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Long Term Comovement among Cryptocurrencies: an Application of Cointegration Analysis

by

Shiza Siddiqui

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Dedicated to the people I love and admire...My Parents.

CERTIFICATE OF APPROVAL

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Abstract

The purpose of this study is to examine the long term relationship among the ten cryptocurrencies namely, Bitcoin, Ripple, Litecoin, Bitshare, Monero, Dash, Dogecoin, Byte coin, Digibyte and Monacoin selected on the basis of market capitalization and time frame available. The study employs historical daily prices of cryptocurrencies for the period of August 01, 2014 to September 30, 2019. Johansen cointegration method is used to explore the long-run relationship and Vector Error Correction Model (VECM) is used to examine the speed of adjustment of disequilibrium and short term relationship. The findings from trace and maximum eigenvalue statistics suggest that cryptocurrencies are cointegrated. The results of VECM reveal the presence of relationship among various cryptocurrencies in the short-run. This study also shed light on the adjustment speed of the above mentioned cryptocurrencies by using Error Correction Model. Error correction model suggest that six out of ten cryptocurrencies namely BTC, XMR, XRP, MONA, DGB and BCN indicate that co-integrated series converge at long run equilibrium at adjustment speed of 0.4%, 0.9%, 1.7%, 1.1%, 1.8% and 2.6% respectively. To study the lead lag relationship Granger Causality test is applied. Granger Causality test finds significant causality at the 5 percent significance level that the Bitcoin's daily returns Granger causes of the dash's daily returns, and so on. The study provides information to crypto market investors for allocation of assets and risk diversification. It also provides the crypto-investors an insight about the long term comovement of cryptocurrencies.

Keywords: Cryptocurrency, Multivariate Cointegration, Johansen's Test, Vector Error Correction Model (VECM), Lead Lag Relationship, Granger Causality Test, Adjustment Speed, Error Correction Model

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Abbreviations

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroscedasticity
ARDL	Autoregressive Distributed Lag
BEKK	Baba, Engle, Kraft and Kroner
FBI	Federal Bureau of Investigation
FinCEN	Financial Crimes Enforcement Networks
FPE	Final Prediction Error
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
HQ	Hannan-Quinn Information Criterion
PP	Phillips-Perron
SC	Schwarz Information Criterion
SEC	Security Exchange Commision
VAR	Vector Autoregression
VECM	Vector Error Correction Model

Chapter 1

Introduction

Cryptocurrency is a computerized resource intended to function as a mode of trade utilizing cryptography to verify the exchanges and to control the production of extra units of the cash (Greenberg, 2011). Another definition of cryptocurrency is "Cryptocurrency is a form of digital / virtual currency which utilizes cryptography for security purposes and it is one of the new technological innovations advancements" (Monterio, 2014). Cryptocurrencies are like virtual, digital and alternative currencies. The most unique distinction among cryptocurrencies and traditional flat currencies seems to be that the former creates a new shared system of payment built on cryptographic protocols that can assure peer-to-peer transfers are secure, low cost, and quick. Another characteristic of cryptocurrencies is their use as a virtual trading system or simply stated, they are virtual currency used for the purchase and sale of goods and services with payment made through the crypto-wallet (Monterio, 2014). These are not protected by any regulatory bodies that separate cryptocurrencies from other fiat currencies and gold (Sontakke & Ghaisas, 2017). In past years, amongst the more experienced speculators, cryptographic types of money are now an interesting area of research.

Money is generally used as a means of exchange, legal tender for debt repayment, cost equivalent, accounting unit and a means of investing and retaining buying power (Phillips & Gorse, 2018). Bitcoin might not perform all functionalities of money, however its scarcity value, secrecy (or pseudonymity), limpidity and government autonomy make it more appealing to users who are disillusioned with fiat money, speculators, dealers, retailers and customers (Kam, 2017). Given the popularity of blockchain, it is not protected from future abuses such as cyber terrorism, tax fraud, corruption, digital black markets, money laundering and terrorist financing (Sánchez, 2017).

1.1 Theoretical Background

Digital currency serves as another wonder on worldwide money related markets. By giving an elective cash and venture opportunity, they work outside incorporated monetary foundations. While offering a more affordable option in contrast to standard monetary standards as far as exchange costs, the costs of virtual monetary standards are growing impressively more sporadically and changes are more extensive than conventional currencies (Bouoiyour, Selmi, & Tiwari, 2014; Ciaian, Rajcaniova, & Kancs, 2016).

