). There the price of gold is by default calculated unit per troy ounce in US dollars unless otherwise stated. The summary statistics of gold daily log returns are displayed in Table 12 below.

Table 12. Gold daily log return summary statistics

Variable	Min	Median	Mean	Max
Gold log returns	-0.0474163	0.0011811	0.0007457	0.0577751

Note: composed by author.

It can be seen from Table 12 that during the period Gold daily logarithmic returns were close to 0 as both mean and median values of the series were close to 0. Similar situation applies to S&P500 series, which was introduced before as its median and mean were close to 0 too.

Lastly, exchange rates variables are introduced in the analysis. In this thesis USD/EUR as well as USD/CHF daily log returns were selected. USD/EUR exchange was chosen because USD and EUR currencies are the most traded currencies in the world as suggested in IG.com (2020). USD/CHF rate was selected because as mentioned in literature review section, Swiss Franc is believed to be one of the most stablest currencies in the world. In Table 13 the summary statistics of daily log returns of USD/EUR and USD/CHF exchange rates are presented. The initial data of currency exchange was obtained as daily closing rate from Yahoo Finance (Yahoo.com 2020).

Table 13. USD/EUR and USD/CHF daily log returns summary statistics

Variable	Min	Median	Mean	Max
USD/EUR log returns	-0.0144675	-0.0001601	-0.0001828	0.0281439
USD/CHF log returns	-0.0150472	0.0000713	-0.000259	0.022600

Note: composed by author.

From Table 13 it is possible to see that both USD/EUR and USD/CHF log returns variables mean was negative meaning that USD became weaker against EUR and CHF currencies.

Social factor The last variable of social factor is introduced in the model. The variable of daily deaths from COVID-19 in the world was selected for Granger causality test because the changepoint analysis in the last section resulted in COVID-19 possible impact on cryptocurrency volatility. Daily deaths were selected to check if there is any causal relationship between daily deaths number and daily log returns of cryptocurrencies. It is also notable, that Covid-19 daily cases variable has period from 2020.01.01 to 2020.11.06 unlike the previous variables that have period of 2019-11-07 to 2020.11.06. COVID-19 daily deaths variable period is shorter because there were no Covid-19 cases before 2020 year. In Table 14 the summary statistics of COVID-19 daily deaths is presented. The data was obtained from Our World In Data website (OurWorldInData.com 2020).

Table 14. Daily deaths from COVID-19 summary statistics

Variable	Min	Median	Mean	Max
Daily deaths from COVID-19	0	4677	4013	10491

Note: composed by author.

Looking at the Table 14 it can be seen that the maximum deaths from COVID-19 number was 10491 from period 2020.01.01 to 2020.11.06. The mean of the series was 4013 deaths per day.

3.2.2 Model and Methodology

In order to implement Granger causality test on the data, first of all, the data must be stationary. Thus, firstly tests for stationarity are done. Then, after the data is stationary, lag selection for VAR model is introduced and VAR model constructed. Lastly, Granger causality test is run.

Tests for stationarity

One of the most important criteria in order to run Granger causality test is stationarity. It means that the data used must be stationary. There are few tests that can be used for testing stationarity, such as KPSS, PP tests. If data appears not to be stationary, differentiation of data might help. In other words, the non-stationary data can be differenced and then tested for stationarity. KPSS and Phillips-Perron tests are selected for stationarity testing. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for the null hypothesis that x is level or trend stationary. The Phillips-Perron test for the null hypothesis that x has a unit root. If series have unit root, it is believed that series are non-stationary as unit roots are one cause for non-stationarity. In the Table 15 below the tests of KPSS and PP are described. The computational results from R are located in Appendix B.

Table 15. Variables test for stationarity

Variable	KPSS Test p-value at 5% significance level	Result	PP test p-value at 5% significance level	Result
BTC daily log returns	0.1	stationary	0.01	stationary
ETH daily log returns	0.1	stationary	0.01	stationary
XRP daily log returns	0.1	stationary	0.01	stationary
Gold daily log returns	0.1	stationary	0.01	stationary
S&P500 daily log returns	0.1	stationary	0.01	stationary
FSI daily index	0.01	non-stationary	0.905	non-stationary
USD/EUR daily log returns	0.1	stationary	0.01	stationary
USD/CHF daily log returns	0.1	stationary	0.01	stationary
BTC Wikipedia views	0.1	stationary	0.01	stationary
ETH Wikipedia views	0.07684	stationary	0.01	stationary
XRP Wikipedia views	0.07706	stationary	0.01	stationary
COVID-19 daily deaths	0.01	non-stationary	0.01	stationary

Note: composed by author.

From the tests for stationarity as presented in Table 15 it can be seen that most of the variables were found to be stationary at 5% significance level by both KPSS and PP tests. The non-stationary variables found by both test were FSI daily index. COVID-19 daily deaths variable was found non-stationary by KPSS test, but stationary by PP test. In this case it was decided to call this series non-stationary and try to make it stationary by implementing differencing method because as mentioned before one of the possibilities of making non-stationary series stationary is by differencing them.

The differencing equation is written below:

$$\Delta y_t = y_t - y_{t-1}, \tag{8}$$

here:

Δy_t = differenced series at time t,

y_t = observation of the original series,

y_{t-1} = previous observation of the original series.

After differencing non-stationary variables of FSI index and COVID-19 daily deaths, the tests for stationarity on newly differenced series were implemented. The results can be seen in Table 16.

Table 16. FSI index and COVID-19 daily deaths test for stationarity after differencing

Variable	KPSS Test p-value at 5% significance level	Result	PP test p-value at 5% significance level	Result
FSI daily index	0.09192	stationary	0.01	stationary
COVID-19 daily deaths	0.1	stationary	0.01	stationary

Note: composed by author.

As it can be seen from Table 16, after differencing the non-stationary series and then running the tests for stationarity, the series are now stationary at 5% significance level by both KPSS and PP tests. The computational of calculation in R can be found in Appendix B.

Lag selection for VAR

Afer variables were tested for stationarity and now are stationary, an important preliminary step in empirical studies is to select the order of the autoregression based on the same data used subsequently to construct the impulse response estimates. The most common strategy in empirical studies is to select the lag-order by some pre-specified criterion and to condition on this estimate in constructing the impulse response estimates (Ivanov et al. 2005).

The importance of lag length determination is described by Ozcicek et al. (1999) who claims that estimates of a VAR whose lag length differs from the true lag length are inconsistent as are the impulse response functions and variance decompositions derived from the estimated VAR.

For lag selection to model VAR, VARselect function from VARS package in R was used. As lag selection is modelled for each cryptocurrency and variable separately, results are split in 3 parts. The first part consists of Bitcoin lag selection, second of Ethereum lag selection and lastly, the third of Ripple lag selection. The results of selection criteria for VAR modelling is provided in Appendix B. Results of Bitcoin with selected variables are listed in B1 Table. Results of Ethereum can be found in B2 Table and finally the results of Ripple can be found in B3 Table in Appendix B. From the composed lag selection criteria results for VAR, the selected lag number for future analysis is based on the most often number of lags suggested by AIC, HQ, SC, FPE criteria.

VAR models

After identyfing and selecting the lags, the VAR models can be described. The particular structure of VAR(p) suggested by Chen et al. (2020) is as follows:

$$X_t = \alpha + \sum_{j=1}^{p} \beta_j X_{t-j} + \varepsilon_t, \tag{9}$$

here:

α is a vector of constants,

β_j is a quadratic n x n dimentional parameters matrix,

ε_t is a vector of independent white noise residuals,

p is the order of the process.

