The Virtual Relationship Between Bitcoin & Altcoins

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Master Thesis

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Abstract

The aim of this paper is to find a detailed answer to whether there is a relationship between Bitcoin and Altcoin Cryptocurrencies or not. The three chosen Altcoins are Ethereum, XRP and Litecoin. The closing price data are taken from Yahoo Finance over the period from 1st July 2016 to 1st July 2021. All the coins are integrated of order one. Johansen Cointegration test, VAR and VECM models were developed in this paper and Impulse Response Function was employed to draw a conclusion. It is found that there is strong evidence for the short-run relationship between Bitcoin and Altcoins, apart from Ethereum. However, no Long-run relationship was found. It is recommended to investors to include cryptocurrency in their portfolio, especially Ethereum. Investors must diversify their portfolios and further study the macroeconomic factors to reduce risks and volatility in their portfolios.

Acknowledgments

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Notation and Acronyms

Symbol	Definition
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BTC	Bitcoin
BtcLogRtn	Bitcoin Log Return
Ct	Closing price on Day t
ETH	Ethereum
EthLogRtn	Ethereum Log Return
FPE	Final Prediction Error
HQIC	Hannan-Quinn Information Criterion
LL	Log Likelihood
LR	Likelihood Ratio
LTC	Litecoin
LtcLogRtn	Litecoin Log Return
Rt	Return on day t
SBIC	Same as BIC
T	Number of observations
tp	Total number of parameters in the model
XrpLogRtn	XRP Log Return
g	Number of variables

k	Number of lags
r	Number of cointegration vectors
tp	Total number of parameters in the model
βk	Coefficient matrices for each lag
Γ	Contains short run dynamics
λ_i	ith ordered eigenvalue prediction
μt	White noise disturbance
Π	Long run coefficient matrix

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1.0 Introduction

In his book, The Richest Man in Babylon, George Samuel Clason (1955) dispenses seven basic principles of effective money management. One of which is to save at least 10% of one's earnings to use as investment for the future (Clason, 1955). Investment is important for any human being on earth that desires the accumulation of riches and financial freedom. Both short-term and long-term financial security can be achieved with the right financial analysis, planning, and execution. In modern society, there are multiple methods for individuals to invest to increase their wealth including Stocks, Bonds, ETFs and Cryptocurrencies (Crypto).

Cryptocurrency has been a major revolution to the monetary system's field. According to the studies by Urquhart and Platanakis (2020), cryptocurrencies are receiving ever more attention from regulators, governments, and investors. Therefore, it is important for an in-depth understanding of the financial and economic dynamics of these assets.

The term Cryptocurrency is a portmanteau of cryptography and currency (Hogan, 2020). This is because cryptocurrency uses cryptographic techniques for people to secure transactions. Crypto is digital cash that enables people to transmit value in a digital setting. Whether investors should include crypto in their portfolios or not, depends on their familiarity with crypto and the level of risk they are willing to take. However, any mature and experienced investor is fully aware of the importance of diversification when it comes to investing. Therefore, Urquhart and Platakanis (2020) argue that not investing in crypto may cause more harm than good to a portfolio.

Bitcoin is the most popular and well-established form of cryptocurrency designed by Satoshi Nakamoto in his 2008 whitepaper (Hogan, 2020). Bitcoin has proved not only to be a great investment for individuals and daily traders but a solution to the financial difficulty of some of the nations around the world. An article by Irrera (2021) suggests that Iran is using cryptocurrency to overcome the sanctions imposed by the United States. Iran has adapted to crypto mining so quickly that the nation is responsible for 4.5% of all bitcoin mining around the world. If Iran continues to keep up the hard work, it can revenue an estimated amount of $1 Billion a year. The prospect of low-priced power in Iran has caught the attention of other bitcoin miners such as China. Iran allows cryptocurrencies to be mined in Iran which allows it to pay for imported goods instead, which is indeed a method to overcome the sanctions. The global competition within this industry should impact the cryptocurrencies price fluctuation (Irrera, 2021).

A research paper developed by the Financial Conduct Authority (FCA) (2019) explains that the word "Bitcoin" has been a more frequently searched word on Google than "Election results" during the 2018 campaign. This is alarming to any investor that had previously neglected the idea of investing in crypto, as the popularity of this digital currency continues to rise. FCA (2019) investigations show many people purchase Bitcoin as a method to "get rich quick", given the high volatility that Bitcoin shows. Other people have different reasons to purchase Bitcoin such as the fear of missing out, peer pressure and even their "instinct".

Sinclair (2020) reports that a recent survey conducted by Grayscale Investments has discovered that the interest in cryptocurrency by investors has raised even higher in October 2020. According to the same survey, 55% of the participants were indeed interested in Bitcoin. This is a further 19% increase from the previous year, 2019. Sinclair (2020) discusses this paper further by explaining that the survey provided a negative insight since 40% of investors in their mid-50s and 60s are familiar with Bitcoin and only 30% of them show genuine interest in investing in cryptocurrency. The lack of interest is caused by "high volatility" or "too risky" for the older age bracket. Figure_1 shows that for those who were interested in cryptocurrency investment, the biggest motivation behind this interest is the Covid-19 pandemic. A staggering 63% of 2020 investors have said that the global pandemic has impacted their insights into cryptocurrency positively. That is, they are either considering a cryptocurrency investment or already have (Sinclair, 2020).

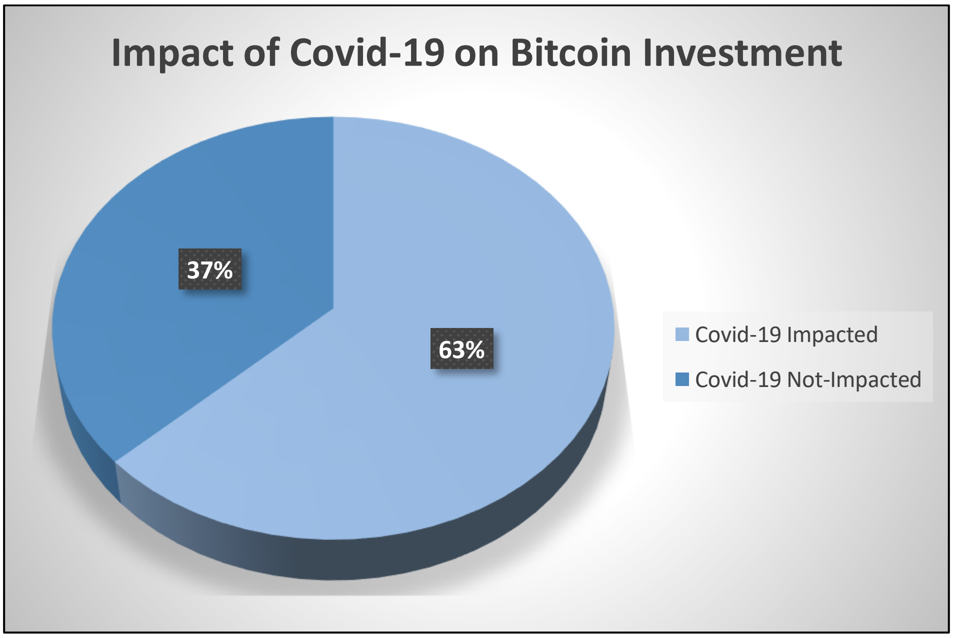

Figure 1: Impact of Coronavirus on Bitcoin Investment (Sinclair, 2020)

Cryptos offers lesser transaction costs, and their value is increasing more erratically than standard currencies (Sheridan, 2011). Crypto also tends to fluctuate far more often and at a greater rate than the standard currencies which can provide a great investment opportunity for investors. The most famous of the cryptos is Bitcoin, which has proven to be more stable and mature in comparison to other cryptocurrencies (Sheridan, 2011).

The relationship between Bitcoin and Altcoins such as Ethereum, XRP and Litecoin is also important. This is because investors and businesses can create data-driven strategies and make critical investment decisions based on their relationship to generate more returns (Hall, 2020). The relationship between these coins allows analysts and traders to find trends and patterns to be used in forecasting future changes and make alterations to their investment if needed. If there is a relationship between Bitcoin and Altcoins, then investors can be proactive with their investment strategy instead of being reactive. By applying precise and reliable analysis on the relationship of Bitcoin and Altcoins, businesses can set goals and plans. Virtual analysis of the trends can assist businesses in budgeting and making alterations to their investment strategies (Hall, 2020).

1.1 Aim

This paper aims to find a detailed answer to whether there is a relationship between Bitcoin and Altcoin Cryptocurrencies or not.

1.2 Objectives

This paper analyses both short-term and long-term relationships of coins and what this would mean to investors. The examination is based on Bitcoin and its relationship with three altcoins where investors have shown the highest interest. These coins include Ethereum, XRP and Litecoin. The analysis should help the investors to make enhanced investment decisions to see if they should further diversify their portfolio or not.

2.0 Literature Review

2.1 Cryptocurrency

Normally, currencies are an accepted form of money which includes coins and paper notes (Seetharaman et al., 2017). These currencies, such as European Euro (EUR) and Swiss Franc (CHF) are systems of money in terms of monetary units and are issued by the government and circulated in different nations. These currencies are called Fiat currencies as they are issued by a central authority (Seetharaman et al., 2017). On the other hand, cryptocurrencies are decentralized digital assets that use cryptography to transfer funds from one party to another without any influence of monetary authority.

The academic literature on cryptocurrency is continuously growing with Urquhart and Hudson (2019) focusing on Technical Trading in Cryptocurrency, Gargesa and Sathyanarayana (2019) examining cryptocurrencies using Vector Autoregressive (Var) models. Aysan et al., (2021), Ibrahim et al., (2020) and Leatham et al., (2019), all examine and discuss the interrelationship of Bitcoin and Altcoins. An Altcoin is a commonly used terminology for Alternative coins, which are coins other than Bitcoin (Figà-Talamanca, 2020).

Cryptocurrencies offer a range of advantages over fiat currencies. Digital currencies offer a phenomenon called “Decentralization”. This means the data is saved on millions of different computers simultaneously rather than a single computer (Yarovaya and Urquhart, 2020). This would disable the influence of any central authority and blockchain who can tamper with the agreement of all the participants. Another advantage is the transparency of all transactions. This means all the transactions can be tracked, allowing the parties to observe who has added blocks. There is also consensus which is for the community of members to have for anything to occur (Yarovaya and Urquhart, 2020).

In their 2020 paper, Yarovaya and Urquhart, further explain that Bitcoin and other cryptocurrencies remove the intermediaries. That is the removal of any dependency on middlemen such as banks to exchange money. Large amounts of money can be transferred across the globe within minutes, surpassing financial intermediaries who need at least 24 hours. And finally, there is only a limited supply of cryptocurrencies such as Bitcoin with 21 million maximum supplies (Antonopoulos, 2014). This makes Bitcoin a scarce asset that is unlikely to depreciate. This is an advantage over fiat currencies which are easily affected by inflation.

One method of obtaining a cryptocurrency such as Bitcoin is through mining (Antonopoulos, 2014). The mining process includes supercomputers that require extensive energy consumption. These supercomputers are competing with each other to solve complicated mathematical problems. Blockchain is the technology behind most cryptocurrencies such as Bitcoin. A recent study by Deloitte (2021), has discovered that 53% of their clients who participated in a survey in 2019 have said blockchain technology is a priority in their organisation, and more than 83% believe that there is advantage in using the blockchain.

In October 2018, HM Treasury together with the Bank of England and Financial Conduct Authority (FCA) examined and reported the main motivations that drove the consumers to obtain cryptocurrency assets. Their report shows that the main motivation to purchase cryptocurrencies came from family members and friends. It is reported that in some cases the consumers took advice from taxi drivers and neglected the opinions of analysts and other professional advisers (Financial Conduct Authority, 2019). Urquhart (2018) mentions that social media and state's media also played a critical role to disseminate digital currency information also.

Since cryptocurrencies are not as liquid compared to other forms of currencies, understanding and analysing the behaviour of digital assets have drawn insights as to how an investor should effectively capitalise on this asset. Considering that society has become more dependent on digital technology, the viability of digital currency to become a normal currency is more of a possibility than ever before. There are potential losers and winners for capital market transactions. The average blockchain size, number of available Bitcoins and the difficulty level of Bitcoin mining are examples of factors that impact the Bitcoin market. Hence, discovering the exogenous and endogenous drivers are critical tasks. Exogenous and endogenous variables are recommended to be used as a time series, thus multivariate time series forecasting prototypes are required.

2.1.1 Cryptocurrency development processes

There are risks associated with new digital currencies from the establishment to maturity. To be deemed an overall well-grounded form of crypto, there are three different fundamental characteristics that are required to be satisfied. These three success factors are Cryptocurrency Pegging Technology, The Network Effect, and Cryptocurrency Volatility (Barski et al., 2015). These requirements are explained in the following paragraphs.

2.1.2 Cryptocurrency Pegging Technology

Bitcoin is limited to a total of 21 million coins (Chuen, 2015) coins. This has made bitcoin scarce and consequently, it has caused more people to use Bitcoin which has slightly reduced its volatility. Bitcoin is the most established cryptocurrency and had become credible and reliable for users. This has assisted Bitcoin to outpace rival cryptocurrencies to normalize volatilities. Therefore, for e-coins that want to enter the market, that coin should merge its volatility/stability according to more mature and stable crypto such as Bitcoin or Ethereum. This is an important aspect, as in this paper the relationship between Bitcoin and Altcoins are examined (Ibrahim et al., 2020).

2.1.3 The Network Effect

There is a requirement for an appropriate network for payment mechanisms. People tend to use any currency as long as the receiver would willingly accept that type of currency. For example, with more and more countries or businesses accept that particular cryptocurrency, people will be more willing to use that currency (Chuen, 2015).