Bitcoin without doubt is the most prevalent digital currency with Market Capitalisation at present being worth US 144 billion (coinmarketcap.com). Bitcoin is the principal decentralized record money. Since its initiation in 2009 as a digital currency, the growth of cryptocurrency market has increased. Bitcoin keeps on being the most generally utilized virtual money and is the largest regarding the market esteem.

Bitcoin has directly inspired the new altcoin crop, and the enthusiasm around Bitcoin frames the altcoins marketplace participant's hopes and desires. The achievement of Bitcoin has prompted the rise of numerous digital currencies, such as Litecoin, Bitshare, Ripple, Monero, Dash, Dogecoin, Bytecoin, Digibyte, Monacoin and a lot more. The greater part of altcoins depend on the equivalent or comparative blockchain innovation as Bitcoin, and plan to either supplement or strengthen certain Bitcoin attributes. Many altcoins, however, reflect only minor changes to Bitcoin's source code (Krafft, Della Penna, & Pentland, 2018). For instance, Bytecoin is one of the oldest created digital currencies. With a comparable working coin, the Bytecoin group is attempting to enhance a considerable lot of the issues that have surfaced inside bitcoin explicitly the one's encompassing security, Litecoin seeks to save the computing energy that coin mining requires, Dash seeks at quicker transaction processing and provides improved protection of privacy, Bitshares and Ethereum provide extra characteristics to operate smart contracts, such as a digital platform, Ripple is based upon a dispersed open source convention and promotes fiat currency, cryptocurrency, or other value units such as regular flier miles or mobile minutes, Dogecoin is based on scrypt (for example in view of a secret key) and empowers quick installments to anybody, anyplace over the globe, Digibytes are computerized resources that can't be demolished, hacked or forged, making them perfect for ensuring objects of significant worth like money, data, property or significant advanced information. Regardless of the equivalently high market unpredictability, there is minimal thought about their value development systems and altcoin interdependencies with the Bitcoin advertise.

There are excellent reasons to think that the prices of Bitcoin and altcoin might be reliant, Since Bitcoin is the prevalent virtual currency and there are comparable patterns in Bitcoin and altcoin price trends and a significant majority of altcoin purchases in Bitcoins. Halaburda and Gandal (2016) analyse the effect of network effects on the six altcoin markets and Bitcoin and identify heterogeneous price conduct after some time. The findings indicate that Bitcoin has powerful network effects against altcoins, which induced differences in prices between them.

Volatility has been conventional in the cryptocurrency market since its initiation. Unpredictability is highly influential for the financial specialists when putting their resources in the cryptocurrency market. The cryptocurrency market is a highly volatile market that can have both favourable and unfavourable consequences for the investors. Cryptocurrency market is likely to originate huge amount of gain but also have the possibility to deprive the investor from its capital. So, Volatility is an important part of crypto market. The great collision in 2018 is a stiff experience in crypto currency market on the uttermost volatility of cryptocurrency. Since last year there is a strenuously fluctuation in prices of cryptocurrency. Crypto currency is seen as a complicated, turbulent and discerning technology that has made many of people rich. So, it is therefore not astonished that many investors are attached to the volatility and risk of cryptocurrencies. The objective of digital currencies is to give a decentralized option in contrast to current types of cash, and a centre part in getting that going is to accomplish standard selection. This involves the boundless utilization of digital forms of money as a vehicle of trade for basic products and enterprises. It could along these lines be set up that retail appropriation is the principle driver for standard acknowledgment. The essential obstruction is the scandalous instability of the digital money showcase; it is hard for retailers to acknowledge, and for buyers to spend, in an atmosphere that sees costs spike so drastically.