Firstly, the Bitcoin VAR models are introduced. For BTC daily log returns and S&P500 daily log returns, and BTC daily log returns and FSI index order 10 vector autoregression model VAR(10) is appropriate. BTC daily log returns and gold daily log returns order 1 vector autoregression model VAR(1) is appropriate, for BTC daily log returns and USD/EUR, USD/CHF daily log returns VAR(8) model is selected. Finally, for BTC daily log returns and BTC daily wikiviews VAR(5) and for BTC daily log returns and COVID-19 daily deaths VAR(9) models are selected.

Ethereum VAR models are as follow. For ETH daily log returns pair with S&P500, FSI index, USD/EUR, USD/CHF daily log returns and COVID-19 daily deaths, VAR(10) model is selected. For ETH daily log returns and Gold daily log returns VAR(1) is chosen. Finally, for ETH daily log returns and daily ETH wikiviews VAR(5) is selected.

Finally, VAR models for Ripple are described. For XRP daily log returns and S&P500 daily log returns, FSI index, XRP daily wikiviews, the VAR(10) model is selected. For XRP daily log returns and gold daily log returns, VAR(1) is selected, for XRP daily log returns and USD/EUR daily log returns the VAR(4) model is chosen. Finally, for XRP daily log returns and USD/CHF daily log returns VAR(8) is built and for XRP daily log returns and COVID-19 daily deaths VAR(9) is chosen.

3.2.3 Results

In this part of the paper, the analysis of Granger causality tests was chosen as the main interest to check the usefulness of one time series for forecasting the other one. Thus VAR results are not being described.

With Granger causality test the relationships of cryptocurrencies Bitcoin, Ethereum and Ripple daily log returns were tested in pairs with S&P500 daily log returns, FSI index, Gold daily log returns, USD/EUR, USD/CHF daily log returns, BTC,ETH,XRP wikipedia daily views and COVID-19 daily deaths to check whether knowing past values of time series X together with past values of time series Y can be used to make better predictions of time series Y as opposed to only using past values of time series Y.

Granger causality test results

In the following part of the paper the results for the Granger-causality tests for each of the pairs of time series of interest will be presented: Bitcoin, Ethereum, Ripple daily log returns against

S&P500 daily log returns, Gold daily log returns, FSI index, USD/EUR, USD/CHF daily log returns, Wikipedia views and daily COVID-19 deaths number.

Cryptocurrencies daily log returns and S&P500 daily log returns

Modelling against S&P 500 variable can be found nearly in any financial related research. From Table 17 it can be seen that after testing Bitcoin, Ethereum, Ripple daily log returns against S&P500 daily log returns the Granger-causality relationship is found. It can be concluded that the series of Bitcoin, Ethereum, Ripple daily log returns Granger causes S&P500 daily log returns as we rejected the null hypothesis of no Granger cause relationship.

The identical results occurs when modelling S&P500 daily log returns pair with Bitcoin, Ethereum, Ripple daily log returns. It means that S&P500 daily log returns Granger causes the selected cryptocurrencies daily log returns as we reject the null hypothesis of no Granger cause relationship. This thesis findings of relationship between cryptocurrencies and S&P500 were also found by Kjærland et al. (2018), Sovbetov (2018), and Georgoula et al. (2015).

Table 17. Cryptocurrencies and S&P500 daily log returns Granger causality tests

H0: Bitcoin daily log returns do not Granger cause S&P500 daily log returns		H0: Ethereum daily log returns do not Granger cause S&P500 daily log returns		H0: Ripple daily log returns do not Granger cause S&P500 daily log returns	
P-value	Result	P-value	Result	P-value	Result
<0.01	reject	<0.01	reject	<0.01	reject
H0: S&P500 daily log returns do not Granger cause Bitcoin daily log returns		H0: S&P500 daily log returns do not Granger cause Ethereum daily log returns		H0: S&P500 daily log returns do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
<0.01	reject	<0.01	reject	<0.01	reject

Note: composed by author.

The daily log returns series of Bitcoin, Ethereum, Ripple are plotted against S&P500 daily log returns series and can be seen in Figure 5. Interestingly, the similar log returns movement can be seen in all series especially around 100-130 day.

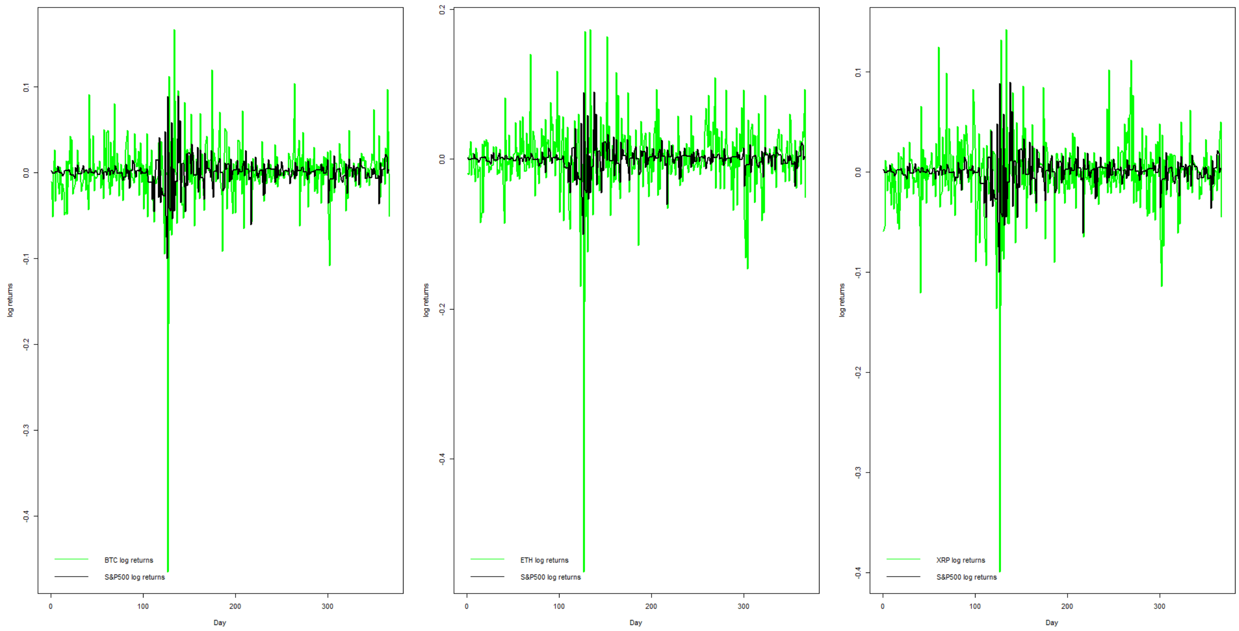

Figure 5. Cryptocurrencies daily log returns against S&P500 daily log returns

Cryptocurrencies daily log returns and GOLD daily log returns

The following relationship test between Granger causality and selected variable was performed on cryptocurrencies paired with Gold daily log returns. As it can be seen from Table 18, we accept all null hypothesis that neither of cryptocurrency in this analysis Granger cause Gold log returns.

The opposite results occurs when modelling if Gold daily do not Granger cause Bitcoin, Ethereum, Ripple daily log returns and as it can be seen from tests results, the null hypothesis are rejected and it can be concluded that Gold daily log returns Granger cause selected cryptocurrencies daily log returns. Regarding other authors findings, Poyser (2017) in his research found out that Bitcoin price is negatively associated with the gold price. Thus the relationship is found to be existent.