2.1.4. Cryptocurrency Volatility

The stability of a newly set up coin is very important for the consumers. Since Bitcoin is a new asset, the value discovery mechanism requires the traders and investors using the currency arrive at an agreed-upon value for the asset (Yarovaya and Urquhart, 2020). Given that on the 14th of April 2021, the value of Bitcoin was a staggering $63,000, but only a month later, that is 14th of May 2021, the value dropped has dropped to $47,000, it is a huge concern for investors to purchase an asset that has altered so much in a short period. On the other hand, there are plenty of examples where fiat money has been just as volatile. One prime example is the 79,600,000,000% super hyperinflation in Zimbabwe in November of 2008 (Pettinger, 2019). Another example includes the 42.9 quadrillion per cent hyperinflation of Hungary in 1946 (Pettinger, 2019). Although these are extreme cases, it does show, however, that extreme volatility can happen.

2.1.5 Market Participants

There are different participants in the market which include Miners, Individual investors, Payment Mechanisms and Retail investors (Yermack, 2015). Miners add transaction records to crypto's public ledger of previously made transactions and fuel the supply of cryptocurrencies such as Bitcoin. Then the Individual traders invest in goods and services by purchasing cryptocurrency. Next, payment mechanisms that conduct business internationally given that global payments are available through crypto. Finally, retail investors are funds that invest in currencies as a section of their portfolio to hedge (Yermack, 2015).

2.1.6 Stakeholders

Stakeholder requirements and motivations is also a priority since digital currency changes the value of assets. Following are some examples of the stakeholder affected: Bitcoin brokers/exchanges, Black markets, Bitcoin miners, Bullish/savers investors, members of the public, other cryptographers, and the government (Barski et al., 2015). Stakeholders demand strength and stability with medium transactions. Some stakeholders dislike the widespread of Bitcoin especially the government. This is because the government has no control over the value or price of digital assets (Hogan, 2020).

2.2 Bitcoin

2.2.1 Bitcoin Overview

With a market cap of over $892 Billion and a current price of $38,000, Bitcoin remains the most popular cryptocurrency for investors in the world. Bitcoin or altcoins do not have a physical form which means their tangible value is zero. Yermak (2015) examined the functions and features of Bitcoin with bona fide currency, and as a result of his experiment, he concluded Bitcoin's high volatility diminishes its use as a currency. Yermak (2015), also concludes that Bitcoin is a conjectural investment rather than an investment based on facts and statistics.

As of 25th of August 2021, Cryptocurrency has a total market cap of approximately $2 Trillion (Ossinger, 2021). With over 10,000 different cryptocurrencies listed on the Coin Market Cap website (2021), Barsby (2021) argues that this number will only continue to rise. Although more than 60% of this $2 trillion dollar belongs to Bitcoin and Ethereum, alone. The biggest concern for Bitcoin is security. Brito (2014) believes that the lack of intermediary removes the coverage of stolen Bitcoins if any theft does take place.

In a study by Kristoufek (2015), different driving forces behind the Bitcoin prices were studied. The results showed that standard fundamental factors such as money supply, usage in trade and price level all contribute to Bitcoin value in the long run. Secondly, but not surprisingly, the Bitcoin price is driven by the amount of attention the investors and media give to this cryptocurrency. The partnership seems clearer in the long run, as with more attention given to Bitcoin by media and investors, the higher the prices seem to go (Kristoufek, 2015).

Bitcoin is a digital currency and functions as a payment with a goal to disrupt online banking and PayPal (MGT Investments, 2017). Bitcoin uses the SHA-256 hashing algorithm which is a downfall since it requires a large amount of power to run all the computers and servers, resulting in creating mining pools that utilize "application-specific integrated circuits boards" (ASICs) (Chuen, 2015).

Figure_2 illustrates the Bitcoin value in United States Dollar (USD). As it can be seen, a nonstationary random walk process (RW) is illustrated since there is a shifting variance and mean. There is a relatively small spike in this trend near December 2017 where Bitcoin reaches almost $20,000, and a smaller spike by July 2019 with Bitcoin reaching $12,000. However, the positive upward trend experiences its biggest bullish run during the start of 2021 where it reaches a peak value of $63,000 and then falls rapidly to $35,000 in just two months. Brockman (2021) suggests with more adaptation of Bitcoin, the higher the chances of it turning into a mainstream form of payment. By July 2021, more than 15,000 companies have accepted Bitcoin as a payment for the services they provide.

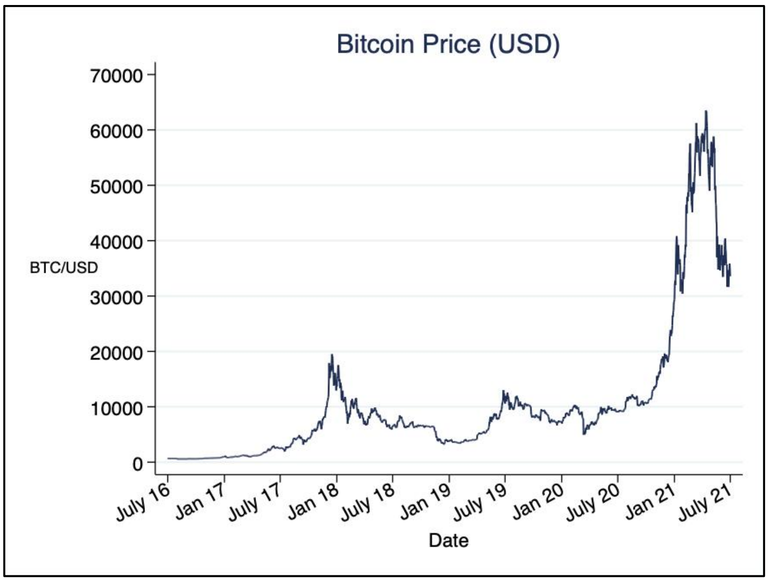

Figure 2: Bitcoin Trend Line

2.2.2 Bitcoin Ledger

Every block in the blockchain of Bitcoin accommodates the summary of each and every transaction in the black using a Binary Hash Tree, (Aka Merkle Tree), thus individual transactions are put in a pool of pending transactions (Ibrahim et al., 2020). Next, they are put in the blockchain (or transaction chain). Individual blocks are linked in a chain via a reference code to the previous header hash. Miners solve cryptographic hashing (A type of mathematical problem) and insert the transactions in the chain (Ibrahim et al., 2020).

2.3 Ethereum

Ether is the currency of Ethereum, and it was launched in 2015 and its value has been increased rapidly since. Figure_3 shows how Ether has suffered a setback in July 2018 all the way to December 2020, where its value oscillated around $400 for most of the time. Ethereum experienced two rapid "bull" runs, one of which was in January 2018 where it rose to $1,500. The second bull run, however, became three times larger than the previous. This is where Ether reached an all-time high value of $4,196.63 in May 2021. Figure_3 shows that there is a positive upward trend in Ethereum, and it is therefore non-stationary. Ethereum is currently ranked number two for the market cap with $362 billion.

In this paper, the relationship between Ethereum and Bitcoin is one of the pairs that will be examined and discussed. From Figure_3 the Bitcoin and Ethereum trends follow a similar path with Ethereum being a "step" behind Bitcoin. For example, at point A, Bitcoin reaches its peak value in December 2017, whereas Ethereum reaches its peak in January 2018. Also at point B, Bitcoin reaches its peak first and Ethereum follows, as a small gap between the peaks can be observed. Other than the slight "delay" from Ethereum, the trends of both digital currencies appear almost identical by reaching their peaks at similar time, having a bullish run upward at a similar rate and the fall of currency occurs at a similar rate and time frame. The difference in value is however very different. Bitcoin seems to be fifteen times more valuable than Ethereum almost all the time.

Consequently, from the trends of these graphs, it does appear that there is indeed a relationship between the two cryptocurrencies since they follow a similar trend. Graphs do also suggest that it is Bitcoin that "drives" the value of Ethereum since there is a small gap between the two with the Bitcoin trend having a small shift to the left of Ethereum, meaning it influences the Ethereum cryptocurrency.

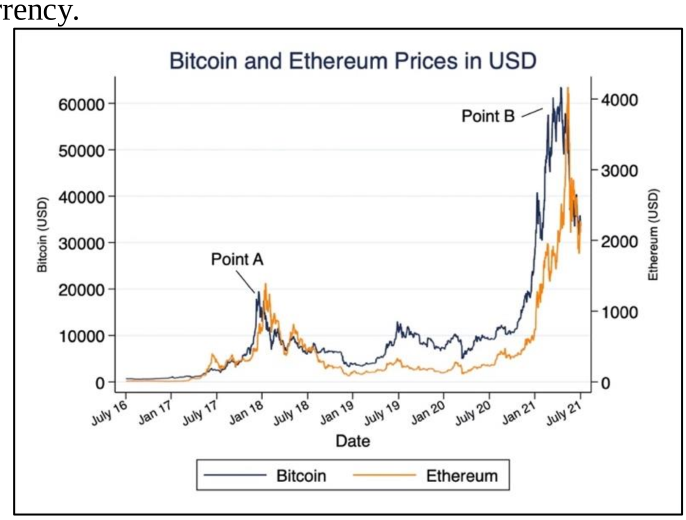

Figure 3: Ethereum & Bitcoin Trend Comparison

Ethereum aims to use the blockchain to take the place of internet third parties. These included parties that store complex financial instruments store data and transfer mortgages (Danial, 2019). Ethereum is planning to become a "world computer", as it forms a platform through which individuals utilize Ether token to design and round applications and smart contracts. In one of its books called "Cryptocurrency Investing", Danial (2019), explains that Ethereum replaces clouds and servers with nodes. In short, Ethereum removes the intermediate party and connects the "consumer" and "supplier" directly, which reduces the downtime, interference of third parties and eliminate fraud (Yarovaya and Urquhart, 2020).

Figure_4 demonstrates a visual illustration of the centralized, decentralized, and distributed network concepts. Fiat currencies such as USD is an example of centralized currency where everything is under unified control. Ahmad (2018) explains a small percentage of a fee on every transaction will be awarded to centralised exchanges. Whereas a decentralized, as illustrated in Figure_4, removes the intermediate party and no extra fees are needed to be paid.

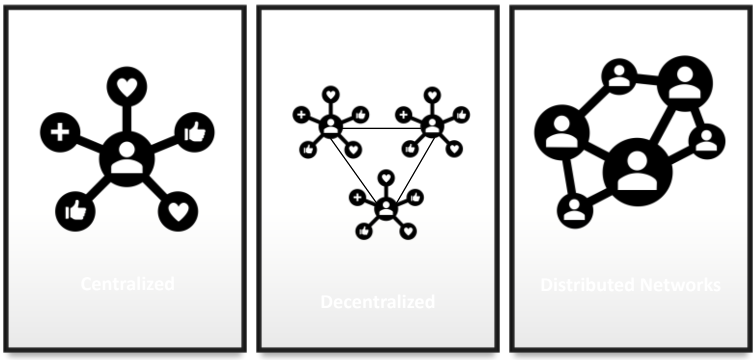

Figure 4: Visual Guidance for Different Networking Systems (Diagrams.net, 2021)

Smart contracts are artificial intelligence that once it is set up, it can carry out orders and agreement (Danial, 2019). Ethereum is connected to a bigger community than Bitcoin, as it impacts the applications which people download on their smartphones. Based on this, Brockman (2021) believes that Ethereum has a great potential to impact different industries and its value could potentially surpass Bitcoin. Google, Amazon, and Facebook will face a revolution if Ethereum manages to decentralize data storage. Due to this extreme excitement behind the Ethereum network, this paper uses Ether as one of the cryptocurrencies to be examined in this paper.

2.4 Ripple (XRP)

Ripple is a digital currency platform that has connections to authorized banks such as American Express, Bank of America, UBS, and Santander, which of course makes it different to other cryptocurrencies. Established in 2012, Ripple also aimed to facilitate global financial transactions (Danial, 2019). Ripple coin is known as XRP, and it has a maximum supply of 100 billion with 46.4 billion currently in circulation according to the Coin Market Cap website (2021). Therefore, the trend of XRP is also examined in this paper to see its relationship with Bitcoin.

Ripple is not decentralised like Bitcoin or Ethereum, as its supply is controlled by a single company, Ripple (Danial, 2019). The Company controls the supply and 1 billion XRP can be released in a single month, which in effect can reduce the XRP value. This is a crucial factor as it can be seen as a big risk by investors and analysts. It is reported by Todd (2015), that the financial transaction by Ripple takes seconds to go through which is of course much faster than Bitcoin, which takes an average of 10 to 15 minutes. It can be argued that Ripple is the traditional banking system but with more enhancement (Todd, 2015). That is, banks and financial institutions can transfer funds within a couple of minutes rather than days, and it is achieved with a lower fee.

XRP is currently at $0.90 with a market cap of more than $45 billion (Coin Market Cap, 2021), which puts XRP in the 6th position for market cap. However, Ripple company owns a staggering 60% of the total XRP coins that will be circulating. Thus, it has been dismissed by many investors who believe the coins are "pre-mined". Ripple is founded by Arthur Britto, Chris Larsen, and Jed McCaleb, who have given themselves 20 billion XRPs (Todd, 2015). Some experts may argue that the market can easily crash if the company decides to cash out. Another downfall of Ripple is that as the network fee is paid by "burning" the coins, the system automatically enriches individuals proportionally to the number of coins they hold. For example, assuming 2% of XRPs are "burnt", the remaining XRPs are now worth 2% more. XRP is currently ranked 6th for the largest market cap with $45 billion.

Figure_5 shows a non-stationary XRP trend with overall positive movement upwards. Two "shocks" are also observed in January 2018 and May 2021. The rate of shocks does differ since the initial shock for XRP, marked as "Point X" on the graph is much larger than that of Bitcoins for the same time frame in January 2018. Point Y on the graph shows a different trend however, since the Bitcoin shock is double the size that of XRP. There may be a relationship between these two digital currencies since they experience their "bull" and "bearish" movements in a similar time frame. For example, from the period of July 2016 to July 2017, both cryptocurrencies are relatively stable.