In 2017, utilization of cryptographic forms of money has expanded drastically. Individuals are "contributing" tremendous aggregates of cash into "resources" that have no history of creating income, and those benefits are ascending in cost simply because other individuals are likewise consuming cash into them. Billions of dollars have been filled in excess of 1,000 new computerized coins given by new businesses in 2017. These coins copy the development of Bitcoin, which means they can be uninhibitedly exchanged on advanced trades and have no national bank remaining behind them. This has brought up numerous questions and issues about present and eventual fate of decentralized cryptographic forms of money. There are two noteworthy perspectives about digital currency. One side contends that it is an air pocket with no genuine resources that unavoidably will end with burst. The opposite side opines that cryptographic money markets will turn into a road that will offer a huge number of individuals a chance to partake in a worldwide monetary system worth several trillions of dollars. From youthful twenty to thirty year olds in creating countries with little investment funds and huge desire to mother and-pop entrepreneurs looking to reinvest a few benefits in promising crypto-ventures, these sorts of individuals will be the foundation of this industry. There is broad agreement that the cryptocurrencies would influence not only the trade activities of various countries and business groups, but also the complexities of international relations. There are still many individuals who never get the notion that cryptocurrencies will transfigure the way we do business. They cannot find out how the entire technology of blockchain and other annexes operates. Moreover, technological advances introduce digital tools that businesses can use to interact better with their clients. A growing shift from classical systems to digital platforms has also resulted in an abundance of data from sources such as social networks, portable devices, online shopping platforms, etc. Because of advances in technology in the fields of data collection, storage and distribution, large data sets are easily transferred among businesses in each sector or country for little to no charge. Data's widespread accessibility has also raised concerns about individual's data privacy and their online payments. Since every online activities or transaction ends up leaving a digital footprint, people choose more anonymous methods of using the internet and conducting online transactions. The Bitcoin cryptocurrency has been launched to address the privacy issue.

Even though the decentralization of cryptocurrencies, transaction anonymity and payment's irreversibility offer many benefits, (Brill & Keene, 2014) are of the opinion that these attributes also encourage illegal acts (cybercrime) such as laundering money, drug trafficking, weapons procurement and smuggling. This problem has caught the attention of prominent regulatory agencies as well as other government agencies including the Financial Crimes Enforcement Networks (FinCEN). Economics professor Kenneth Rogoff argues that Bitcoin will never replace cash issued by the government because it "will make collecting taxes and combating criminal activity extremely difficult".

Cryptographic forms of money are likely the most unpredictable resource in presence today. Along with here exists long-run relationships between many variables of interest. Then the point behind cointegration is the recognition and investigation of long run connections among financial time series factors. Ciaian et al. (2016) use an Autoregressive Distributed Lag model to study interdependencies between Bitcoin and other cryptocurrencies and discover that Bitcoin and other cryptocurrencies, such as Ether, are mutually dependent. Recently, a study is conducted in the background of Fractional integration and cointegration by (Yaya, Ogbonna, & Olubusoye, 2019), this study explores Bitcoin's persistence and reliance on other common alternative coins. In their persista-nce assessment, it uses a fractional integration strategy and the fractional cointegration method suggested by Johansen in the VAR set-up to explore the dependency of the combined factors. The study of Yaya et al. (2019) considers Bitcoin's crash period and finds higher persistency of shocks in the minds of digital currency dealers are anticipated after the crash. Analysis of cointegration among alternative currency and Bitcoin occurs during both phases with poor correlation is mostly found after the crash. Several studies have revealed the bitcoin price relationship with economic variables. Su, Li, Tao, and Si (2018), reveals that four bursting bubbles occurred in the U.S. market and China during phases of massive increases in bitcoin prices. Earlier, a study examines the ability to diversify seven cryptocurrencies with the highest market size against economic risk variables such as price of gold, crude prices, rate of interest, Dollar strength and S & P 500. Using weekly data of Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash and Bytecoin from August 2014 to June 2018. The study reports that each cryptocurrency has structural splits and ARCH fluctuations, indicating a systematic risk on the digital currency market and cryptocurrencies have negligible financial correlations (Canh, Binh, & Thanh, 2019).

1.2 Gap Analysis

Many studies have been conducted on cryptocurrencies being an emergent assets class. Katsiampa (2017) gauges the instability of Bitcoin through a correlation of GARCH models and finds that the AR-CGARCH model gives the most ideal fit. Katsiampa (2019a) estimates the Co-movement in volatility between Bitcoin and Ether by using a diagonal BEKK model and provides evidence of cryptocurrency market interdependencies. However, study of Katsiampa (2019b) is restricted to just two leading crypto currencies (Bitcoin and Ether). Interestingly, another research study of (Katsiampa, 2019b) is conducted to investigate volatility dynamics in the cryptocurrency market by utilizing a BEKK model; this paper looks at unpredictability elements of five noteworthy cryptographic forms of money, in particular Bitcoin, Ether, Ripple, Litecoin and Stellar. Nevertheless, Long term comovement among major cryptocurrencies i.e., Bitcoin, Ripple, Litecoin, Bitshare, Monero, Dash, Dogecoin, Byte Coin, Digibyte and Monacoin through the application of cointegration analysis has not been studied yet. Furthermore, study of (Katsiampa, 2019b) does not address returns but this study investigates the relationship of prices too.