Table 18. Cryptocurrencies and Gold daily log returns Granger causality tests

H0: Bitcoin daily log returns do not Granger cause gold log returns		H0: Ethereum daily log returns do not Granger cause gold log returns		H0: Ripple daily log returns do not Granger cause gold log returns	
P-value	Result	P-value	Result	P-value	Result
0.7355	accept	0.4348	accept	0.3237	accept
H0: Gold daily log returns do not Granger cause Bitcoin daily log returns		H0: Gold daily log returns do not Granger cause Ethereum daily log returns		H0: Gold daily log returns do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
<0.01	reject	<0.01	reject	<0.01	reject

Note: composed by author.

From Figure 6, where the daily log returns of cryptocurrencies are plotted against daily Gold log returns it can be seen that similarly to the previous analysis of cryptocurrencies and S&P500, the similar movement pattern can be identified especially around 100-130 days.

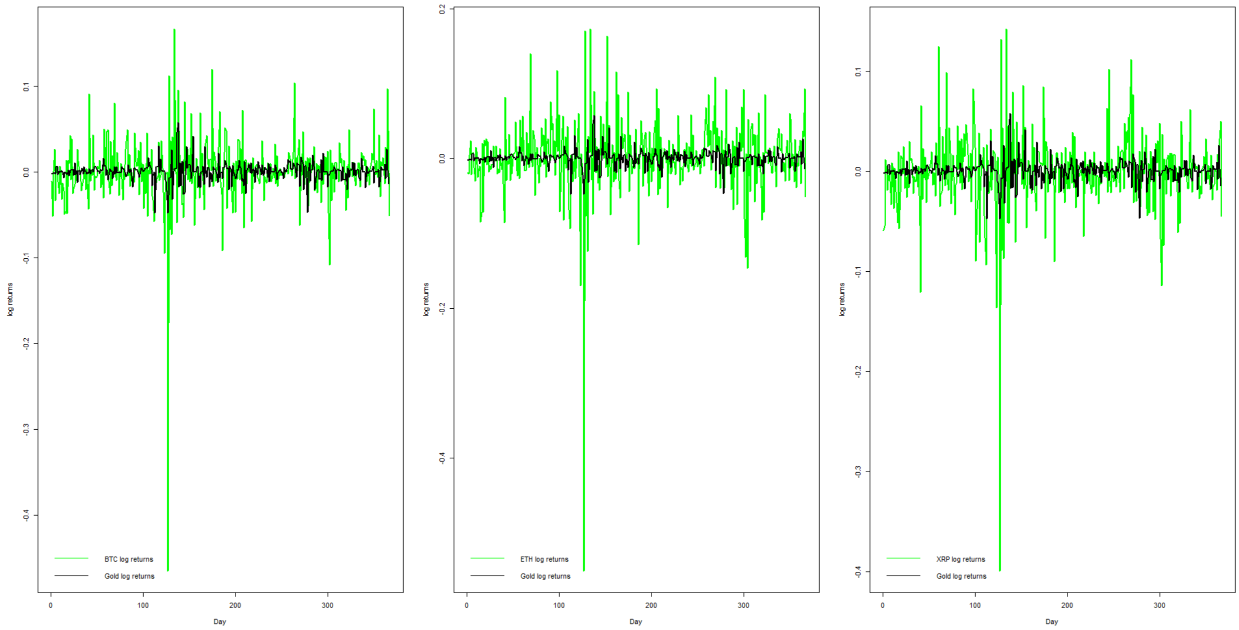

Figure 6. Cryptocurrencies daily log returns against Gold daily log returns

Cryptocurrencies daily log returns and FSI daily index

The FSI daily index series were the ones that needed to be differenced in order to be stationary because the initial data was not stationary. The Granger causality test between cryptocurrencies daily log returns and FSI daily differenced index resulted in null hypothesis rejection. Meaning that there is a vice-versa Granger causality relationship between cryptocurrencies daily log returns and FSI daily index. It is concluded in regards to Table 19 findings where in all tests the null hypothesis were rejected. The relationship between FSI index and cryptocurrencies was analysed by Bouri et al. (2018) and Kristoufek (2015). The first author found out that financial stress index strongly Granger-caused Bitcoin returns thus confirming this research results. The second author found out that FSI influences Bitcoin prices in one period of time.

Table 19. Cryptocurrencies daily log returns and FSI daily index Granger causality tests

H0: Bitcoin daily log returns do not Granger cause FSI daily index		H0: Ethereum daily log returns do not Granger cause FSI daily index		H0: Ripple daily log returns do not Granger cause FSI daily index	
P-value	Result	P-value	Result	P-value	Result
0.0153	reject	0.009844	reject	0.04507	reject
H0: FSI daily index do not Granger cause Bitcoin daily log returns		H0: FSI daily index do not Granger cause Ethereum daily log returns		H0: FSI daily index do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
<0.01	reject	<0.01	reject	<0.01	reject

Note: composed by author.

The differenced daily FSI index plotted with Bitcoin, Ethereum, Ripple daily log returns can be seen in Figure 7.

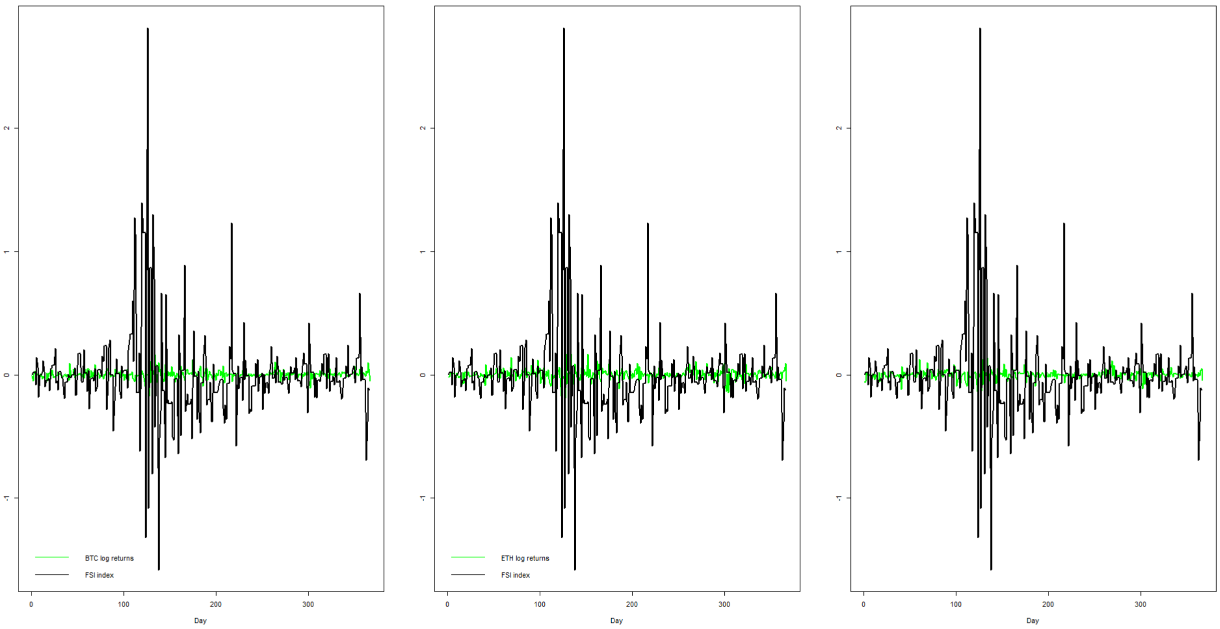

Figure 7. Cryptocurrencies daily log returns against FSI differenced daily index

Cryptocurrencies daily log returns and USD/EUR daily log returns

The following variable tested for Granger causality against BTC, ETH, XRP daily log returns was USD/EUR daily log returns. The test resulted in different results as it can be seen from Table 20. Firstly, null hypothesis were rejected and Granger causality relationship was found between Bitcoin and Ethereum daily log returns paired with USD/EUR daily log returns. Another null hypothesis of Ripple daily log returns do not Granger cause USD/EUR daily log returns was accepted.