In a deeper analysis of the XRP trend, points A, B and C show a small shock that does not seem to impact Bitcoin at that given time. However, a shorter time frame after the ladled points (between 2 to 6 months) Bitcoin does show a positive upward trend. Whether that is an indicator of the long-term influence of XRP on Bitcoin or just a coincidence will be discussed later in this paper.

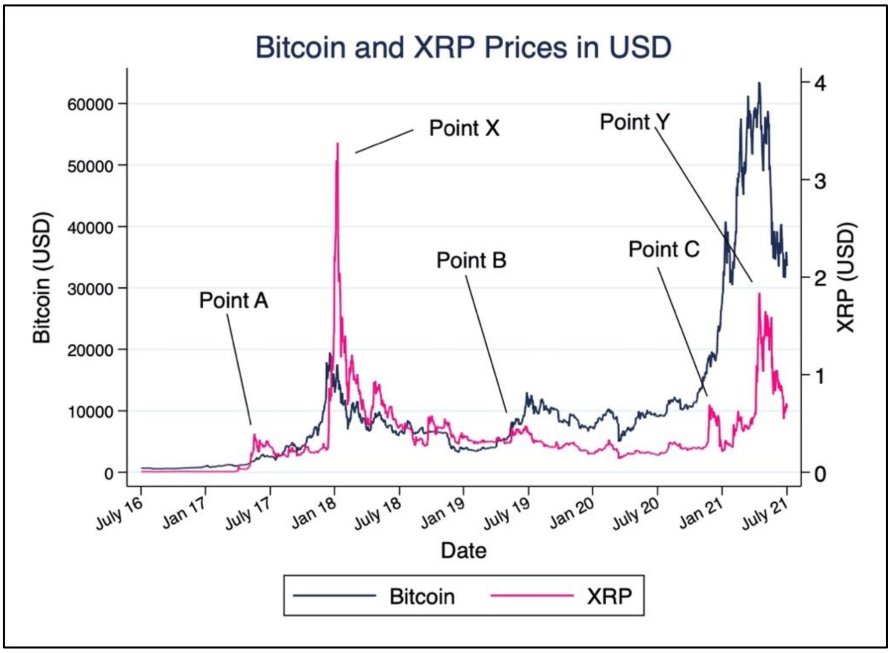

Figure 5: XRP & Bitcoin Trend Comparison

2.5 Litecoin

Litecoin was created by Charlie Lee, a former Google employee, in October 2011 (Danial, 2019). Litecoin has a max supply of 84 million coins and is regarded as a peer-to-peer mechanism that eases the financial transactions. Litecoin is currently ranked at number 11 with a market cap of $11 billion (Coin Market Cap, 2021). Like Bitcoin, computers are required to solve advanced puzzles to mine a Litecoin. The mining process takes place on the S-crypt algorithm and uses ASICs serially, which means running many algorithms one after the other (Danial, 2019). Whereas Bitcoin uses ASICs parallel, meaning running many algorithms at the same time.This causes Litecoin mining to be more efficient in terms of power usage.

Charlie Lee has created Litecoin as a complementary to Bitcoin and not for competition, as he believed Bitcoin was too scarce which made it too expensive and slow. Hence, Charlie Lee created another digital crypto that had a lower value and was also more common.

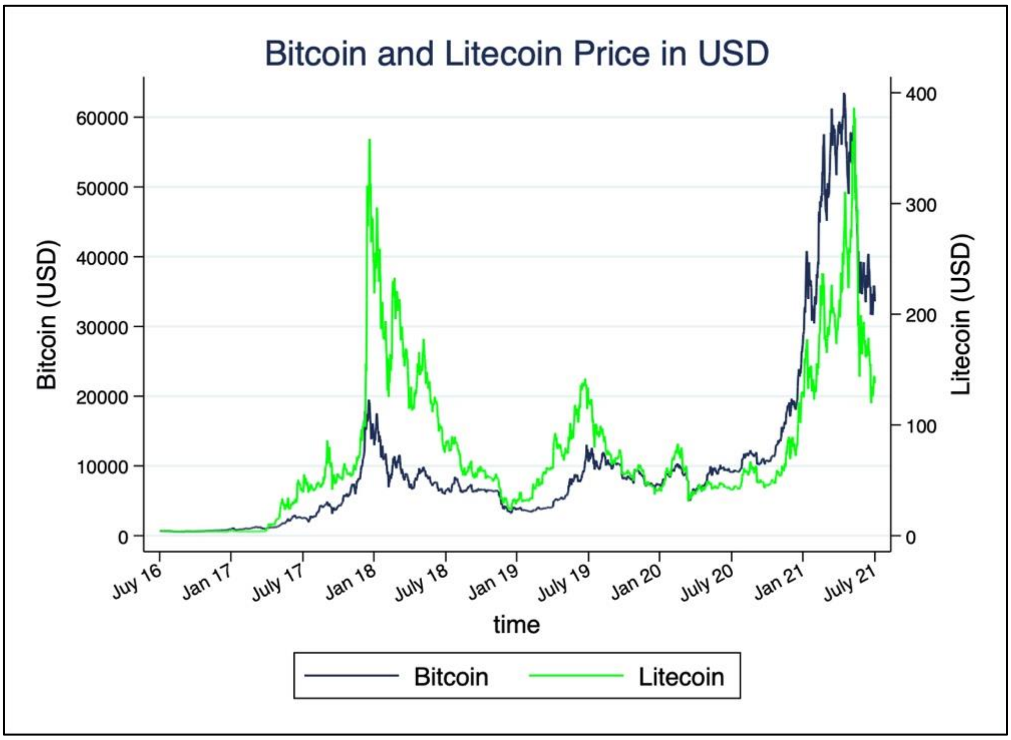

Figure 6: Litecoin & Bitcoin Trend Comparison

Figure_6 shows the Bitcoin and Litecoin price in USD. Litecoin appears to be nonstationary as there is a constant change of mean and variance and there is also a positive upward trend. Litecoin has experienced three major bull runs, with the smallest being from January 2019 to June 2019. The first bull run started in November 2017 with a value of $55 and ended 47 days later with a value of $358. The value had jumped almost 8 times. The last bull run occurred from November 2020 to April 2021, where Litecoin reached its all-time high of $386.

The trends show that the trend lines are almost a clone of each other but with different intensities. Where Bitcoin soars, Litecoin seems to follow, and similarly, where Bitcoin falls, Litecoin also follows but more vigorously. This may not come as a surprise since Charlie Lee wanted to design a coin that is very similar to Bitcoin. By studying the profile of Litecoin, its goals, plans and ambitions, it may be easily suggested that Bitcoin has a strong impact on Litecoin.

2.6 Summary Table

Table_1 shows a summary of four of the most well-known and established cryptocurrencies that will be tested for their interrelationship with each other, and mainly Bitcoin.

Table 1: Summary Table of Four Major Cryptocurrencies

Cryptocurrency	Bitcoin	Ethereum	Ripple	Litecoin
Founder	Satoshi Nakamoto	Vitalik Buterin	Chris Larsen Jed McCaleb	Charlie Lee
Release Date	Jan-08	Jan-14	Jun-12	Oct-11
Coin	Bitcoin (Satoshi)	Ether	XRP	Litecoin
Algorithm	SHA-256	Ethash	Ripple Protocol Consensus Algorithm (RPCA)	Scrypt
Blocks Time	10 Minutes	12-14 Seconds	4 Seconds	2.5 Minutes
Mining	ASIC miners	GPUs	Not mined	Memory Intensive
Maximum Amount	21 million Coins	18 million per Year	100 Billion XRP	84 million Coins
Current Price	$ 45000	$ 3000	$ 1.2	$ 170
Description	Decentralised crypto used for peer-to-peer network	Decentralised platform which runs smart contracts	A Currency Exchange, Remittance network and a real-time gross settlement system	Decentralised crypto used for peer-to-peer network

2.7 Related Work

The research papers of similar experiments for Bitcoin and Altcoin relationships are discussed in this section. Although not all papers examine the same coins, the relevant sections of each case study have been extracted.

2.7.1 Case Study 1: Using the VECM Model

A study by Leatham et al., (2019) have used the Vector Error Correction Model (VECM) to test and explore the causal relationships between Bitcoin, Litecoin, Ethereum and XRP over a three-year horizon between August 2015 to August 2018. Using a Johansen Cointegration, their studies showed that the four digital currencies have three cointegration vectors, meaning they are cointegrated. Leatham et al., (2019) suggest that according to the Granger Causality tests based on the VECM model they carried out, Bitcoin has a causal effect on all of the altcoins; Ethereum, XRP and Litecoin. Similarly, they found that Litecoin has a causal effect on Ethereum and XRP. Since Litecoin is a complementary coin to Bitcoin, and it follows Bitcoin according to their studies, it can be suggested that Litecoin does not directly have an impact on Ethereum and XRP, but rather, it is because of Bitcoin that Ethereum and XRP are affected.

Leatham et al., (2019), also executed a VECM test, which suggested that the lagged Bitcoin prices impact Ethereum and XRP. And similarly, the lagged Litecoin impacts Ethereum and XRP.

In their discussion, Leatham et al., (2019) argue that Altcoins do not have causal effects on Bitcoin price but rather, Bitcoin is mostly influenced by its past price. Also, Ethereum and Litecoin have a smaller impact on Bitcoin, than Bitcoin's own past price. This would suggest that the small impact that Ethereum, Litecoin and XRP are rather negligible. The Impulse Response Function graphs in this paper showed that in the long run, Ethereum, XRP and Litecoin response positively to Bitcoin price shock. On the other hand, Bitcoin, Ethereum and XRP response negatively to the Litecoin price shock. The shocks of Ethereum and XRP cause a small impact on other digital currencies, but the impact is not long-lasting and diminishes with time.

Conclusively, the paper suggests that there is an impact from Bitcoin on Altcoins in the short run, and a small effect in the long run. However, there is a very limited causal effect from Altcoins to Bitcoin (Leatham et al., 2019).

2.7.2 Case Study 2: Using the NARDL Model

In this study by Demir et al., (2021), the asymmetric impact of Bitcoin on alternative coins were tested using the Non-linear Autoregressive Distributed Lag model (NARDL). This paper investigates the relationship between Bitcoin, Ethereum, Ripple and Litecoin between July 2015 to March 2019. This paper has an advantage over the previous case study as it includes 365 more observations due to the added year, therefore, it is potentially a more reliable paper.

This paper is important as it provides evidence from a NARDL model, which is different to the previous study which used VAR and VECM, therefore providing results from a different perspective and method. This model is based on an Ordinary Least Square model (OLS), and it can be applied to time series with mixed integration orders and non-stationary time series.

According to the results obtained in this paper, Bitcoin price has an impact on all of the Altcoin prices asymmetrically in the short run. The in-depth analysis shows evidence of a greater influence of Bitcoin on altcoins when the Bitcoin shock is negative. That is, a drop in Bitcoin price causes a greater impact on altcoins than an increase in Bitcoin price (Demir et al., 2021). Although this paper does not discuss the reasoning for such occurrence, it can be suggested that the cause of this effect may be more on the investor and trader's behaviour and their personal response to financial surprises rather than mainstream finance.

Behavioural Finance suggests that a method that the individuals make decisions are rather irrational and there is a limit to arbitrage. Behaviour Finance further explains that some individuals investing behaviour cannot be explained by mainstream finance (Taleb,2004). These behaviour biases can be cognitive, emotional or social, which is one suggestion as to why the decrease of Bitcoin price impacts the altcoins more than an increase of its price. This study, however, suggests that there is indeed a short-term causality from Bitcoin to altcoins. Additionally, Demir et al., (2021) state that “from the 16 coins that have been tested, 15 of these digital currencies does indeed have a short-term causality, which is much greater than the four cryptocurrencies that have shown a long-run relationship”.

From this paper, it can be concluded that there is a short-term causality between Bitcoin and Altcoins, but the long-term causality is rather weak, and insignificant. This is especially true for Litecoin and Ethereum, whereas XRP does show a small, long-run relationship (Demir et al., 2021).

2.7.3 Case study 3: Short and Long-run Relationship Tests

Different papers have all suggested that there either is a weak long-run relationship or there is no long-run relationship at all between Bitcoin and Altcoins. However, a more detailed research paper by Ciaian et al., (2018) shows a rather broader picture of the relationship between Bitcoin and altcoins. In this research paper, the relationship between Bitcoin and 16 altcoins (which includes Ethereum, Ripple and Litecoin) are tested between April of 2013 to July 2016. The empirical findings also verify that altcoins and Bitcoin are interdependent. Ciaian et al., (2018) suggest that the relationship is significantly greater in the short run compared to that of the long run.

The examination by Ciaian et al., (2018) shows that 15 out of 16 altcoins experience a shock with a change in the price of Bitcoin. Yet, with the long-run relationship, only 4 of the altcoins show a connection to Bitcoin. Conclusively, as the researchers confirm, there is indeed a strong short-run relationship between Bitcoin and Altcoins, but the long-run relationship is rather weak and insufficient to draw any conclusions from.

This paper explains further that macroeconomic factors play a crucial role in Bitcoin and Altcoin prices both on short and long-run relationships. Macroeconomic factors are any influential fiscal, geopolitical, or natural event that has an impact on the national or regional economy (Bloomenthal, 2020). Macroeconomic factors such as gold price, important exchange rates such as CNY/USD and USD/EUR, as well as the 10-year Treasury Constant Maturity Rate, all play a bigger role on Altcoin and Bitcoin prices than Bitcoin’s past prices for a long-run relationship, as suggested by Ciaian et al., (2018).

Demira et al., (2018) examine the relationship between the Economic Policy Uncertainty (EPU) of the United States with Bitcoin. This paper by Demira et al., (2018) does in fact support the argument made by Ciaian et al., (2018) that the EPU does have predictive power on Bitcoin returns. The findings suggest a positive change in EPU results in a negative response from Bitcoin returns. The impact is significant and positive at both higher and lower quantiles. Although the paper does not explain what causes this phenomenon, some can argue that this links to the behaviour of investors. For example, at high levels of EPU, Bitcoin shows a negative response, suggesting investor’s levels of risk-taking may drop, hence fewer people would invest, causing the demand for bitcoin to fall. And similarly, when EPU levels drop, the confidence levels of investors increase, leading to investment in Bitcoin, and as a result, soaring the bitcoin price. Another study by Cheng et al., (2020) shows that EPU of China also has an impact on the Bitcoin price. Although given the countries large population and economical power, this may not be a surprise.