The current literature in the area of cryptocurrencies focuses primarily on Bitcoin as it is the main cryptocurrency that means that there is limited research on other significant cryptocurrencies. Earlier work explores the uncertainty in Bitcoin (Dyhrberg, 2016; Dwyer, 2015) and inefficiency (Cheah, Mishra, Parhi, & Zhang, 2018; Urquhart, 2016; Nadarajah & Chu, 2017). Just a handful studies have reported on the long-term relationship among cryptocurrencies, despite being highly interconnected (Leung & Nguyen, 2019). The objective of this study is to bridge that gap by analyzing the ten cryptocurrencies selected on the basis of time frame and market capitalization by using cointegration analysis.

1.3 Problem Statement

In literature there are many studies of long and short term relationships in currency market, commodity market and stock market. The debate of asymmetric behaviour is also there. Conrad, Custovic, and Ghysels (2018) studied long and short-term volatility components of bitcoin by applying GARCH-MIDAS analysis. (Leung & Nguyen, 2019) note that the statistically significant correlation between Bitcoin (BTC), Litecoin (LTC), Bitcoin Cash (BCH) and Ethereum (ETH) is a cause for research into cointegration. One of the important domains of cryptocurrency market is long term comovement among cryptocurrencies. As, cryptocurrency is emerging class and there are few studies in cryptocurrency market in the background of long term relationship. Cointegration analysis is the best tool to study the long term relationship. Cointegration is a field where cryptocurrencies are relatively unexplored, that makes it interesting to study.

1.4 Research Questions

The following questions will be answered by this research:

Research Question: 1

Does long term relationship exist between Cryptocurrencies?

Research Question: 2

Does short term relationship exist between Cryptocurrencies?

Research Question: 3

Does Lead Lag relationship exist among Cryptocurrencies?

Research Question: 4

What is adjustment speed of the Cryptocurrency in returns?

1.5 Research Objectives

The study's main objectives are:

Research Objective: 1

To provide insight about the long term and short term interactions of cryptocurrencies.

Research Objective: 2

To provide insight about lead lag relationship among cryptocurrencies.

Research Objective: 3

To provide understanding about the adjustment speed of cryptocurrencies.

1.6 Significance of the Study

Digital currency has developed quite a thrill because of rise in the prices unexpectedly for certain kinds of cryptocurrencies. As we can see that, for true fair reasons, this is becoming a fresh trend in the business globe. Individuals who have invested into them have been profited in unimaginable manners. Indeed, even with every one of the dangers related with putting resources into cryptographic forms of money, millennials specifically are taking their risks. Digital currency markets have got a lot of media and investor attention since most recent couple of years. With the consistently utilization of virtual money and its instability, cryptographic forms of money are being embraced over world for different exchanges legal and illegal.

This study is significant in multiple perspectives. Firstly, from academic point of view, the cryptocurrency asset class is emergent. Digital money in the background of cointegration is a generally unexplored region of research. As cryptographic forms of money seem to pick up premium and authenticity, especially with the foundation of subordinates markets, it is imperative to comprehend the main impetuses behind market developments. Therefore, this study is an effort to explore the co-movement and cointegration in this new emerging class.

Secondly, as the cryptocurrency market continues to grow with new coins, recognizing long-term movement between cryptocurrencies is very significant for individual investors, crypto fund managers as well as regulators. Investigating cointegration between cryptocurrencies may provide information about the long term price movement of crypto currencies to the stakeholders who are trading in cryptocurrency market. This study is helpful for those investors who are making transaction in crypto-currency market. Investors may be able to determine how to act in the cryptocurrencies market. When crypto currencies are co-integrated, showing that they have a relationship in long run. Investors can use this to make strategic investing decisions. This study is helpful for the crypto-market investors when making investment decision because the investment strategy aims to identify two or more assets which have similar price movements and may be used by investors when the assets are co-integrated. This study is also beneficial to investors in the way when there is a long-run equilibrium deviation, investors may act on that in the perception that it will revert back to the long-run equilibrium. Furthermore, it is also helpful for portfolio managers in diversifying the investment.