While testing whether USD/EUR daily log returns Granger cause cryptocurencies daily log returns, all the null hypothesis of no Granger causality relationship were accepted and no causal relationships were found. Bitcoin price relation was found to be positively related to USD/EUR exchange by Poyser (2017). Negative relationship between Bitcoin price and USD/EUR exchange rate was identified by Georgoula et al. (2015) and Ciaian et al. (2016). Meaning that the results of this thesis identifying relationship between Bitcoin daily log returns, Ethereum daily log returns and USD/EUR daily log return might be useful for further analysis.

Table 20. Cryptocurrencies daily log returns and USD/EUR daily log returns Granger causality tests

H0: Bitcoin daily log returns do not Granger cause USD/EUR daily log returns		H0: Ethereum daily log returns do not Granger cause USD/EUR daily log returns		H0: Ripple daily log returns do not Granger cause USD/EUR daily log returns	
P-value	Result	P-value	Result	P-value	Result
<0.01	reject	<0.01	reject	0.1195	accept
H0: USD/EUR daily log returns do not Granger cause Bitcoin daily log returns		H0: USD/EUR daily log returns do not Granger cause Ethereum daily log returns		H0: USD/EUR daily log returns do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
0.2882	accept	0.236	accept	0.5712	accept

Note: composed by author.

Cryptocurencies daily log returns plotted together with USD/EUR daily log returns can be found in Figure 8.

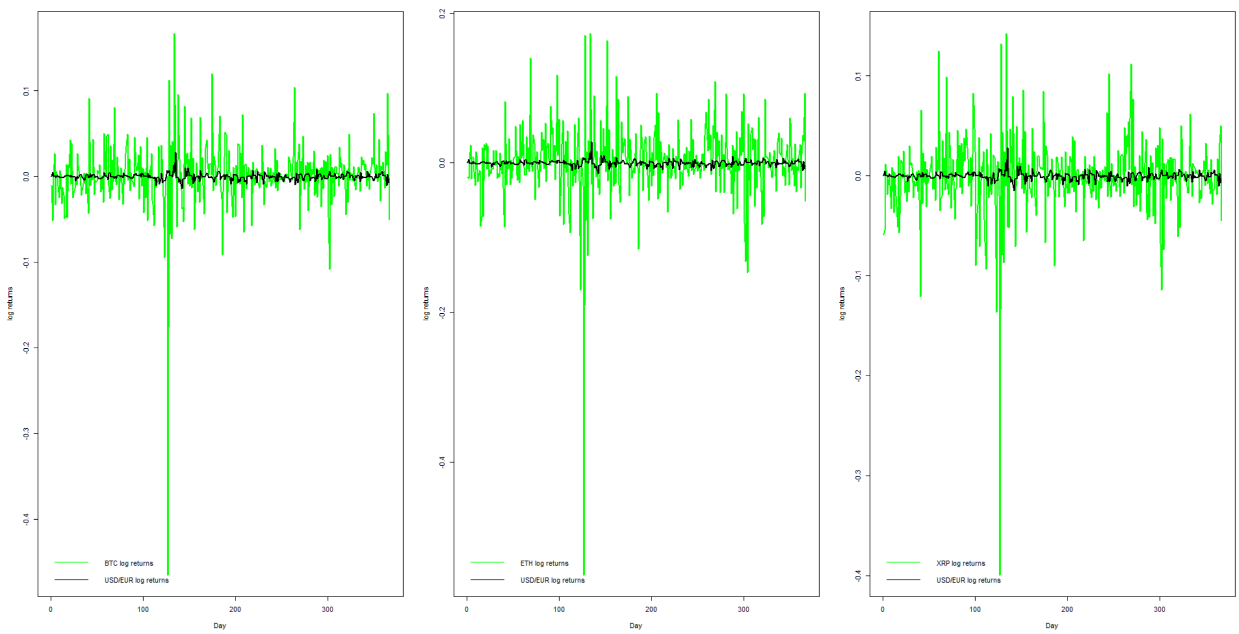

Figure 8. Cryptocurrencies daily log returns against USD/EUR daily log returns

Cryptocurrencies daily log returns and USD/CHF daily log returns

Another Granger causality test analysis was performed in pair with cryptocurrencies daily log returns and USD/CHF daily log returns. As it can be seen from Table 21 Bitcoin, Ethereum and Ripple Granger cause USD/CHF daily log returns as the null hypothesis of no Granger causality were rejected.

Talking about whether USD/CHF daily log returs Granger cause cryptocurrencies daily log returns, it was found out that there is no Granger causality relationship between USD/CHF daily log returns and Bitcoin and Ethereum. The only Granger causality was found in USD/CHF and Ripple daily log returns where it can be said that USD/CHF daily log returns Granger cause Ripple daily log returns as the null hypothesis was rejected.

Table 21. Cryptocurrencies daily log returns and USD/CHF daily log returns Granger causality tests

H0: Bitcoin daily log returns do not Granger cause USD/CHF daily log returns		H0: Ethereum daily log returns do not Granger cause USD/CHF daily log returns		H0: Ripple daily log returns do not Granger cause USD/CHF daily log returns	
P-value	Result	P-value	Result	P-value	Result
<0.01	reject	0.04121	reject	0.02507	reject
H0: USD/CHF daily log returns do not Granger cause Bitcoin daily log returns		H0: USD/CHF daily log returns do not Granger cause Ethereum daily log returns		H0: USD/CHF daily log returns do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
0.129	accept	0.1297	accept	0.01033	reject

Note: composed by author.

The plot of Bitcoin, Ethereum and Ripple daily log returns together with USD/CHF daily log returns can be seen in Figure 9.