In conclusion, Ciaian et al., (2018) suggest there is a short-run causal effect between Bitcoin and Altcoin. However, it also argues that the long-run effect is insignificant, and the altcoin prices are altered by macroeconomic factors.

2.7.4 Case study 4: Relationship between Cryptocurrency and Fiat Currency

Following the suggestion by Ciaian et al., (2018), which suggested that there may be macroeconomic factors which influence cryptocurrencies, led to further research in this topic. As a result, the paper by Sathyanarayana and Gargesa (2019) was studied which has added further weight to the Ciaian's et al., (2018) theory. In their studies, Sathyanarayana and Gargesa (2019) model a sample cryptocurrency, Bitcoin, against the top five fiat currencies naming USD, GBP, Euro, Japanese Yen and Swiss Franc. By using the EGARCH and GARCH models, the leverage effect and the time varying volatility was captured. Next, the Johansen Cointegration was conducted to find any cointegration and later, VECM and VAR models has been used to discuss the long and short run relationship between the fiat currencies and Bitcoin.

This paper find that GBP and USD have a long run relationship with Bitcoin. The paper states although Bitcoin itself has a much greater impact on the future prices, there is still a long-run relationship between GBP and USD. This research paper has found that a shock to USD can fluctuate Bitcoin price by 6.97% in three months period, and 1.56% in the tenth month. This is where a shock to GBP causes 2.07% fluctuation in three months and 0.58% fluctuation in the tenth months (Sathyanarayana and Gargesa, 2019). It is worth mentioning that the Japanese Yen and Swiss Franc did not have any relationship with Bitcoin. Swiss Franc accounts for 4.8% for most traded currency and Japanese Yen 21.5% (CMC Markets, 2021). Therefore, given that the USD is involved in up to 87.6% of trading volumes globally, and GBP with 12.8%, the impact of these currencies may not be a surprise (CMC Markets, 2021).

Although the long run relationship between powerful fiat currencies and are small percentages, but the combination of these factors with other macroeconomic factors such as EPU, Gold prices and other natural events, can add up and become significant). Conclusively, the research by Sathyanarayana and Gargesa (2019) does support the argument made by Ciaian et al., (2018), since fiat currencies count as a macroeconomic factor and they do have a long-run relationship with Bitcoin.

3.0 Research Design

3.1 Objectives of the Study

- To generate a Vector Autoregressive (VAR) model to relate observations of Bitcoin with observation of Altcoins in the system namely Ethereum, Ripple and Litecoin.
- To utilize Granger causality test for determining whether Bitcoin series are useful in forecasting Altcoins or not.
- To use Impulse Response Function (IRF) to observe the reaction in Altcoin series in response to change in Bitcoin series.
- To discuss the theoretical findings and make comparison with similar papers.
- To provide implications for the investors and other market participants based on this paper.

3.2 Source of Data

Due to the analytical nature of this empirical study, the data for this investigation relied on secondary sources. Therefore, I have used the daily adjust closing price of all the coins for the time frame between 1st July 2016 to 1st July 2021, which is a five-year period. This provided me with 1827 total observation. Next, I have calculated the daily returns Rt as follows

$$Rt = \ln\left[\frac{Ct}{Ct-1}\right] \qquad \text{Eq.1}$$

This is where:

Rt = Return on t day
Ct = Closing price on t day
$Ct - 1$ = Closing price on t-1 day
ln = Natural log of series

The source of the data for this study has been accumulated from Yahoo (2021) website. The data was also compared to the Coin Market Cap website for robustness.

3.3 Plan of Analysis

To begin with, I start by plotting the logarithmic prices of the cryptocurrency coins to get an overall view of the trends and patterns over the 5-year period. Next and by employing STATA software, I used the autocorrelation function of coins and their return series to visually check for a white noise process. Next, I perform the Augmented Dicky Fuller (ADF) (Dickey et al., 1979), Kwiatkowski Phillips Schmidt Shin (KPSS) (Kwiatkowski et al., 1992) and Phillips Perron (PP) (Phillips and Perron, 1988) test to check for stationarity. The series is stationary if they have a constant variance, covariance and mean. Hence, any external shock to the series should disappear over time. However, for a random walk process (unit root), the applied shock will not "die away" (Brooks, 2019).

The Akaike Information Criteria (AIC), Bayesian information criterion (BIC) or (SBIC), and Hannan Quinn information criterion (HQIC) were used to select the number of lags. The formulas are:

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2tp}{T} \qquad \text{Eq.2}$$

$$BIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T}tp \qquad \text{Eq.3}$$

$$HQIC = -2\left(\frac{LL}{T}\right) + \frac{2\ln\{\ln(T)\}}{T}\,tp \qquad \text{Eq.4}$$

Where

LL = Log likelihood
tp = Total number of parameters in the model
T = Number of observations

Furthermore, after selecting a suitable lag length based on the VAR model, I used the Johnsen cointegration test to help me find if the coins have a common stochastic trend between them. That is, to assess the long-run connection between the four digital currencies. Johansen cointegration test considers all the series to be endogenous. This was advantageous as I did not have to decide on the nature of time series (exogenous or endogenous), whereas with the other methods I would have had to work that out. Also, Johansen works on the basis of systematic elimination of multi-variate TS (Johansen and Juselius, 1990).

This cointegration test is founded on the total number of the independent linear combinations (Johansen and Juselius, 1990), which depends on VAR. The model is given by

$$yt = \beta 1\, Yt - 1 + \beta 2\, Yt - 2 + \cdots + \beta k\, Yk - 2 + \mu t \qquad \text{Eq.5}$$

Where:

βk = Coefficient matrices for each lag
μt = White noise disturbance

Next, the VAR model above should be transferred into a VECM model. This is achieved by adding an error correction component

$$\Delta yt = \Pi y(t-1) + \Gamma 1\, \Delta yt - 1 + \Gamma 2\, \Delta yt - 2 + \cdots + \Gamma k - 1\, \Delta yt - (k-1) + \mu t \qquad \text{Eq.6}$$

Where:

$\Delta yt = yt - y(t-1)$ = differencing equation
k = Number of lags

$\Pi = (\sum \mathrm{Bi}) - \mathrm{Ig}$ and $\Gamma \mathrm{i} = (\sum \mathrm{Bj}) - \mathrm{Ig}$ include two matrices.

Where:

Π = Long run coefficient matrix
Γ = Contains short run dynamics
g = Number of variables

Johansen cointegration focuses on a long-run coefficient matrix, Π, which has two test statistics:

$$\lambda_{trace}\,(r) = -T\; g\text{^}\Sigma \ln(1-\lambda_i) \qquad \text{Eq.7}$$

$$\lambda \max(r, r+1) = -T \ln(1-\lambda_r + 1\,) \qquad \text{Eq.8}$$

Where

λ_i = ith ordered eigenvalue predicted using Π.
r = Number of cointegration vectors

This formula includes a g-1 rank. This is the maximum number of ranks possible. For example, having 2 time series for investigation, the maximum number of cointegration would be 1. Rather, if we have 5 time series, the maximum number of cointegration will be 4.

To examine the cointegration between variables, I have employed the maximum eigenvalue and trace statistic tests (where null (H0) for the maximum number of cointegration is r = r* < k vs alternative (H1) k = r). Next VAR and VECM models were employed to investigate the relationship between the cryptocurrencies. Finally, the impact of Bitcoin return shock on altcoins has been based on Orthogonalized Impulse Response Function. The formula is given:

$$H0{:}\, r = 0 \quad Vs \quad H1{:} < r \leq g$$

$$H0{:}\, r = 1 \quad Vs \quad H1{:}\, 1 < r \leq g$$

$$H0{:}\, r = 2 \quad Vs \quad H1{:}\, 2 < r \leq g$$

$$H0{:}\, r = g - 1 \quad Vs \quad H1{:}\, r = g$$

Thus, when $H0{:}\, r = 0$ and $H0{:}\, r = 1$, meaning the null hypothesis cannot be rejected, it can be suggested that there is 1 cointegration vector. However, when $H0{:}\, r = 0$ is not rejected, it would mean there is no cointegration vector. Therefore, the r value is increased until the null hypothesis, $H0$, cannot be rejected.

4.0 Data Analysis

Figure_7 shows the co-movement of four cryptocurrencies from July 2016 to July 2021. On the y-axis the Ln(price) are shown, whilst on the x-axis is the timeline. It can be suggested that the trend is non-stationary, and a trend line follow a similar path. It is also apparent that the value of cryptocurrencies is continuously growing. However, to have a robust answer, the Autocorrelation, KPSS, ADF and PP tests are carried out in the future steps.

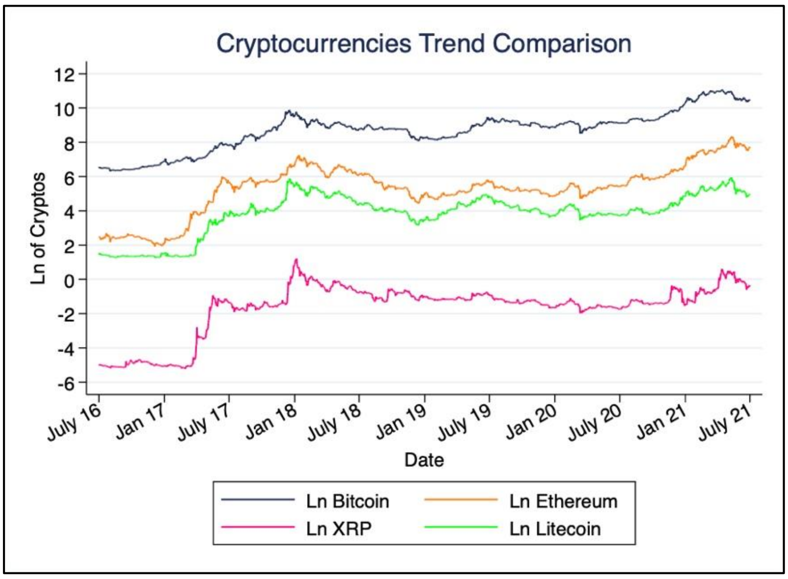

Figure 7: Logarithmic Trend Lines of Cryptocurrencies

4.1 Stationarity Tests

Autocorrelation tests, which is a visual examination of the Bitcoin times series shows that the ρ values are either one or stays very close to one. This shows that there is a strong persistence throughout the time series. However, once the Bitcoin values become first differenced, the data points change and instead become zero or stay very close to zero. Hence, this would make the first differenced series model very suitable for further analysis since the model shows a white noise process. Meaning this model is stable. Conclusively, I can tell that the series is stochastic and there is a possibility of a spurious correlation and regression, therefore, the fundamental Bitcoin price time series is unsuitable for prediction and forecasting. Similar results are observed for the altcoins time series (See Appendix A).

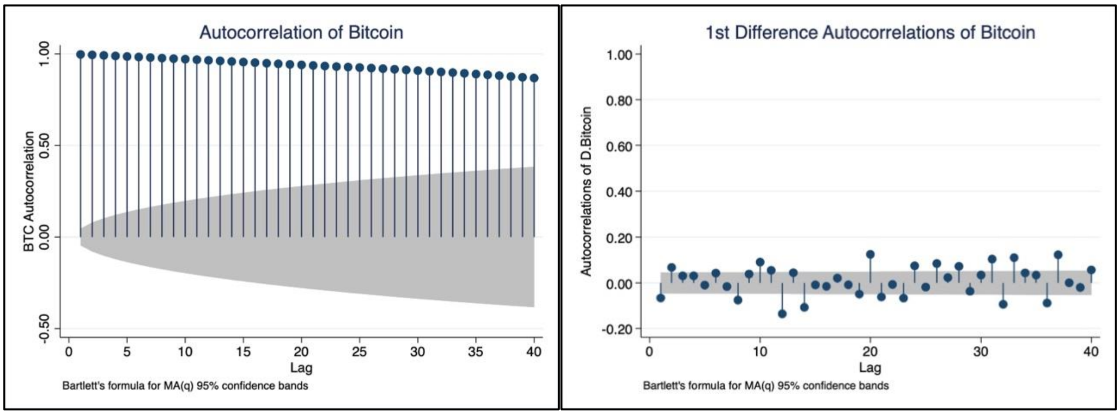

Figure 8: Autocorrelation of Bitcoin in Level and 1st Differenced Terms

To perform the stationary tests, the optimum lag numbers of Bitcoin, Ethereum, Ripple and Litecoin are required separately to compensate for serial correlation in the error term. SBIC attempts to find the true model and it does so by basing the calculations on the previous observations. Whereas AIC selects the models that adequately describe an unknown. Ultimately, I prefer to use the SBIC value, but also look at the AIC value for guidance. Based on the tests carried out, Table_2 suggest using 3 lags for Bitcoin. This is because the SBIC and HQIC values are the lowest, 16.089 and 16.082, respectively. Although AIC suggests 4 lags, I use 3 lags since SBIC is generally more consistent.

Table 2: Optimal Lag Selection of Bitcoin

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-19817		1.70E+08	21.77	21.7675	21.769		
1	-14642	10350	1	0	565753	16.084	16.086	16.089
2	-14638	7.846	1	0.01	563940	16.081	16.084	16.090
3	-14635	7.5363	1	0.01	562228	16.078	16.082	16.089*
4	-14633	3.0069	1	0.08	561917	16.077	16.083	16.092
5	-14632	1.8849	1	0.17	561952	16.077	16.084	16.095
6	-14632	0.1645	1	0.69	562519	16.07	16.086	16.099

I then follow the same procedure as before for the altcoins. Therefore, from Table_3, I have selected the lowest SBIC value for the number of lags I will be using for the ADF tests. Hence, I will use 3 lags for Bitcoin, 11 for Ethereum and XRP and only 1 for Litecoin for the ADF, PP and KPSS tests.