Chapter 2

Literature Review

Digital currency has been one of the most debated topics in finance during the last decade. One of the main key drivers behind developments in the financial services sector is Fintech (financial technology). One of the technologies that are most debated in cryptocurrencies is blockchain technology that allows direct electronic transfer among two individuals. This transfer is carried out in the absence of third party (like a bank) or costly intermediaries that could lead to cost savings (Labbé, Crabb, & Lai, 2018). Blockchain is a digital financial transfer database with a list of documents stored in blocks (Ram, Maroun, & Garnett, 2016). Blockchain database includes two types of records; one is transaction and the other in blocks. Every Block is a payment collection. Every block is dated upon which transactions have taken place and it is also connected to prior block (Carlozo, 2017). Blockchain is a database of records that are stored in blocks and an entirely public ledger, i.e. anyone can access the ledger (Carlozo, Banham, Farr, Kunigis, & Meyer, 2017). Cryptocurrencies are intended to act as exchange channels, but some analysts claim that cryptocurrencies should be viewed as speculative or risky instruments due to high uncertainty (Bação, Duarte, Sebastião, & Redzepagic, 2018). Cryptocurrencies evolution had an effect on the financial sector. The world is moving towards cashless direction, that is, most Swedish stores are no longer accepting cash. Cryptocurrencies offer worldwide quick transfers with lower transaction costs, making them attractive to people living under oppressive regimes (Göttfert, 2019). The competing cryptocurrencies appeared after Bitcoin is launched in

2008, which are considered altcoins (alternatives to Bitcoin). Today, Coinmarketcap shows that, there are more than 4700 different cryptocurrencies of different functions.

Digital currency is virtual money in online portfolios of null intrinsic value provided by a binary code that cannot be turned into anything and has no central bank or government support (Murray, 2018). Cryptocurrency's value is not measured by either a convertible tangible asset (like gold) or a fiat currency (like dollar), it is assessed by its demand and supply interplay (Low & Teo, 2017). This emerging cryptocurrency may perform various functions of business. Without intermediaries, it can promote transactions of business from individual to individual globally. It can lessen barriers to trade as well as costs and boost productivity (Phillips & Gorse, 2018). Nonetheless, utility of cryptocurrency remains uncertain due to its significant price fluctuations, the inelastic essence of the computational formula-coded money supply and the lack of government protections (Kiviat, 2015). Cryptocurrency is closely linked to several threats resulting from its excessive uncertainty and speculative nature.

Cryptocurrencies that may seem the same as traditional currencies but has significant differences relative to the "fiat" currencies. Central banks do not control the cryptocurrencies i.e., it is not published or released by a state or regulator, it is mined through the use of technology. It has begun to become popular as a way to settle e-commerce purchases and needs the benefit for goods and services and is also said that there is no intrinsic value (Ram & Jaywant, 2015).

The literature on cointegration is addressed first in this chapter. Then the cryptocurrencies literature is presented. The literature on the study of cointegration was chosen in order to provide an overview of the cointegration.

2.1 Cointegration in Cryptocurrency Market

Since the literature on cryptocurrencies is finite, the prior studies that were the part of literature were the studies that relates with the topic of cointegration between cryptocurrencies. Since (Engle & Granger, 1987) came up with the concept of cointegration in 1987, this residual-based approach has been used by most economists to examine non-stationary time series. Johansen (1988) introduced a new approach to co-integration analysis that allowed the testing of multiple co-integration connections. Stock and Watson (1988) claimed that multiple variables co-integrated represent at least one common pattern and established a common multivariate time series trend test. (Phillips, Ouliaris, et al., 1990) suggested a test for residual co-integration that offered critical values ranging from (Engle & Granger, 1987). Another test for residual based cointegration, proposed permits for regime changes possibilities (Gregory & Hansen, 1996).