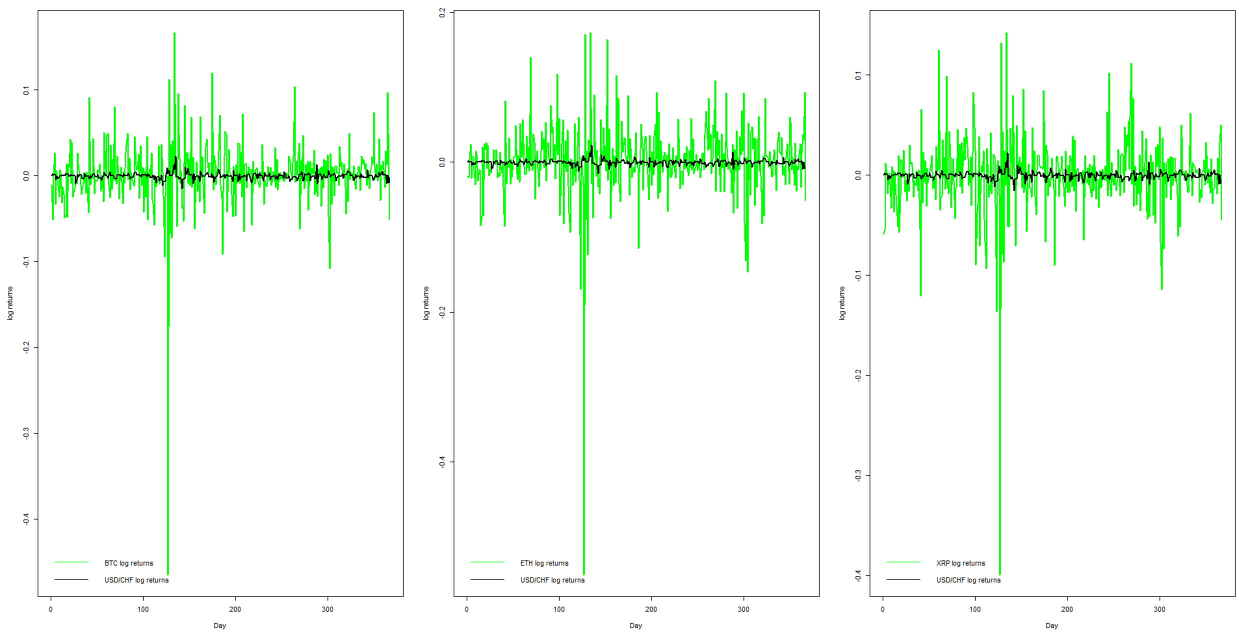

Figure 9. Cryptocurrencies daily log returns against USD/CHF daily log returns

Cryptocurrencies daily log returns and Wikipedia daily views

Looking at the Granger causality test between cryptocurrencies and its wikipedia daily views, it can be clearly seen that there is no Granger causality relationship as the null hypothesis are accepted. It can be seen from Table 22.

Regarding Wikipedia views of BTC, ETH, XRP and its pair with BTC, ETH, XRP daily log returns, the null hypothesis are accepted again and it can be concluded that none of the BTC, ETH, XRP wikipedia daily views Granger cause BTC, ETH, XRP daily log returns. Regarding wikipedia views causality tests and comparing to other authors findings it can be seen that this paper results are opposite as suggested by Georgoula et al. (2015) as author found that wikipedia views of Bitcoin was a significant and positive factor on Bitcoin price increase.

Table 22. Cryptocurrencies daily log returns and their Wikipedia daily views Granger causality tests

H0: Bitcoin daily log returns do not Granger cause BTC wikipedia daily views		H0: Ethereum daily log returns do not Granger cause ETH wikipedia daily views		H0: Ripple daily log returns do not Granger cause XRP wikipedia daily views	
P-value	Result	P-value	Result	P-value	Result
0.7125	accept	0.902	accept	0.1917	accept
H0: BTC wikipedia daily views do not Granger cause Bitcoin daily log returns		H0: ETH wikipedia daily views do not Granger cause Ethereum daily log returns		H0: XRP wikipedia daily views do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
0.4551	accept	0.7132	accept	0.8599	accept

Note: composed by author.

The graphs of daily cryptocurrencies log returns and daily wikipedia views of Bitcoin, Ethereum, Ripple can be seen in Figure 10. Interesting to notice, that all of the three analysed cryptocurrencies daily views had an significant increase in views at around 50-75 days.

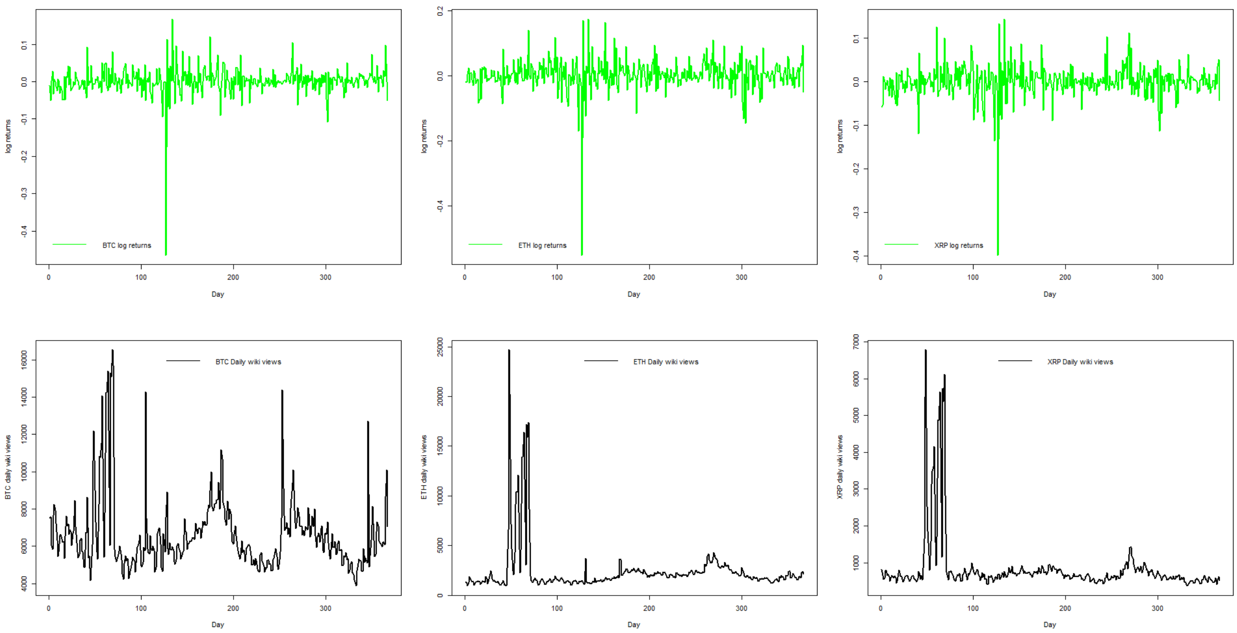

Figure 10. Cryptocurrencies daily log returns and their Wikipedia views

Cryptocurrencies daily log returns and COVID-19 daily deaths

Lastly, the Bitcoin, Ethereum and Ripple pairs with COVID-19 daily deaths are introduced. From Table 23 it can be seen that Bitcoin daily log returns, Ehtereum daily log returns and Ripple daily log returns do not Granger cause COVID-19 daily deaths.

The same results occurred when tested whether COVID-19 daily deaths do not Granger cause Bitcoin, Ethereum and Ripple daily log returns. The null hypothesis of no Granger cause relationship was accepted. Opposite results regarding the relationship between daily COVID-19 deaths number and Bitcoin daily price was found by Goodell et al. (2020). Author identified that for the period from 2020.04.05 to 2020.04.29 the death levels from COVID-19 caused a rise in Bitcoin prices. Moreover, Chen et al. (2020) indicated that Google search queries on coronavirus-related words influence Bitcoin returns negatively.

Table 23. Cryptocurrencies daily log returns and differenced daily COVID-19 deaths Granger causality tests

H0: Bitcoin daily log returns do not Granger cause COVID-19 daily deaths		H0: Ethereum daily log returns do not Granger cause COVID-19 daily deaths		H0: Ripple daily log returns do not Granger cause COVID-19 daily deaths	
P-value	Result	P-value	Result	P-value	Result
0.89	accept	0.6753	accept	0.9925	accept
H0: COVID-19 daily deaths do not Granger cause Bitcoin daily log returns		H0: COVID-19 daily deaths do not Granger cause Ethereum daily log returns		H0: COVID-19 daily deaths do not Granger cause Ripple daily log returns	
P-value	Result	P-value	Result	P-value	Result
0.9344	accept	0.8334	accept	0.9698	accept

Note: composed by author.

From Figure 11 it can be seen the differenced COVID-19 daily deaths and cryptocurrencies daily log returns. COVID-19 daily deaths series were differenced as the initial data was not stationary thus not appropriate for Granger causality test analysis.