Table 3: Optimal Lag Selection of Altcoins

lag	Bitcoin	Ethereum	XRP	Litecoin
0	21.7707	15.7134	0.837263	11.2668
1	16.0932	10.7773	-2.97251	6.93718
2	16.093	10.76	-2.96957	6.94066
3	16.093	10.7497	-2.96842	6.94412
4	16.0955	10.7536	-2.96661	6.94825
5	16.0986	10.755	-2.96448	6.94313
6	16.1026	10.7483	-2.96036	6.94701
7	16.1053	10.7199	-2.96013	6.93835
8	16.1093	10.7168	-2.95991	6.94145
9	16.1064	10.7043	-2.96093	6.94314
10	16.1096	10.6995	-2.95797	6.94717
11	16.1017	10.6942	-2.99598	6.94273
12	16.1003	10.697	-2.99289	6.94578

For the PP and ADF tests, H(0), the null hypothesis exhibits that there is a unit root and H(1) means the time series is stationarity. The tests on the raw data for both ADF and PP tests indicate that the null hypothesis should be accepted since the t-stat is less than the 10% of Critical Value (CV), therefore it is closer to zero. Additionally, the p-values are larger than the significant level alpha = 0.1, hence we accept the null hypothesis, which means there is a unit root. Therefore, meaning the time series is not stationary. The PP test attempts to correct the standard error for Heteroskedasticity and Autocorrelation (HAC) (Brooks, 2019).

By differencing the time series, we can remove the unit root, therefore the time series becomes stationary (Brooks, 2019). This is supported by larger t-statistic values than their CV under all confidence levels and significant p-values.

The KPSS has a different approach to PP and ADF tests. For the KPSS test, H(0), the null hypothesis indicates that there is no unit root (Brooks, 2014). From Table_4, the t-stats are bigger than the critical values at all of the given intervals, thus the null hypothesis is ignored, signifying that there is a unit root. After the first differencing of time series, all of the t stats descend below the critical value and are near to zero, which is a sign of the series becoming stationary. The presence of random walk in the time series indicates a weak-form efficient market (Brooks, 2019). In a weak-form efficient market, it is impossible to predict and forecast the future prices of cryptocurrencies based on historical price, since this is a random walk process. However, when the unit root is absent, the time series data becomes stationary and thus forecasting the future prices by using the historical prices becomes possible.

The trend option and constant option were used. The trend option adjusts the critical value and checks for trend stationarity. Trend enhances the critical values, however, the overall results remain unchanged. Regression with constant is employed to investigate for a simple random walk, additionally, regression with trend and constant is applied to examine for a random walk with drifts. Having said that, under all cases, the trend is not stationary at all, and in fact, it only becomes stationary when the series has been differenced of order one. Therefore, I did not include the trend and constant options in Table_4.

Table 4: Dicky-Fuller, KPSS & PP Tests

			Critical Values				
		t-stat	1%	5%	10%	p value	Stationary
Dicky-fuller							
(3_Lags)	Btc	-0.804	-3.43	-2.86	-2.57	0.8181	No
	D.Btc	-19.689	-3.43	-2.86	-2.57	0	Yes
(11_Lags)	Eth	-1.048	-3.43	-2.86	-2.57	0.7354	No
	D.Eth	-13.991	-3.43	-2.86	-2.57	0	Yes
(11_Lags)	XRP	-3.621	-3.43	-2.86	-2.57	0.0054	Close
	D.XRP	-14.955	-3.43	-2.86	-2.57	0	Yes
(1_Lags)	Ltc	-2.412	-3.43	-2.86	-2.57	0.1383	No
	D.Ltc	-29.911	-3.43	-2.86	-2.57	0	Yes
KPSS		t-stat	1%	5%	10%		Stationary
(3_Lags)	Btc	4.75	0.216	0.146	0.119		No
	d.	0.0674	0.216	0.146	0.119		Yes
(11_Lags)	Eth	1.52	0.216	0.146	0.119		No
	d.	0.0591	0.216	0.146	0.119		Yes
(11_Lags)	XRP	0.878	0.216	0.146	0.119		No
	d.	0.0179	0.216	0.146	0.119		Yes
(1_Lags)	Ltc	5.54	0.216	0.146	0.119		No
	d.	0.0361	0.216	0.146	0.119		Yes
Pperron		t-stat	1%	5%	10%	p value	Stationary
(3_Lags)	Btc	-1.775	-20.7	-14.1	-11.3	0.8423	No
	d.	-2029	-20.7	-14.1	-11.3	0	Yes
(11_Lags)	Eth	-3.429	-20.7	-14.1	-11.3	0.7776	No
	d.	-2406	-20.7	-14.1	-11.3	0	Yes
(11_Lags)	XRP	-28.42	-20.7	-14.1	-11.3	0.0031	No
	d.	-2029	-20.7	-14.1	-11.3	0	Yes
(1_Lags)	Ltc	-11.79	-20.7	-14.1	-11.3	0.1286	No
	d.	-1878	-20.7	-14.1	-11.3	0	Yes

4.2 Johansen Cointegration Outcome

A Johansen Cointegration test was implemented to check whether there is a long-run relationship between the four digital currencies or not. By performing a sequence of trace tests for a given significance level, produces an approximation of the number of cointegrating equations contained in the time series (Johansen and Juselius, 1990). The star sign (*) in

Table_5 reflects that this estimator has chosen the total number of cointegrating equations corresponding to this row of the table. Maximum rank symbolises the total number of cointegrating vectors. Accordingly, if the null hypothesis H0: r = 0 is not rejected, then one can assume that there are no cointegrating vectors. On the other hand, assuming that null hypothesis H (0): r = 0 is not accepted, and the other null hypothesis H(0): r = 1 cannot be dismissed, then the experiment suggests that there is a cointegration vector.

From Table_5, we can see that the maximum rank is zero. The trace statistic is less than the 5% critical value for 0 rank with 7 lags, hence the null hypothesis is accepted. This is illustrated in Table_ 5 with trace statistic being 35.7, which is lower than the 47.21% for the 5% critical value. This means that there are no cointegrating vector equations in this series. Max statistic was also employed for robustness and a more reliable result. However, even the Max statistic is lower than the critical value in the second table (of Stata output) for rank zero. Table_5 shows the max statistic is 19.07 which is lower than the 27.07 of 5% critical value. This is further support for the lack of cointegration between Bitcoin and Altcoins in the long run.

Table 5: Johansen Cointegration Results

Maximum Rank	parms	LL	Eigenvalue	Trace Statistic	5% Critical Value
0	100	12216.461	.	35.7000*	47.21
1	107	12225.995	0.01042	16.6321	29.68
2	112	12231.478	0.00601	5.6663	15.41
3	115	12233.883	0.00264	0.8559	3.76
4	116	12234.311	0.00047		
Maximum Rank	**parms**	**LL**	**Eigenvalue**	**Max Statistic**	**5% Critical Value**
0	100	12216.461	.	19.0679	27.07
1	107	12225.995	0.01042	10.9658	20.97
2	112	12231.478	0.00601	4.8104	14.07
3	115	12233.883	0.00264	0.8559	3.76
4	116	12234.311	0.00047		

Given the studies by Demir et al., (2021) and Ciaian et al., (2018) suggested that there is a long-run relationship, I had to make sure that my answers held true. I then carried out the Lagrange-multiplier test to check for autocorrelation. My findings in Table_6 show the result for the Lagrange-multiplier autocorrelation test with the null hypothesis, H(0), being “No Autocorrelation at Lag Order”.

The value for lags 1, 2 and 3 were 37%, 21% and 59% which are significant, and lag 2 was 1.7% significant. Conclusively, there was no autocorrelation at log orders, which gives me further confidence that there are no cointegrating vector equations in this series.

Table 6: Lagrange-multiplier Test

Lag	lag chi2	df	Prob > chi2
1	17.2276	16	0.37102
2	30.0355	16	0.01782
3	20.061	16	0.21749
4	14.0868	16	0.59225

This suggests, if there is a shock in the short run by Bitcoin, then the altcoins will not coverage with time in the long run. The equation for the long-run relationship from Table_7 can be written as:

$$ECT1: \quad LnBtc + 0.8494\ LnEth + 4.531\ LnXrp - 7.362\ LnLtc + 21.65 \qquad \text{Eq.9}$$

$$LnBtc = \ -21.66 - 0.8494\ LnEth - 4.531\ LnXrp + 7.362\ LnLtc \qquad \text{Eq.10}$$

$$\underset{}{Ln\ Btc} \ = \ \underset{(1.0637)}{0.8494\ Ln\ Eth} + \underset{(1.0539)}{4.531\ Ln\ Xrp} - \underset{(1.773)}{7.362\ Ln\ Ltc} + 21.65 \qquad \text{Eq.11}$$

If the values were to be true, and autocorrelation was absent from the series, this could have meant that a 1% increase by BTC would cause a 7.362% increase in LTC and a reduction of 0.8494% in Ethereum and a 4.531% reduction in XRP prices.

Table 7: VECM Results

	beta Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
_ce1						
LnBtc	1	.	.	.	.	.
LnEth	0.8494189	1.063689	0.8	0.425	-1.235374	2.934212
LnXrp	4.531278	1.053954	4.3	0	2.465567	6.596989
LnLtc	-7.361621	1.773198	-4.15	0	-10.83703	-3.886216
_cons	21.65317	.	.	.	.	.

4.3 VAR and 2 Way Causality Checks

From the previous section, I have found that there is no cointegration among the variables in the system. Therefore, I utilised the Var model to establish causal relationships between the variables and estimate the shocks introduced to the system and trace out the effects of these shocks on the endogenous variables. This method enables forecasting (decomposing shocks to the VAR system). However, for the Var model, I will use the Log return of cryptocurrency prices. It is important to note that all of the cryptocurrencies in a VAR system are endogenous, meaning that their statistical model is determined by other variables within the system (Kenton and Khartit, 2020). To get a robust answer, I have completed two different methods of t-statistic and Granger/Wald tests.

4.3.1 Causality Check Using t-statistic

Initially, I have used the t-statistic method, and the results are in Table_9 in Appendix B. This method allows the individual interpretation of each lag on each dependant variable.

From Table_9, out of the 6 lags, the 4th lag of bitcoin has a negative effect on Bitcoin at a 1% significant level, whilst the 5th lag has a positive impact on Bitcoin itself at 10% on average ceteris-paribus. On the other hand, 1st lag of Ethereum has a negative effect at a 5% significant level. Similarly, the 1st lag of XRP has a negative effect but at a 10% significant level. And finally, the 4th lag of Litecoin has a positive effect on Bitcoin at a 1% significant level.

The outcome of the tests shows that the 5th lag of Bitcoin has a positive effect on Ethereum at a 5% significant level. The 1st lag of XRP has a negative effect, whilst its 6th lag has a positive effect on Ethereum, both at 5% significant levels. However, I find that there is no impact from any of the lags from Ethereum and Litecoin.

Unlike, Bitcoin and Ethereum, I find that XRP does seem to be affected much more by other variables. I find that the 1st and 3rd lags of Bitcoin negatively affect XRP at 5% and 1% on average ceteris-paribus, respectively, whilst the 6th lag has a positive effect at a 10% significant level. Similarly, the 3rd and 5th lags of Ethereum have a negative impact on XRP at 5% and 10% significant level, respectively, whilst the 4th lag has a positive impact at 1% significant level. I have also discovered that the 2nd and 5th lags of XRP have a positive impact, both at 10% on average ceteris-paribus. Finally, 1st, 3^{rd,} and 5th lags of Litecoin have positive effects at 10%, 1% and 5%, respectively.

Like XRP, I find that Litecoin is affected much more by other variables than Bitcoin and Ethereum. I find that the 4th lag of Bitcoin has a negative impact at 10% and the 5th lag of Bitcoin has a positive effect at a 1% significant level. I also find that the 3rd lag of XRP has a positive impact at a 1% significant level, whilst the 4th lag of Litecoin has a positive impact at a 1% significant level on Litecoin itself. Interestingly, I find four of the lags from Ethereum having an impact on Litecoin. The 1st, 3rd and 5th lags have negative effects at 5%, 5% and 10% significant levels, respectively, whilst the 6th lag of Ethereum impacts Litecoin positively at a 5% significant level.

4.3.2 Causality Check Using Granger Test

The previous method does not provide an overall causal effect of variables onto each other. Therefore, I have discovered the joint significance of regressors on the dependant variable by using Granger Causality Test. In this test, If the P-value is higher than 0.05 we cannot reject the null hypothesis H (0): No granger causality. Table_8 shows the output from STATA. The Chi2 value measures how strong these variables are connected, and the p-value illustrates the probability and the chances of it begin true.

From Table_8, it can be observed that neither Ethereum, XRP or Litecoin returns have any causal impact on Bitcoin return. However, the combination of these three together Granger causes Bitcoin. This is because the p-value is less than 0.05, hence I reject the null hypothesis. Interestingly, I find that none of the Bitcoin, XRP and Litecoin returns has and any causal effect on Ethereum return whether it is individually or a combination of the coins. This “resistance” from Ethereum is very surprising and will be discussed in the next chapter.

On the other hand, Bitcoin, Ethereum and Litecoin return all Granger cause the XRP return. The table shows chi2 values of 49.56 from Litecoin respectively which is greater than Ethereum and Bitcoin with 16.13 and 20.15 respectively. The combination of these three coins also Granger cause XRP return. The same can be said about Litecoin return, as it is Granger caused by Bitcoin, Ethereum, XRP and a combination of these three returns. The table shows a higher chi2 value from Bitcoin than other coins, which shows Bitcoin Granger causes Litecoin at a greater rate than altcoins, and this is supported by a p-value of zero.