Most of the prioir cointegration studied are either stock market-related (Lettau & Ludvigson, 2001; Kasa, 1992; Bessler & Yang, 2003; Chen, Firth, & Rui, 2002) or energy-related (Ang, 2007; Acaravci, Ozturk, & Kandir, 2012; Soytas & Sari, 2003).

Sovbetov (2018) analyses the factors that affect Bitcoin, Dash, Ethereum, Litecoin, and Monero's weekly prices during 2010-2018. The finding indicates that such prices are being co-integrated and that variables along with beta of the market, volume of trade and uncertainty tend to be important in both short and long run.

Alexakis and Apergis (1996) studied ARCH impacts and foreign exchange market co-integration. Another study was conducted on commodities future markets i.e., (Beck, 1994) studied Cointegration and market efficiency in commodities futures markets. Tursoy and Faisal (2018) studied effect of gold and unrefined petroleum prices on securities exchange in Turkey by applying ARDL limits test. Another study was conducted by (Khemili, Belloumi, et al., 2018) which was based on cointegration relationship between Growth, Inequality and Poverty in Tunisia. (Ciaian, Rajcaniova, et al., 2018) studied long- and short-run relationships in the markets for Bitcoin and Altcoin using ARDL. Mitra (2017) examined elements of instability overflow between the Indian financial exchange and outside trade market return by using cointegration Analysis.

There are about limited studies among cryptocurrencies which have been conducted on cointegration. Many Prior studies have focused on uncertainty (Baek & Elbeck, 2015), efficiency (Cheah et al., 2018; Urquhart, 2016) cryptocurrencies. Bação et al. (2018) studies the transmission of information among the Bitcoin, Ripple, Litecoin, Ethereum and Bitcoin Cash prices. They believe that in both short- and long-run, the price among cryptocurrencies must be closely related. The study further finds that the cryptocurrencies are in general closely linked, and that most transfers of information take place within one day.

Ciaian et al. (2018) suggest three key reasons for believing that the Bitcoin and altcoin markets can be strongly interdependent. So begin with, the main dominant cryptocurrency is Bitcoin. In addition, the price changes in altcoins price levels are close to the changes in Bitcoin's price. Furthermore, Bitcoin is sometime utilizes as a means of exchange while buying altcoins. Ciaian et al. (2018) study the short- and long-run interaction between Bitcoin and altcoin prices. The objective is to explore how Bitcoin powered the altcoins price. The study analyze how the altcoin and Bitcoin are co-integrated by evaluating daily data for the period 2013-2016 from 17 various cryptocurrencies and conducting out an ARDL-test. The findings report that the interdependence among altcoins ' prices and the price of Bitcoin in the short run is stronger than in the long run. The study notices that Bitcoin's price has a shot-run effect on the prices of 15 altcoins. However, only four altcoins are co-integrating with Bitcoin for a long time.

2.2 Bitcoin and Cryptocurrency Market

This study links the Bitcoin and digital currency market to the enormously hot topic. Corbet, Lucey, and Yarovaya (2018) carry out a great and systematic review of cryptocurrencies research as a financial asset. Cryptocurrency, which is a modern form of technological development in the finance area, is important to study its effect on different professions and practitioners (Boomer, 2016). There are many discussions in the existing literature on the existence of cryptocurrency and on whether cryptocurrencies are regarded as a trading tool or a speculative investment. Frisby (2014) believes that Bitcoin appears to have the qualities of money and even better performance: Its mining process and restricted supply process enable it to operate as a value store. Its divisibility, resilience, accessibility, greater volatility and less transaction fees make it possible for the stock to trade. Dyhrberg (2016) has same findings in the Bitcoin and Gold's GARCH model. The results show that Bitcoin has capabilities of allied hedging, so it can be characterized as a hybrid among a commodity and a currency. By using quantile-on-quantile regressions, Demir, Gozgor, Lau, and Vigne (2018) explores the relationship among Bitcoin and the index of economic policy volatility and argues that Bitcoin may be used as a medium of hedging toward uncertainty. Although several researches notice that speculative bubbles in cryptocurrencies and low intrinsic value results in several unpredictable factors and decrease stability in prices, Although several researches notice that speculative bubbles in cryptocurrencies and low intrinsic value results in several unpredictable factors and decrease stability in prices, thus weakening their function. Urquhart (2016) concludes that Bitcoin is an unstable cryptocurrency throughout the time studied and notes that after mid-2013, Bitcoin provides evidence of being more effective. Fry and Cheah (2016) find the simple price of Bitcoin is expected to be zero. Considerably, high instability and weak Bitcoin correlation, flat currencies and gold show that Bitcoin is tough to use as a traditional currency or even as a hedging tool. Table 1 in the appendix A shows the legality of the Bitcoin in different countries. (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014) also consider that it is more likely to be used by new Bitcoin users for the purpose of speculative investment.