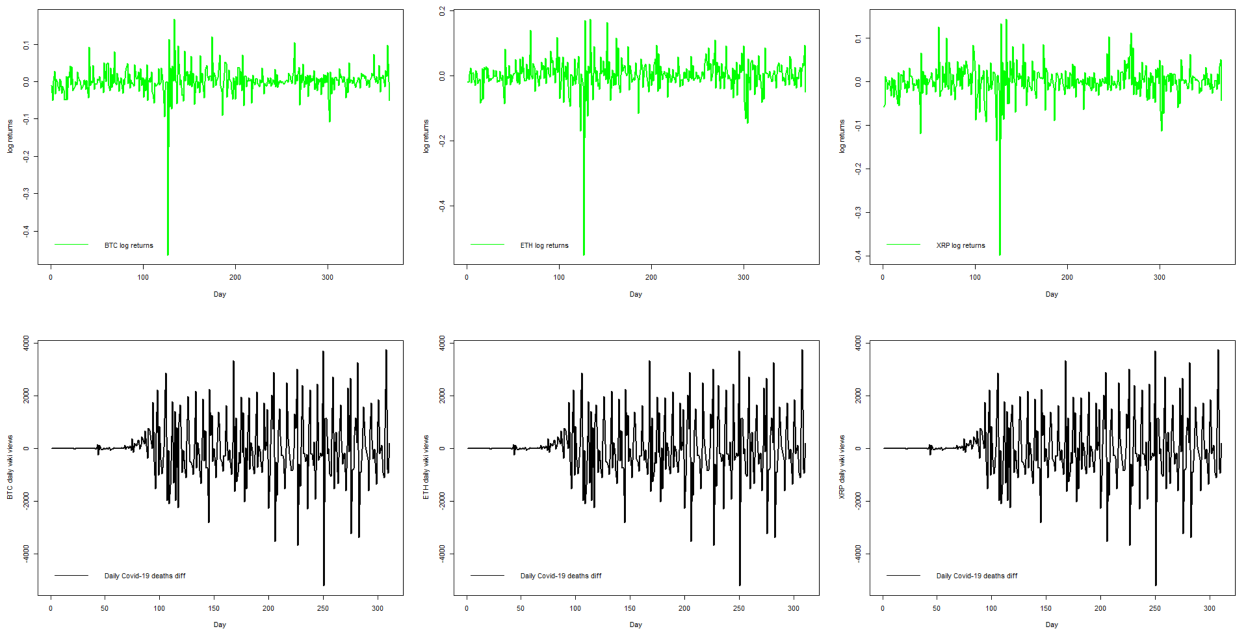

Figure 11. Cryptocurrencies daily log returns and differenced COVID-19 daily deaths

4 Conclusion

The thesis aim was using daily data from Bitcoin, Ethereum, Ripple cryptocurrencies and selected variables, including COVID-19 to explain and model the dynamics of selected cryptocurrencies. In the thesis two parts of the analysis were completed. The first one consisted of Changepoint analysis in variance of daily Bitcoin, Ethereum and Ripple logartihmical returns and here the PELT, BinSeg, and AMOC techniques for changepoint detection were implemented. The results from each of the techniques were very similar. For instance, the AMOC method which detect at most 1 changepoint, found the same changepoint for Bitcoin and Ethereum - 2020.03.07. While BinSeg found the same 2 changepoints for Bitcoin and Ethereum: 2020.03.07 and 2020.03.19. The PELT method resulted in the same changepoints for Ethereum and Ripple: 2020.03.07 and 2020.03.19 days. The dates of the founded changepoints varied from 2020.03.07 to 2020.03.19, but it is worth to mention, that for Ripple, the 2020.02.11 date was found by AMOC and BinSeg methods. Summarizing the changepoint detection results there is a possibility that the changepoint points in March occurred due to the COVID-19 pandemic which was announced as a worldwide on 2020.03.11 by World Health Organization as the methods for changepoint detection only found statistically significant results in the beginning-mid March.

After changepoint detection it was decided to exclude the period of 2020.03.07-2020.03-19 and check the change in variance before and after this period. The results have shown that variance before and after the excluded dates was noticeably smaller if compared to the variance on full dataset. It means that the variance during that excluded period could be significant in changepoint detection analysis.

Another part of the analysis consisted of VAR implementation and Granger causality tests. Regarding the literature review part, the variables from financial, economical, social factors were selected for pairing with Bitcoin, Ethereum, Ripple daily log returns. Then, time Series data from 2019.11.07 to 2020.11.06 of all variables were introduced and VAR models build. Next, the Granger causality test implementation was done and it was founded out that there was a bidirectional relationship between cryptocurrency daily logarithmic returns and S&P500 logarithmic daily returns and FSI daily index. The one-sided relationship of Granger causality has been found between the logarithmic returns of gold and cryptocurrencies (Bitcoin, Ethereum, Ripple daily log returns). Also, the daily logarithmic returns of Bitcoin and Ethereum had a Granger causality relationship with USD/EUR daily logarithmic returns. All of the cryptocurrencies were found to Granger cause the daily logarithmic returns of the USD/CHF, and the latter had a causal relationship with the daily logarithmic returns of the Ripple. Also, there were no links between cryptocurrency daily logarithmic returns and Wikipedia daily views on Bitcoin, Ethereum, Ripple. Also, no significant results were found when Granger causality test was paired between BTC, ETH, XRP daily log returns and COVID-19 daily deaths worldwide.

It is also important to note, that the dynamics of cryptocurrency change everyday, thus using this thesis selected models approach, but implementing different daily data, for example, results can differ. Nonetheless, every study regarding cryptocurrency and its dynamics, movement is helpful to understand more about the factors, causes of the unstable prices and the results can be used for the future studies. For the further studies, it would be wise to include the longer period of the COVID-19 data, to look deeper into the VAR models results and by using, for example, GARCH method to compare the results with models in this thesis and choose another variables for pairing against cryptocurrencies and their prices.