Table 8: Granger Causality Results

Equation	Excluded	Chi2	df	Prob>chi2
Bitcoin Log Return	Ethereum Log Return	10.683	6	0.099
Bitcoin Log Return	XRP Log Return	6.2795	6	0.393
Bitcoin Log Return	Litecoin Log Return	10.591	6	0.102
Bitcoin Log Return	ALL	36.872	18	0.005
Ethereum Log Return	Bitcoin Log Return	6.442	6	0.376
Ethereum Log Return	XRP Log Return	11.414	6	0.076
Ethereum Log Return	Litecoin Log Return	5.4443	6	0.488
Ethereum Log Return	ALL	20.102	18	0.327
XRP Log Return	Bitcoin Log Return	20.153	6	0.003
XRP Log Return	Ethereum Log Return	16.133	6	0.013
XRP Log Return	Litecoin Log Return	49.564	6	0.000
XRP Log Return	ALL	68.692	18	0.000
Litecoin Log Return	Bitcoin Log Return	24.5	6	0.000
Litecoin Log Return	Ethereum Log Return	16.456	6	0.012
Litecoin Log Return	XRP Log Return	17.553	6	0.007
Litecoin Log Return	ALL	50.973	18	0.000

4.3.3 Impulse Response Function

Figure_9 shows an orthogonalized shock to one cryptocurrency return that causes a small impact on other digital currencies. A shock to Bitcoin price temporarily reduces the Ethereum, XRP and Litecoin, but in the next step, it moves it slightly back to the equilibrium line at zero. These fluctuations in the response gradually stabilise and “fade” with time. It is apparent that after step 6 there is no change of price in altcoin in response to the shock caused by Bitcoin. The impact is larger on Litecoin by at 4, compared to Ethereum and XRP which are slightly lower than 4.

A shock by Ethereum return has a small negative impact on Litecoin, XRP by two units. The negative impact is much smaller on Bitcoin return with half a unit. These graphs suggest a shock in Ethereum will cause a smaller impact on other digital currencies compared to Bitcoin. However, just like Bitcoin, Ethereum shocks “die” after the 6th step.

A shock to Litecoin has a caused a small response from Bitcoin and Ethereum, however, these are very small that is almost negligible. On the other hand, a small positive impact (1 unit) is experienced by XRP on the 3rd step, which again moves back to zero in the 4th step. No changes are observed in any of the graphs after the 6th step.

Lastly, Bitcoin and Ethereum have a very small response to a shock to XRP which is again negligible, and the line eventually stabilise. A small negative response is observed in Litecoin, and the positive and negative fluctuations show a greater peak and trough compared to Bitcoin and Ethereum. It is also observed that all the variables show a strong negative impulse function to their own past values.

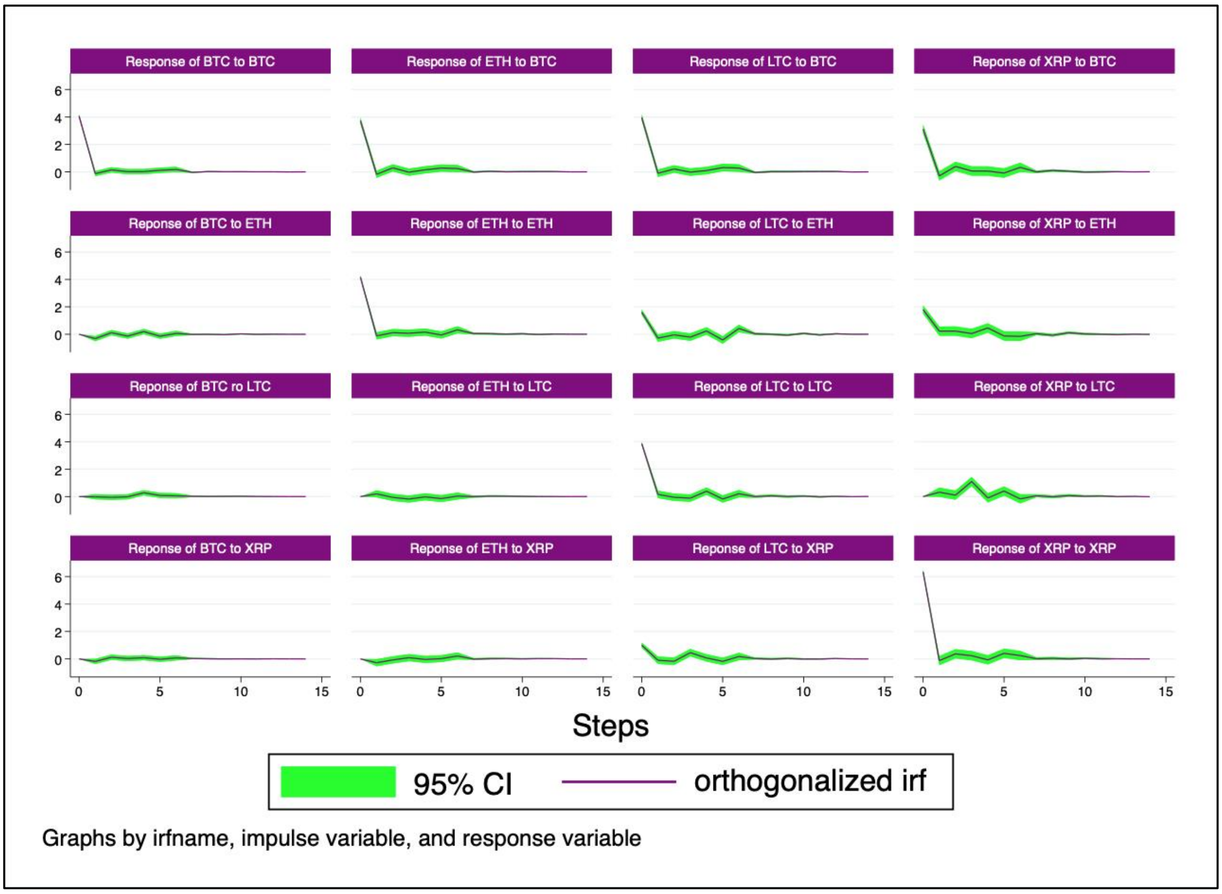

Figure 9: Impulse Response Function Results

5.0 Discussion

From the short-term and long-term relationship analysis of Bitcoin and Altcoins, it can be suggested that there is, indeed, a relationship between them.

5.1 Johansen Cointegration Discussion

From the Johansen cointegration test I have found that there is no long-run relationship between Bitcoin and Altcoins, or any of the altcoins with each other. This is because I found that the maximum rank among the variables is zero. This suggests that there is no cointegration vector equation in the time series. This was backed up by the Trace statistic being 35.7 which is lower than the 5% critical value of 47.21. I also employed the Max statistic which further supported that there is no long-run relationship between the variables. The Max statistic value was 19.07 on rank 0, which was lower than the 5% critical value of 27.07. The robustness of these outcomes was checked using the Lagrange-multiplier test, which checks for autocorrelation. My findings did not have any autocorrelation at any of the lag orders.

The outcome of this section opposes the findings of Leatham et al., (2019). Their results show that Bitcoin, although small, does have an impact on the Altcoins for the long-run relationship. This might be because their findings cover a three-year period, whereas in this experiment I covered a 5-year period. Also, their findings do not include the "bull" run of 2021, which may have altered the result of this experiment.

Additionally, a study by Demir et al., (2021) also found that there is a weak long-term relationship between Bitcoin and 15 altcoins. Their findings did not find any long-run relationship between Bitcoin, Ethereum and Litecoin, which is in line with the findings of this paper. Demir et al., (2021) used the NARDL method, which is a different method to this paper. However, tackling the hypothesis from a different angle and finding a similar answer gives me more confidence in my findings.

Furthermore, the findings of Ciaian et al., (2018) is also in line with this paper that there is a weak long-run relationship between Bitcoin and Altcoins. However, Ciaian et al., (2018) suggest in their paper that the prices of Bitcoin and Altcoins are affected not by each other, but rather by macroeconomic factors. Given this suggestion, I believe that this holds true because a paper by Sathyanarayana and Gargesa (2019) discovered that GBP and USD tend to have a long-run relationship with Bitcoin. Their findings show that a shock to USD can fluctuate Bitcoin price by 6.97% in three months and similarly, a shock to GBP causes a 2.07% fluctuation in Bitcoin price. Additionally, Demira et al., (2018) found that another macroeconomic factor, Economic Policy Uncertainty have an impact on Bitcoin, and similarly, Cheng et al., (2020) discovered that the EPU of China also has an impact on Bitcoin prices.

5.2 T-statistic Discussion

In this test, I found that there is certainly a strong short-run relationship between cryptocurrencies. I found that 8 different lags have a causal impact on Litecoin from all the cryptocurrencies included. However, I also found that 11 lag orders have an impact on XRP, which shows that XRP is the most affected cryptocurrency among the variables. On the other hand, Ethereum showed that it is the least impacted as only 4 lags were statically significant which impacted Ethereum. In the case of Bitcoin, 5 lags had an impact on Bitcoin, however, 2 of the lags were from Bitcoins own lag orders. This suggests that the Bitcoin price is more likely to be impacted by its own previous prices than the altcoins.

Paper by Sathyanarayana and Gargesa (2019) also found that Bitcoin is more impacted by its own lag orders than other variables. The findings in this section showed that there is a short-run relationship between Bitcoin and Altcoins. This was in line with all of the similar papers in studies; Leatham et al., (2019), Demir et al., (2021), Demira et al., (2018), Ciaian et al., (2018).

5.3 Granger Causality Discussion

As previously explained, no individual cryptocurrency Granger causes Bitcoin, unless they are combined. This outcome should not be surprising as Bitcoin is the original movement archetype and it has a trustworthy infrastructure compared to other altcoins. Barsby (2021) reports that over 10 million Bitcoin wallets exist globally, which shows the currencies large user base. Additionally, Bitcoin was early on the market and has been a successful asset for many investors which means it is accredited by more people.

I then discovered that none of the coins Granger causes Ethereum. This result may not come as a surprise because, as previously explained in the literature review, more than 60% of the $2 trillion total market cap belongs to Bitcoin and Ethereum (Coin Market Cap, 2021). This shows the great influence of Bitcoin and Ethereum. An article by Shabana (2021) reports the popularity between entrepreneurs and developers is high for Ethereum. This is because Ethereum is utilized by many varieties such as SCM (Supply-Chain-Management), decentralized registrations and democratised crowdfunding. Ethereum has reduced the costs and produces secured products and services, which has increased the demand for Ethereum, hence raising its value (Shabana, 2021). Ultimately, I can conclude that the value of Ethereum is not dependant on other coins, but rather the product it provides for the consumers.

Although, the comparison graph in Figure_3 showed that Ethereum tends to follow a similar path to Bitcoin, but with a small delay, I have found that there is no causal relationship between the two, which was against the predictions I made. I had previously believed that Bitcoin should Granger cause Ethereum, however, no such evidence was present from my results. This is also against the findings of Leatham et al., (2019), as they found that Bitcoin and Litecoin both granger cause Ethereum. Not only does no coin Granger cause Ethereum, but I also found that Ethereum Granger causes XRP and Litecoin.

XRP is discovered to be Granger caused by all coins, which verifies the aim of this paper, that there is indeed a short-run relationship between Bitcoin and altcoins. XRP is owned by the Ripple company, and the company itself holds 60% of the total coins (Todd, 2015). This could suggest why XRP is granger caused by Bitcoin and Ethereum and not vice versa, because XRP is still centralised and the control is within the company itself, whereas Bitcoin and Ethereum have shared the “control” freely among people.

In the case of Litecoin, I also find that it is a Granger caused by all of the altcoins. Bitcoin has the strongest relationship with Litecoin, and this should not surprise anyone. As previously explained, Charlie Lee has created Litecoin as complementary to Bitcoin and not for competition (Danial, 2019). Also, from Figure_6, the trend lines illustrated that Litecoin follows a similar path to Bitcoin. Therefore, the predictions made held true that Bitcoin has a strong impact on Litecoin.
Figure_10 compares the findings of the short-run relationship between this paper and Leatham et al., (2019). With the differences that have been previously discussed in red and orange arrows. However, this paper covers 730 more data points, which is also more recent, therefore more accurate answers, which could be why the relationships slightly differ.

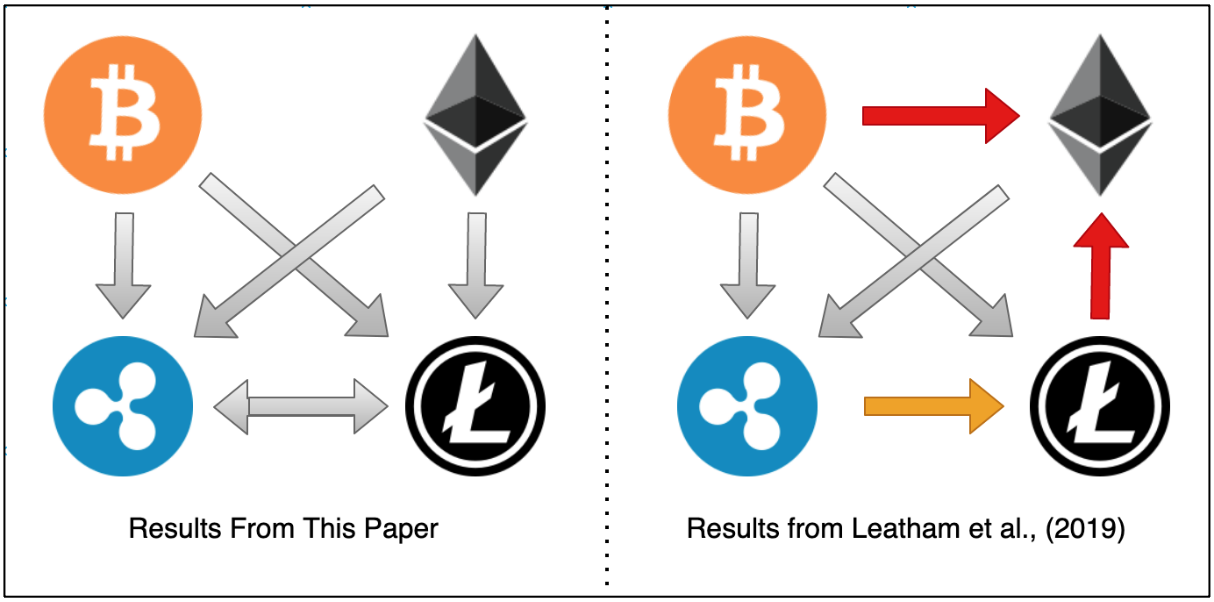

Figure 10: Short-Run Relationship Comparison of Two Different Papers (Diagrams.net, 2021)

5.4 Impulse Response Function Discussion

The graph in Figure_9 visually illustrated and supported the act that there is a relationship between Bitcoin and Altcoins. The graph for Bitcoin showed that Bitcoin does cause a negative response in all three coins, which is in line with the findings of t-statistic. In t-statistic tests, I discovered that different lags of Bitcoin have an impact on different coins, and similar results are found in this section. Although the Granger Causality test suggested there will not be any causal effect from Bitcoin on Ethereum, in this part, we find otherwise. The negative impact caused by Bitcoin is greater than any other digital currency. This is probably because of the high credibility and trustworthy network that Bitcoin has. Ting (2017) argues that the large Bitcoin has a large community and there are sufficient resources available for investors to learn about it. This could be another push factor that Bitcoin has a large impact on altcoins.