There are many studies that seek to specifically check the information efficiency of Bitcoin. (Urquhart, 2016) employs six various kinds of tests for efficiency and claims that Bitcoin is ineffective. Moreover, Urquhart further suggests that Bitcoin is growing toward efficiency after such an early transitory period as the market matures. (Nadarajah & Chu, 2017) implement eight various tests for a simple power transmission of returns of Bitcoin and summarize for Bitcoin returns efficiency. (Bariviera, 2017) further re-examines Bitcoin's efficient market theory employing

Range over Standard Deviation and De-trended Fluctuation Analysis approaches, respectively, to identify long storage and information quality variations. The study concludes that regular returns indicate consistent behavior during the first half of the study period, although their performance has been more effective since 2014. For the duration from July 18, 2010 to June 16, 2017, (Tiwari, Jana, Das, & Roubaud, 2018) use a set of computationally efficient long-term dependency estimators and consider the market to be informationally effective. (Vaddepalli & Antoney, 2018) use permutation entropy to evaluate the time-varying weak-form Bitcoin price efficiency in forms of euro and US dollars at a strong-frequency range. The result of the study shows that since the start of 2016 such markets have become more informatively effective, and therefore that Bitcoin is significantly more effective at USD rates as compare to the prices in EUR. The study further shows that the higher the intensity, the lower the efficiency of pricing and that uncertainty (volatility) has a great positive (negative) impact on Bitcoin's insightful effectiveness.

2.3 Cryptocurrencies and Traditional Assets

Another strand of previous studies focuses on connections among cryptocurrencies as well as other assets. Corbet, Lucey, and Yarovaya (2018) tests the approach of spillover index and its variants to examine relationships between three prevalent digital currencies (Bitcoin, Litecoin and Ripple) and other traditional financial assets (gold, bond, stock and foreign currency). Their empirical findings indicate that the three potent digital currencies are comparatively segregated from the other financial assets and therefore support investor risk diversification from cryptocurrencies. The research is growing on interactions among Bitcoin and other conventional assets and whether Bitcoin can be utilize as a diversifier, a safe-haven or a hedging resource (Corbet, Lucey, & Yarovaya, 2018; Briere, Oosterlinck, & Szafarz, 2015; Giudici & Abu-Hashish, 2019; Feng, Wang, & Zhang, 2018; Symitsi & Chalvatzis, 2018).

In addition to cryptocurrencies behaviours, more attention is paid. Some researches focus on cryptocurrencies ’ reactions to other shocks. Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) investigate the connection among macroeconomic news reports and returns of the Bitcoin and point out that unemployment news and sustainable goods have a significant effect on returns o the Bitcoin while CPI and GDP news does not appear to have a statistically significant connection with Bitcoin.

Only few studies, however, concentrate on the relationships among various cryptocurrencies. For example, (Halaburda & Gandal, 2016) explores competition in the digital currency market by analyzing shifts in the exchange rates of various digital currencies and examine the impact of networking effects on crypto market. The study notes that during the period from May 2014 to July 2014, the performance of other cryptocurrencies and Bitcoin is aligned with winner-take-all dynamics and network impacts.

Gandal and Halaburda (2016) examine competitiveness among various cryptocurrencies and four exchanges online. The study reports that for most cryptocurrencies, arbitration mechanisms may not occur. This finding, though, may be biased by the limited sample size. The study further argue that some cryptocurrencies seem to become more effective as well as less volatile as their prices are expressed in Bitcoins rather than USD due to market divergences among cryptocurrencies and domestic fiat currency.

Fry and Cheah (2016) measure the spillover effect among the two main cryptocurrencies using econophysics models. The study examines the consequences of several incidents, i.e. the closing of the Silk Road website and the ban on the use of Bitcoin by the People’s Bank of China. Their findings support the presence of a negative bubble among these two currencies after 2014. The effect of events that are related is observed to be mixed which suggests that because of speculative bubbles in Bitcoin, the effects of some events are unnoticeable.