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Appendix A

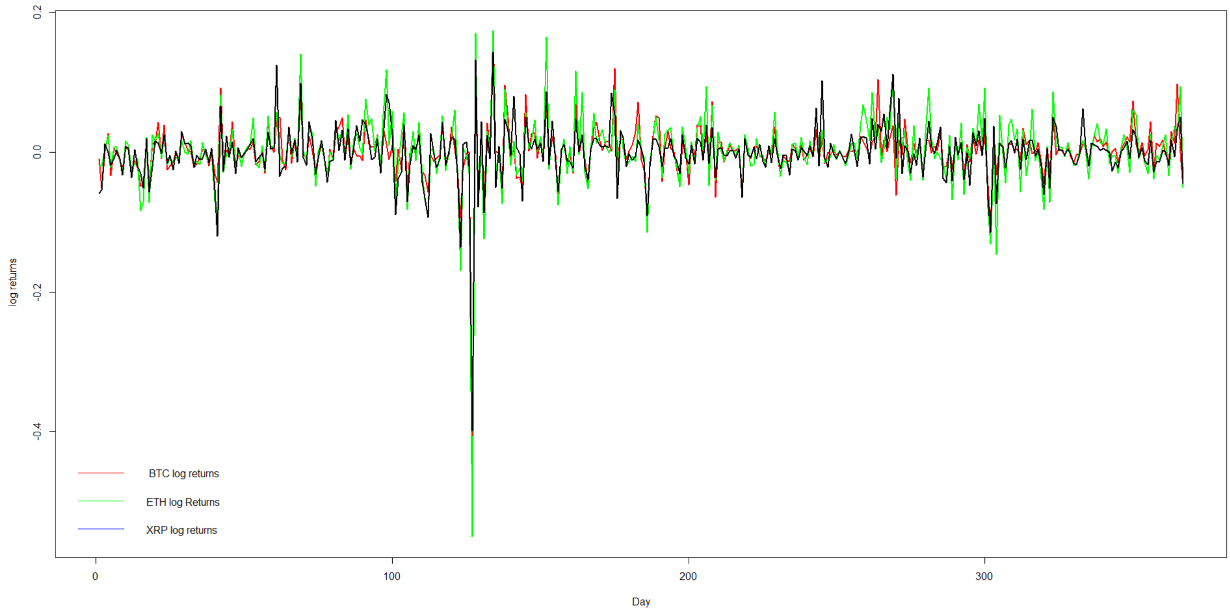

Figure A1. BTC,ETH,XRP log returns from 2019-11-07 to 2011-10-06

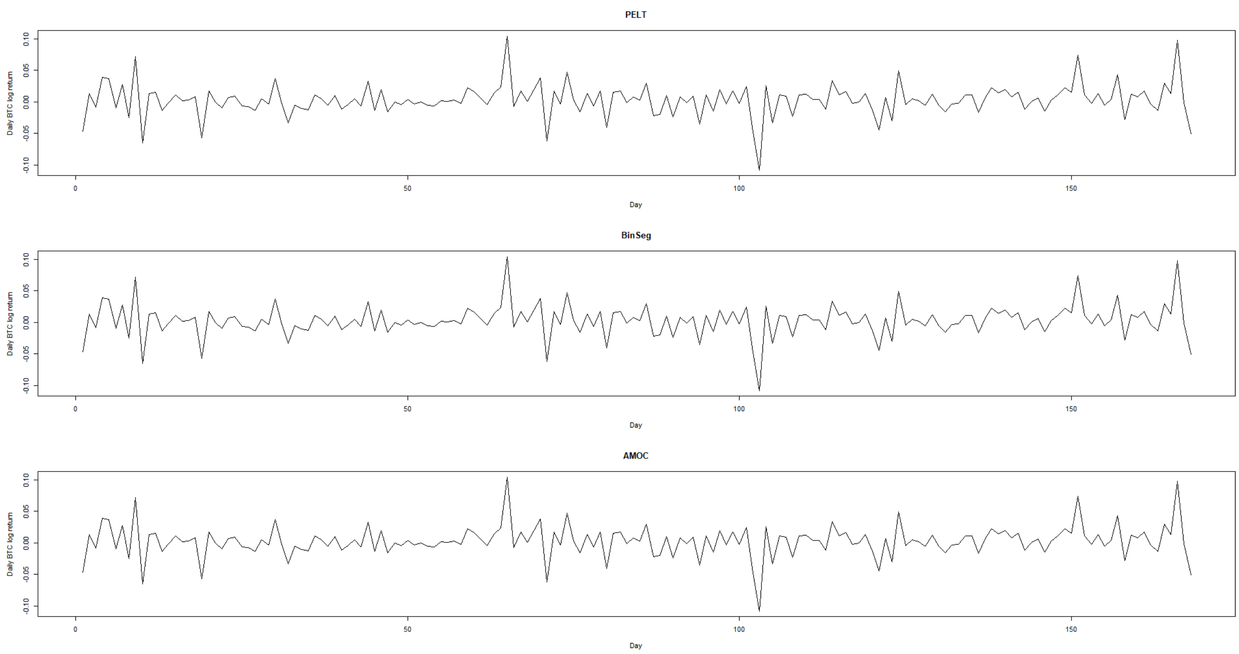

Figure A2. Bitcoin changepoint detection for 2nd period using PELT, BinSeg, AMOC methods

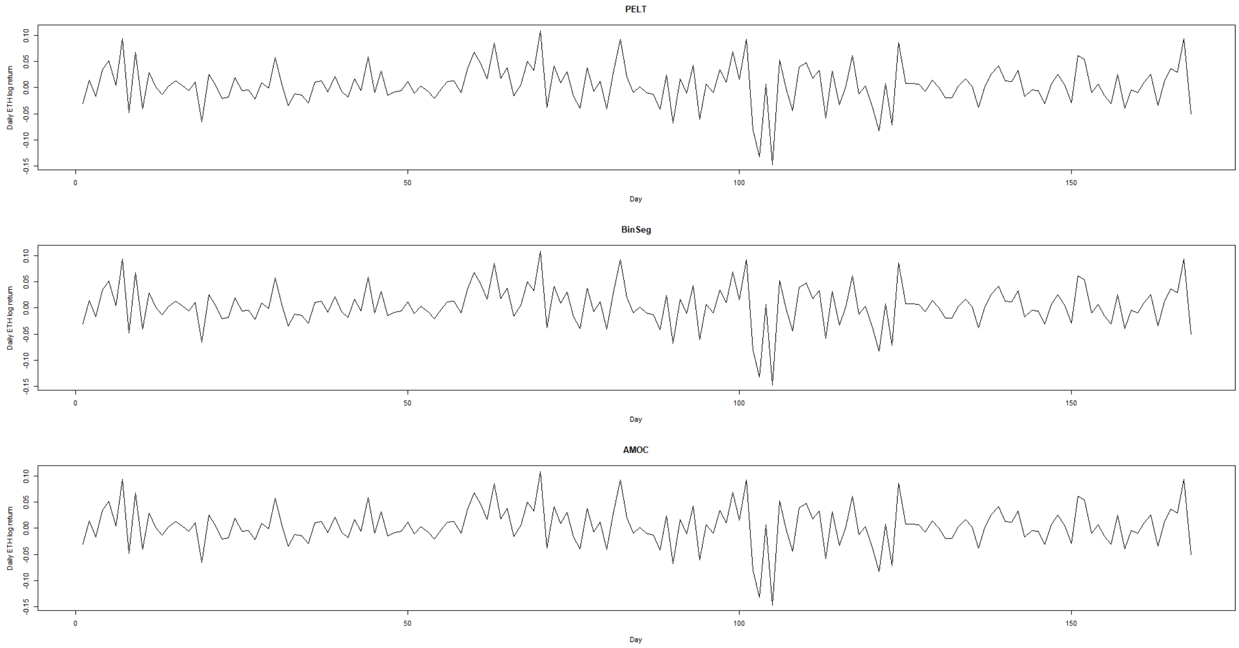

Figure A3. Ethereum changepoint detection for 2nd period using PELT, BinSeg, AMOC methods