Figure_9 also showed that Ethereum has an impact on Litecoin and XRP, which is again in line with the previous findings in the Granger Causality test. However, I find that Ethereum does not have the same impact as Bitcoin. This might be because that there is a certain number of Bitcoins available in the market, whereas, Ethereum does not have a Maximum Supply. Ting (2017) believes that the value of Ether depends on the future success of Ethereum and there is no guarantee that Ethereum would stay ahead of competition from future blockchains projects, for example, the NEM Project.

Finally, the responses of altcoins to a shock from either XRP or Litecoin are very small and insignificant from Bitcoin and Ethereum. A shock in either XRP or Litecoin causes an impact on each other, however, the changes are very small, but they are in line with the findings of Granger Causality tests, shown in Figure_10. Given that Litecoin does not introduce much creativity to the digital currency, there is no surprise that it is easily impacted by Altcoins.

The most important finding in this section is the movement of orthogonalized irf lines after step 6. The irf line tends to stabilise and return the shocks tend to “die” out and eventually stabilise. Therefore, it can be suggested that the irf graphs support the findings from the

Johannsen Cointegration test. This is because, had there been a cointegration vector present, at least one of these lines (from the 16 graphs present) should have continued to move back to where it started or move in an opposite direction. For example, I can see that in the top right corner, a shock from Bitcoin to XRP causes a negative impact to XRP initially, however, XRP stabilises after the 6th step and remains constant. Another example would be to examine the shock caused by Ethereum to Litecoin. Initially, Litecoin shows a small negative response, but after the 6th step, Litecoin is constant and there is no long-run relationship present. These studies are in line with the findings of Demir et al., (2021), Ciaian et al., (2018), Leatham et al., (2019) and Demira et al., (2018).

6.0 Implication for Investors

As a result of research and analysis of the current empirical study, I will offer the following scheme of suggestions. There is still a high degree of uncertainty and concern on cryptocurrency, globally, but the investors should take a stand on Bitcoin and Altcoins. Although there are many unanswered questions such as how to treat cryptocurrency, and under what asset class? Is there taxation under gains from profession or business? These are a few concerns that the investors have. Market participants should take cryptocurrency investments seriously as the yield return by cryptos can be high.

6.1 Investment in Cryptocurrency

As a result of research and analysis of the current empirical study, I will offer the following scheme of suggestions. There is still a high degree of uncertainty and concern on cryptocurrency, globally, but the investors should take a stand on Bitcoin and Altcoins. Although there are many unanswered questions such as how to treat cryptocurrency, and under what asset class? Is there taxation under gains from profession or business? These are a few the concerns that the investors have. Market participants should take cryptocurrency investments seriously as the yield return by cryptos can be high.

Given the amount of attention, time and effort given to digital currencies, it appears obvious that it can significantly have an effect in many industries ranging from healthcare and utilities to manufacturing and finance. Sathyanarayana and Gargesa (2019) estimate that blockchain will raise approximately $350 Billion of economic value by 2027. On the other hand, many companies, institutions and countries are now working harder than ever to obtain this intangible asset.

This paper attempted to issue empirical support on cryptocurrency, which could potentially become a new currency that is attached to a decentralised system. Mitchelhill (2021) argues that there is no clear theory explaining how cryptocurrencies must be priced as it produces no earning, dividends, or cash flow. Based on the research papers such as Urquhart (2018), the popularity of Bitcoin is a key driver behind Bitcoin price determination. Sinclair (2020) and Urquhart (2018) find that the price of Bitcoin (and hence altcoins) tends to increase when the number of people researching the topic on Google increases.

Cryptocurrencies, such as Bitcoin can reduce the standard deviation of a portfolio. For example, during the pandemic, it was discovered that crypto does not have any correlation with other stocks. Mariana et al., (2021) have found that the daily returns of Bitcoin and Ethereum negatively correlate with the S&P500 returns. Mariana et al., (2019) also argue that Ethereum is even a safer haven than Bitcoin for a short-term investment. Another study by Vukovic et al., (2020) also shows that Covid-19 had no impact on the cryptocurrency market. This suggests that there is therefore no correlation between the pandemic and cryptocurrency. Hence, it can be suggested that cryptocurrencies are a "safe haven" and can be used to diversify a portfolio.

Unlike the findings of this paper, Sifat et al., (2019) believe that Ethereum and Bitcoin show a bi-directional causality among them. On the other hand, they suggest that daily traders will not be able to exploit the daily or hourly price discovery.

Massad (2019), believes there is a big gap in crypto-assets regulation, especially in trading and distributing cryptocurrencies. He believes that not only the dependency of intermediaries has not been eliminated, but also given rise to new large financial intermediaries, who are not competent. These institutions have been frequently targeted by cyber-attacks and many of which have been successful.

Given the discussions made above, an investor should give a portion of its portfolio to cryptocurrency. Given the potentials discussed, the negative correlation of crypto with the stock market investors should at least consider it, however, be very cautious with the unknown technology behind it. It is also important that investors be aware of their behaviour and biases when there are fluctuations as there are extreme volatilities in the cryptocurrency market.

6.2 Top Cryptocurrency Investment Coins

Through this paper and online journals, I recommend that Ethereum, followed by Litecoin, Bitcoin and then XRP have great potential for investors, in that order.

Ethereum has the greatest potential from the coins examined. Ethereum offers smart contracts and other applications which makes it popular among program developers (Schmidt and Tretina, 2021). Ethereum has grown over 27,000% in the past 5 years, and I believe it will continue to do so. Ethers will always be needed to execute code on Ethereum, and most projects nowadays are built on top of Ethereum, which makes it the best long-term potential cryptocurrencies. Ethereum aims to take full advantage of the entirety of blockchain technology. Ethereum is has become a major tool for entrepreneurs and developers, and based on this demand, Jane (2018) argues.

Additionally, I found that Ethereum can influence its own price by enhancing its system. Unlike the predictions made, Ethereum does not get impacted by altcoins at all. Conclusively, I recommend that Ethereum will be more important in future, and hence the largest portion of a portfolio should be devoted to Ethereum.

Bitcoin is the most well-known and established cryptocurrency. However, Bitcoin has a high transaction fee and scaling problem: As average block mining time is 10 minutes and blocks in bitcoin are limited to 1MB in size, which allows only 3 transactions per second, the number of transactions to be mined raises incredibly. Transaction fee thus increases while miners are prioritizing transactions with a higher fee (Jane, 2018). Given that there are 21 million Bitcoins available, there are concerns over the regulations. We have discussed that financial intermediaries can be hacked, and money lost or stolen cannot be replaced.

Furthermore, Bitcoin is still following an overall upward trend since its beginning. Bitcoin still has more impact than any other digital currency, hence given that influence, Bitcoin is one of the most important cryptos. I found that Bitcoin is not influenced by altcoins and rather by macroeconomic factors. Hence to be a successful Bitcoin investor, one should constantly monitor the news. Bitcoin has more than double the market cap of Ethereum and in just five years, it has experienced over 8,900% growth in value (Schmidt and Tretina, 2021). Given these discussions, I would recommend that the second most important crypto is Bitcoin.

Although the experts from Forbes Advisor, (Schmidt and Tretina, 2021), do not include Litecoin in their top ten cryptocurrencies, I believe otherwise. In this paper and other research papers, I found that Bitcoin, Ethereum and XRP all have a causal impact on Litecoin. This creates an excellent opportunity for investors. The relationship between Litecoin and altcoins can be studied, and depending on the direction of trend lines, investors can either invest or cash out. The relationship as we found out was the greatest with Bitcoin, therefore, by holding a close eye on Bitcoin, one should be able to generate returns. I do not believe, however, that the speed of the transaction or the value of Litecoin has any impact on the consumers to use this currency, and it is certainly not enough to compete with the new coins. The important aspect of this coin is its strong relationship with Bitcoin.

The value of XRP has risen 19,000% over the past five years (Schmidt and Tretina, 2021). XRP has shown that it can be impacted by all the other three coins that were experimented within this paper. Therefore, given the influence that it takes from altcoins, traders should keep an eye on this coin. By utilising the relationship between Altcoin and XRP, investors can generate a larger Alpha for their portfolios. For example, once there is a shock in Bitcoin price, investors can capitalise on that, and depending on the direction that Bitcoin is moving towards, one can immediately invest in XRP. Given that XRP is a different form of cryptocurrency, as it is controlled by the Ripple company, it can be beneficial to a portfolio. However, this is also the downfall of XRP, since a small number of individuals hold a large share and can easily manipulate the price. Therefore, I would recommend a very small portion (5%<) of a cryptocurrency portfolio to be devoted to XRP.

6.3 Investment Strategy

Assuming an investor is keen on investing in cryptocurrencies, it can be recommended that they should diversify their portfolio using the Modern portfolio theory (MPT), developed by Harry Markowitz or more advanced model Post-Modern Portfolio Theory (PMPT). This method reduces the volatility and level of risks to a portfolio by choosing uncorrelated stocks/cryptocurrencies. Mariana et al., (2021) had previously discovered that cryptocurrencies are uncorrelated with the stock market, hence MPT can be utilised to create what is known as Efficient Frontier. This method generates a portfolio that provides the lowest possible risk with optimum return. This may be a long-term strategy.

However, for active traders, the Johansen cointegration and VAR test showed that there is a short-run relationship between Bitcoin and Altcoins. Hence they can exploit the relationship.

For example, by following the Bitcoin news and trend lines, one can predict the movement of XRP in the near future. Similarly, by studying the Ethereum price movement, one can forecast the Litecoin price. However, I would not recommend using the XRP or Litecoin prices to forecast altcoins, simply because as I found there are small and insignificant causal effects from these coins onto others.

6.4 Further Investment Recommendation

A further mathematical model should be developed with more digital currencies. This would probably increase the likelihood of finding new cryptocurrencies that have interconnection with each other and therefore, increasing the likelihood of better analysis. The time series was limited to a 5-year period, which can be increased in the next research paper. Thus, more reliable datasets can shed more light on the feasibility of the test. However, this can be challenging since there are many new cryptocurrencies in the market which can cause an issue when experimenting with their long-run relationship analysis especially.

Cryptocurrency and Blockchain are complex topics that require more resources and time to be fully understood. Further analysis of the relationship between Cryptocurrencies and macroeconomic factors will certainly help the investors better understand the cryptocurrency market and should enable them to make firm decisions.

6.0 Conclusion

Crypto is digital cash that enables people to transmit value in a digital setting. The interest in the crypto market has been growing over recent years with many countries and even countries investing in this asset. The main objective of this paper is to find any relationship between Bitcoin and Altcoins. I found that there is strong evidence for the relationship between Bitcoin and Altcoin cryptocurrencies. I analysed both short-term and long-term relationships of coins and what this would mean to investors.

The examination is based on Bitcoin and its relationship with three altcoins where investors have shown the highest interest. These coins include Ethereum, XRP and Litecoin, and the time period for the time series was from July 2016 to July 2021. As the data was integrated at first order, Johansen Cointegration test, VAR and VECM models were developed in this paper and Impulse Response Function was employed to draw a conclusion. From an investor or traders' point of view, this paper can be useful to forecast and analyse the crypto market.

This paper suggests that there is a strong short-run relationship between Bitcoin and Altcoins, and Altcoins with each other. From the tests, I found that Bitcoin and Ethereum prices can be used to forecast XRP and Litecoin prices, and XRP and Litecoin prices can be analysed to predict each other. However, Bitcoin and Ethereum are not impacted by any other digital currencies. The method proved to be successful as the autocorrelation was absent in the Lagrange-multiplier test. On the other hand, I found the absence of any long-run relationships between Bitcoin with Altcoins, and any of the coins together. By further studies of different research papers, it can be suggested that Bitcoin and Altcoin prices are more likely to be affected by macroeconomic factors. These can include any influential fiscal, geopolitical, or natural event.

Based on the results of this paper I have offered a recommendation that investors should include cryptocurrency in their portfolio. Cryptocurrency has a great potential to impact different industries ranging from healthcare and utilities to manufacturing and finance. This is especially true for Ethereum as it offers smart contracts and other applications which makes it popular among program developers. I also advise investors to make use of diversification, MPT and the short-run relationship between Bitcoin and Altcoins to invest safely in the market, and further study the macroeconomic factors.

Word Count: 14,700

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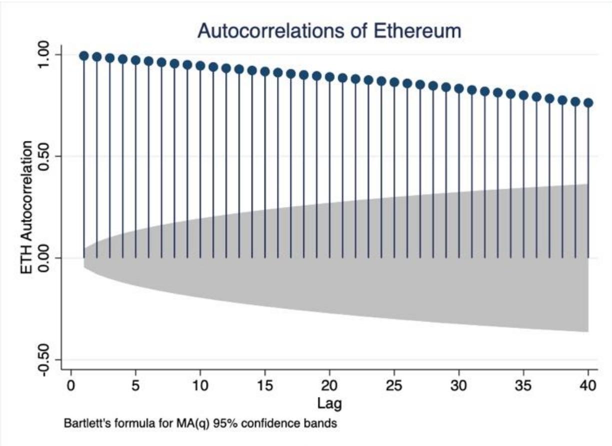
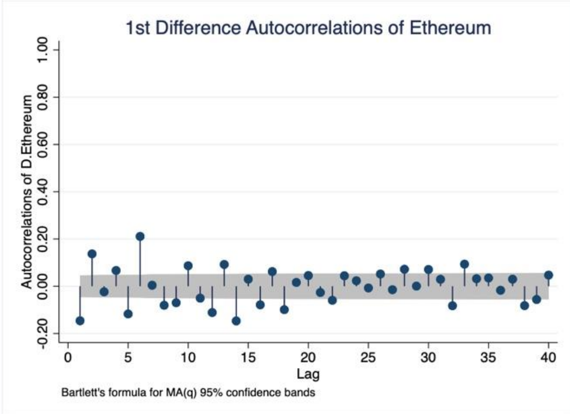
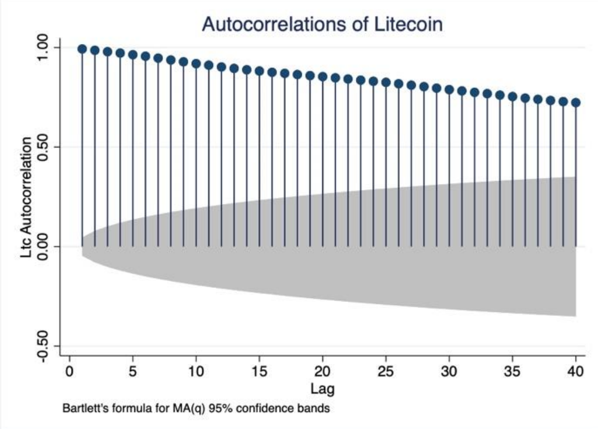
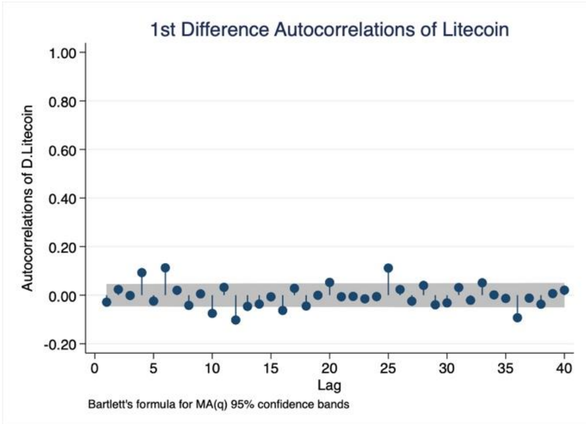
8.0 Appendices

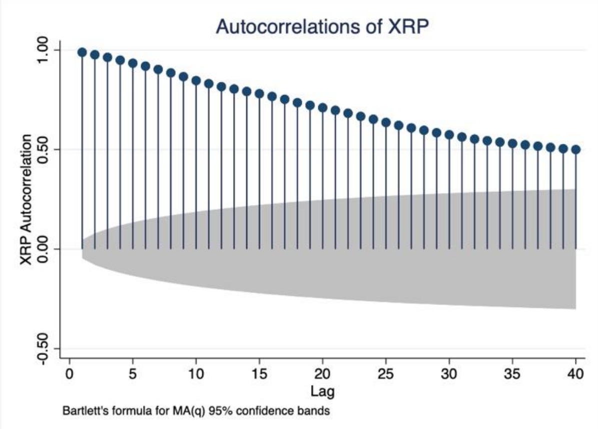
8.1 Appendix A: Autocorrelation of Time Series

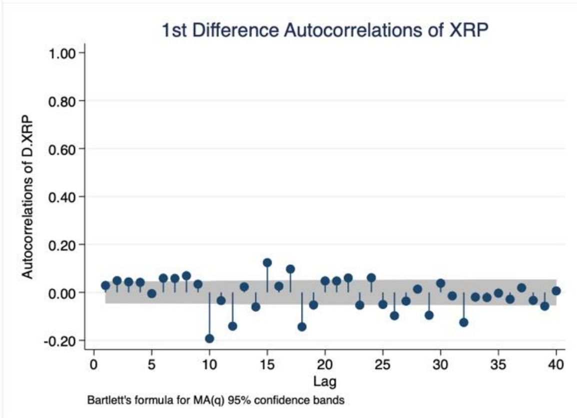












8.2 Appendix B: VAR Results

Table 9: VAR Results

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
BtclogRtn						
BtclogRtn						
L1.	0.0526382	0.034804	1.51	0.13	-0.015577	0.1208532
L2.	0.0028111	0.034955	0.08	0.94	-0.065698	0.0713206
L3.	0.0418226	0.034864	1.2	0.23	-0.026509	0.1101547
L4.	-0.091607	0.034937	-2.6	0.01	-0.160082	-0.023132
L5.	0.060929	0.034939	1.74	0.08	-0.007549	0.1294075
L6.	0.0079252	0.035078	0.23	0.82	-0.060827	0.0766772
EthlogRtn						
L1.	-0.063119	0.025064	-2.5	0.01	-0.112244	-0.013994
L2.	0.0262331	0.02511	1.04	0.3	-0.022981	0.0754476
L3.	-0.031436	0.025026	-1.3	0.21	-0.080486	0.0176141
L4.	0.0176814	0.025037	0.71	0.48	-0.031391	0.0667539
L5.	-0.032291	0.025071	-1.3	0.2	-0.081429	0.016848
L6.	0.0079	0.025054	0.32	0.75	-0.041205	0.0570044
XrplogRtn						
L1.	-0.028024	0.015516	-1.8	0.07	-0.058436	0.0023872
L2.	0.0183886	0.015429	1.19	0.23	-0.011852	0.0486295
L3.	0.0066674	0.015462	0.43	0.67	-0.023637	0.0369715
L4.	0.0024704	0.015343	0.16	0.87	-0.027601	0.0325417
L5.	-0.0095	0.015253	-0.6	0.53	-0.039395	0.0203958
L6.	0.0167376	0.015254	1.1	0.27	-0.013159	0.0466338
LtclogRtn						
L1.	-0.003415	0.024647	-0.1	0.89	-0.051721	0.0448918
L2.	-0.008181	0.024526	-0.3	0.74	-0.05625	0.0398884
L3.	-0.005934	0.024483	-0.2	0.81	-0.053921	0.0420524
L4.	0.0781874	0.024808	3.15	0	0.0295655	0.1268092
L5.	0.007705	0.024807	0.31	0.76	-0.040917	0.0563265
L6.	0.0144036	0.024871	0.58	0.56	-0.034342	0.0631492
_cons	0.2065679	0.09662	2.14	0.03	0.0171968	0.395939

EthlogRtn						
BtclogRtn						
L1.	-0.029693	0.047776	-0.6	0.53	-0.123332	0.0639452
L2.	0.0508377	0.047982	1.06	0.29	-0.043205	0.1448805
L3.	-0.00604	0.047858	-0.1	0.9	-0.099839	0.087759
L4.	0.0035294	0.047958	0.07	0.94	-0.090466	0.097525
L5.	0.0965366	0.04796	2.01	0.04	0.0025364	0.1905367
L6.	-0.037016	0.048152	-0.8	0.44	-0.131392	0.0573593
EthlogRtn						
L1.	-0.025992	0.034406	-0.8	0.45	-0.093426	0.0414418
L2.	0.0406678	0.034468	1.18	0.24	-0.026889	0.1082243
L3.	0.0324858	0.034353	0.95	0.34	-0.034845	0.0998168
L4.	0.0341845	0.034369	0.99	0.32	-0.033177	0.101546
L5.	0.0037469	0.034415	0.11	0.91	-0.063705	0.0711992
L6.	0.0565235	0.034391	1.64	0.1	-0.010882	0.123929
XrplogRtn						
L1.	-0.051693	0.021299	-2.4	0.02	-0.093439	-0.009947
L2.	-0.011855	0.02118	-0.6	0.58	-0.053366	0.0296571
L3.	0.0291527	0.021224	1.37	0.17	-0.012446	0.0707511
L4.	-0.007849	0.021061	-0.4	0.71	-0.049128	0.0334298
L5.	0.0083325	0.020938	0.4	0.69	-0.032705	0.0493699
L6.	0.0423202	0.020938	2.02	0.04	0.0012817	0.0833586
LtclogRtn						
L1.	0.0517628	0.033832	1.53	0.13	-0.014548	0.1180731
L2.	-0.011855	0.033666	-0.4	0.73	-0.077839	0.0541294
L3.	-0.044981	0.033608	-1.3	0.18	-0.110853	0.0208896
L4.	0.0089932	0.034053	0.26	0.79	-0.05775	0.0757363
L5.	-0.039457	0.034053	-1.2	0.25	-0.106199	0.0272861
L6.	0.0088417	0.03414	0.26	0.8	-0.058071	0.0757547
_cons	0.2403904	0.13263	1.81	0.07	-0.019559	0.5003395
XrplogRtn						
BtclogRtn						
L1.	-0.158984	0.062277	-2.6	0.01	-0.281044	-0.036923
L2.	0.0131111	0.062546	0.21	0.83	-0.109476	0.1356984
L3.	-0.167073	0.062384	-2.7	0.01	-0.289342	-0.044803

L4.	-0.073138	0.062514	-1.2	0.24	-0.195664	0.049388
L5.	-0.085449	0.062517	-1.4	0.17	-0.207981	0.0370826
L6.	0.1186186	0.062767	1.89	0.06	-0.004403	0.2416399
EthlogRtn						
L1.	0.0359031	0.044849	0.8	0.42	-0.051999	0.1238051
L2.	0.0197213	0.04493	0.44	0.66	-0.068341	0.1077831
L3.	-0.089121	0.04478	-2	0.05	-0.176889	-0.001353
L4.	0.1244628	0.044801	2.78	0.01	0.0366551	0.2122704
L5.	-0.077926	0.044861	-1.7	0.08	-0.165852	0.0100003
L6.	-0.03894	0.04483	-0.9	0.39	-0.126805	0.0489249
XrplogRtn						
L1.	-0.032403	0.027764	-1.2	0.24	-0.08682	0.0220137
L2.	0.0524005	0.027608	1.9	0.06	-0.001711	0.106512
L3.	0.0034737	0.027666	0.13	0.9	-0.050751	0.0576983
L4.	-0.018626	0.027454	-0.7	0.5	-0.072434	0.035182
L5.	0.059717	0.027293	2.19	0.03	0.0062237	0.1132102
L6.	0.0298561	0.027294	1.09	0.27	-0.023639	0.0833509
LtclogRtn						
L1.	0.0823057	0.044102	1.87	0.06	-0.004132	0.168743
L2.	0.0235914	0.043885	0.54	0.59	-0.062421	0.1096039
L3.	0.2775709	0.043809	6.34	0	0.1917061	0.3634356
L4.	-0.021303	0.044389	-0.5	0.63	-0.108305	0.065698
L5.	0.089176	0.044389	2.01	0.05	0.0021752	0.1761769
L6.	-0.03439	0.044502	-0.8	0.44	-0.121613	0.0528332
_cons	0.2342048	0.172886	1.35	0.18	-0.104646	0.5730556
LtclogRtn						
BtclogRtn						
L1.	0.0201871	0.049886	0.4	0.69	-0.077588	0.1179624
L2.	0.0705058	0.050102	1.41	0.16	-0.027692	0.1687032
L3.	0.0250158	0.049972	0.5	0.62	-0.072927	0.1229589
L4.	-0.086615	0.050077	-1.7	0.08	-0.184763	0.0115329
L5.	0.2096046	0.050079	4.19	0	0.1114517	0.3077574
L6.	-0.076186	0.050279	-1.5	0.13	-0.174731	0.0223595
EthlogRtn						

L1.	-0.074427	0.035926	-2.1	0.04	-0.14484	-0.004014
L2.	0.0091151	0.035991	0.25	0.8	-0.061426	0.0796562
L3.	-0.064242	0.035871	-1.8	0.07	-0.134548	0.0060636
L4.	0.018075	0.035887	0.5	0.61	-0.052262	0.0884124
L5.	-0.066789	0.035935	-1.9	0.06	-0.137222	0.0036429
L6.	0.0922896	0.035911	2.57	0.01	0.0219062	0.162673
XrplogRtn						
L1.	-0.021976	0.02224	-1	0.32	-0.065566	0.0216139
L2.	-0.028022	0.022115	-1.3	0.21	-0.071367	0.0153237
L3.	0.0789551	0.022162	3.56	0	0.0355191	0.1223911
L4.	-0.007579	0.021991	-0.3	0.73	-0.050681	0.0355235
L5.	-0.026942	0.021863	-1.2	0.22	-0.069792	0.0159087
L6.	0.0310482	0.021863	1.42	0.16	-0.011803	0.0738996
LtclogRtn						
L1.	0.0418663	0.035327	1.19	0.24	-0.027374	0.111106
L2.	-0.008888	0.035153	-0.3	0.8	-0.077788	0.0600113
L3.	-0.025824	0.035093	-0.7	0.46	-0.094605	0.0429574
L4.	0.1060592	0.035558	2.98	0	0.0363676	0.1757508
L5.	-0.051875	0.035557	-1.5	0.15	-0.121566	0.0178164
L6.	0.033497	0.035648	0.94	0.35	-0.036372	0.103366
_cons	0.1600935	0.138489	1.16	0.25	-0.11134	0.4315266