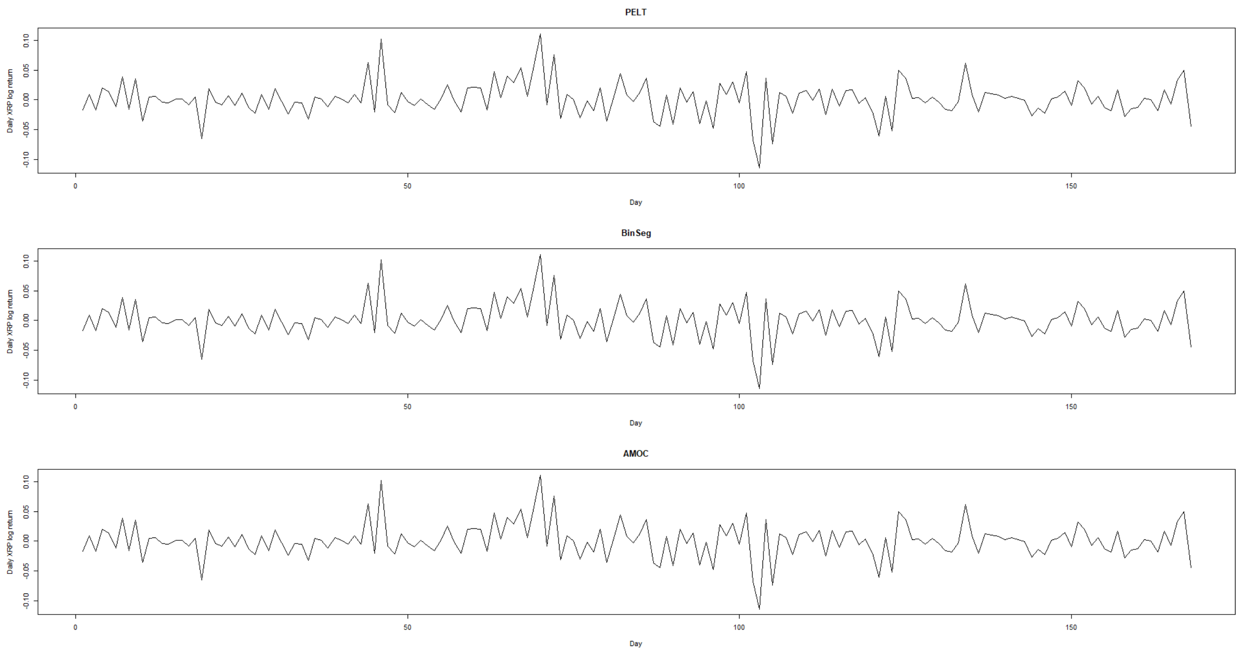

Figure A4. Ripple changepoint detection for 2nd period using PELT, BinSeg, AMOC methods

Appendix B

KPSS and PP tests results for variables

BTC log returns

KPSS Test for Trend Stationarity

data: BTC_rtrns_2020$log_btc KPSS Trend = 0.040468, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: BTC_rtrns_2020$log_btc Dickey-Fuller = -22.005, Truncation lag parameter = 5, p-value = 0.01

ETH log returns

KPSS Test for Trend Stationarity

data: ETH_rtrns_2020$log_eth KPSS Trend = 0.049448, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: ETH_Log_Returns$log_eth Dickey-Fuller = -21.837, Truncation lag parameter = 5, p-value = 0.01

XRP log returns

KPSS Test for Trend Stationarity

data: XRP_rtrns_2020$log_xrp KPSS Trend = 0.057306, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: XRP_Log_Returns$log_xrp Dickey-Fuller = -21.864, Truncation lag parameter = 5, p-value = 0.01

SP500 log returns

KPSS Test for Trend Stationarity

data: BTCSP$log_sp KPSS Trend = 0.061724, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: BTCSP$log_sp Dickey-Fuller = -22.175, Truncation lag parameter = 5, p-value = 0.01

FSI index

KPSS Test for Trend Stationarity

data: FSI$fsi KPSS Trend = 0.9322, Truncation lag parameter = 5, p-value = 0.01

Phillips-Perron Unit Root Test

data: FSI$fsi Dickey-Fuller = -1.2036, Truncation lag parameter = 5, p-value = 0.905

Gold daily log returns

KPSS Test for Trend Stationarity

data: BTCGOLD$log_gold KPSS Trend = 0.024716, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: BTCGOLD$log_gold Dickey-Fuller = -17.987, Truncation lag parameter = 5, p-value = 0.01

USD/EUR daily log returns

KPSS Test for Trend Stationarity

data: BTCUSDEUR$log_usdeur KPSS Trend = 0.041588, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: BTCUSDEUR$log_usdeur Dickey-Fuller = -16.187, Truncation lag parameter = 5, p-value = 0.01

USD/CHF daily log returns

KPSS Test for Trend Stationarity

data: BTCUSDCHF$log_usdchf KPSS Trend = 0.078518, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: BTCUSDCHF$log_usdchf Dickey-Fuller = -28.195, Truncation lag parameter = 5, p-value = 0.01

BTC Wikipedia daily views

KPSS Test for Trend Stationarity

data: Wikiviews$btc_views KPSS Trend = 0.074279, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: Wikiviews$btc_views Dickey-Fuller = -8.0203, Truncation lag parameter = 5, p-value = 0.01

ETH Wikipedia daily views

KPSS Test for Trend Stationarity

data: Wikiviews$eth_views KPSS Trend = 0.13151, Truncation lag parameter = 5, p-value = 0.07684

Phillips-Perron Unit Root Test

data: Wikiviews$eth_views Dickey-Fuller = -6.5973, Truncation lag parameter = 5, p-value = 0.01

XRP Wikipedia Daily views

KPSS Test for Trend Stationarity

data: Wikiviews$xrp_views KPSS Trend = 0.13139, Truncation lag parameter = 5, p-value = 0.07706

Phillips-Perron Unit Root Test

data: Wikiviews$xrp_views Dickey-Fuller = -6.3505, Truncation lag parameter = 5, p-value = 0.01

COVID-19 daily deaths

KPSS Test for Level Stationarity

data: BTCCOVID$dailycovid KPSS Level = 4.9538, Truncation lag parameter = 5, p-value = 0.01

Phillips-Perron Unit Root Test

data: BTCCOVID$dailycovid Dickey-Fuller = -0.92943, Truncation lag parameter = 5, p-value = 0.9489

KPSS and PP tests results for differenced COVID-19 and FSI index series

COVID-19 daily deaths diff

KPSS Test for Trend Stationarity

data: diff_covid KPSS Trend = 0.035546, Truncation lag parameter = 5, p-value = 0.1

Phillips-Perron Unit Root Test

data: diff_covid Dickey-Fuller = -28.837, Truncation lag parameter = 5, p-value = 0.01

FSI index diff

Phillips-Perron Unit Root Test

data: diff_fsi Dickey-Fuller = -17.002, Truncation lag parameter = 5, p-value = 0.01

KPSS Test for Trend Stationarity

data: diff_fsi KPSS Trend = 0.12336, Truncation lag parameter = 5, p-value = 0.09192

Table B1. Bitcoin and selected variables lag selection for VAR

Variables in model	AIC(n) criteria lags	HQ(n) criteria lags	SC(n) criteria lags	FPE(n) criteria lags
BTC log returns and S&P500 daily log returns	10	10	1	10
BTC log returns and FSI index	10	3	1	10
BTC log returns and Gold daily log returns	1	1	1	1
BTC log returns and USD/EUR daily log returns	8	2	1	8
BTC log returns and USD/CHF daily log returns	8	2	1	8
BTC log returns and BTC daily wikiviews	5	1	1	5
BTC log returns and COVID-19 daily deaths	9	9	6	9

Note: composed by author.

Table B2. Ethereum and selected variables lag selection for VAR

Variables in model	AIC(n) criteria lags	HQ(n) criteria lags	SC(n) criteria lags	FPE(n) criteria lags
ETH log returns and S&P500 daily log returns	10	10	1	10
ETH log returns and FSI index	10	3	1	10
ETH log returns and Gold daily log returns	1	1	1	1
ETH log returns and USD/EUR daily log returns	10	2	1	10
ETH log returns and USD/CHF daily log returns	10	2	1	10
ETH log returns and ETH daily wikiviews	5	2	1	5
ETH log returns and COVID-19 daily deaths	10	9	6	10

Note: composed by author.

Table B3. Ripple and selected variables lag selection for VAR

Variables in model	AIC(n) criteria lags	HQ(n) criteria lags	SC(n) criteria lags	FPE(n) criteria lags
XRP log returns and S&P500 daily log returns	10	1	1	10
XRP log returns and FSI index	10	3	1	10
XRP log returns and Gold daily log returns	1	1	1	1
XRP log returns and USD/EUR daily log returns	4	2	1	4
XRP log returns and USD/CHF daily log returns	8	1	1	8
XRP log returns and XRP daily wikiviews	10	5	1	10
XRP log returns and COVID-19 daily deaths	9	6	6	9

Note: composed by author.