ElBahrawy, Alessandretti, Kandler, Pastor-Satorras, and Baronchelli (2017) analyze the behaviour of the overall market between the duration of April 2013 and May 2017 (1469 cryptocurrencies). The study considers that cryptocurrencies are constantly emerging and vanishing, and their market capitalization is exponentially increasing, some market statistical properties have been stagnant for years. In general, the allocation of market share and the crytocurrencies' turnover remain fairly constant.

Most of the current studies that are in the background of cryptocurrencies based on returns from Bitcoin. For instance, (Baur, Hong, & Lee, 2018) indicate that returns from Bitcoin are largely uncorrelated to classical asset classes like bonds or stocks, pointing to possibilities for diversification. Others are examining the Bitcoin returns determinants. Li and Wang (2017) results, among others, indicate that financial and macroeconomic activity indicators are generators of Bitcoin returns.

Baumöhl (2019) examines the link among cryptocurrencies and forex and find evidence of a minimum link among these markets. Corbet, Meegan, et al. (2018) examine three different cryptocurrencies and other financial assets and notice some segmentation among them, finding that investing in cryptocurrencies can provide incentives for investors to diversify, especially in the short term. Symitsi and Chalvatzis (2018) explore the links among Bitcoin and companies in energy and engineering, and thereby identify some associations amongst these sectors. In addition, Bouri, Lucey, and Roubaud (2019) investigate cross-correlations among cryptocurrencies and traditional currencies, highlighting significant asymmetric qualities in cross-correlations. Ji, Bouri, Roubaud, and Kristoufek (2019) employee network techniques to examine relations among cryptocurrencies as well as other commodities and to find links with some of these commodities. Bouri et al. (2019) explore the interactions among cryptocurrencies, reflecting on the correlation between measures of volatility and distinction between temporary and permanent causalities. The researchers note that the more important is lasting shocks. Ji, Bouri, Lau, and Roubaud (2019) have studied the interdependence of data among commodities and cryptocurrencies by using time-varying approach, and indicated that in broadly defined markets of commodity, cryptocurrencies are embedded.

The possibility of herding activities in the digital currency market is examined by

(Bouri et al., 2019). Whereas by using the dynamic analysis, the study provides that the effect tends to be observed due to the presence of breaks and non-linearity of data. Bouri et al. (2019) performs in another analysis to see whether explosivity in a cryptocurrency can result in explosivity in many other cryptocurrencies, providing evidence of relations amongst these resources.

2.4 Bubbles in the Cryptocurrency Market

Recent studies examine the presence of bubbles in digital currencies (Corbet, Lucey, & Yarovaya, 2018; Fry & Cheah, 2016). A major threat to digital currencies arises from these resources is speculative nature. Several market participants' trade as they anticipate demand to grow in value from one or the other cryptocurrency. This shared enthusiasm can respond to bubbles and crashes in the market. The online exchange design decisions where digital currencies are exchanged can also lead to this effect when facets of accessible graphical user interfaces (GUI), functionality and application programming interfaces (API) foster shared anticipation. Previously, the literature has begun to explore the link between cryptocurrencies and assets of the mainstream. Corbet, Lucey, and Yarovaya (2018) analyze interactions between cryptocurrencies and mainstream assets and report that digital currency are rather segregated from other markets and find weak associations among cryptocurrencies and other resources. A bunch of literature has tended to focus on cryptocurrencies categories or performance. Most literature, however, focuses only on Bitcoin and pays little attention to the connection between different cryptocurrencies, particularly comovement, volatility connection or spillovers (Corbet, Meegan, et al., 2018).

2.5 Volatility in Cryptocurrency Market

As investors are vulnerable to extremely undifferentiated threats of cryptocurrencies market. (Katsiampa, 2019b), analysis of changes in the prices of cryptocurrency and its co-movements is of primary importance to participants and other institutional investors to understand better interconnections of the digital currency market and to make informed decisions. Volatility has become an important facet of this emerging class. Past studies show that there are many studies on volatility. For instance, inconsistency in the prices of cryptocurrency has been observed by (Phillips & Gorse, 2018; Katsiampa, 2019a). The interdependency in cryptocurrency market is also studied by (Katsiampa, 2019b). (Katsiampa, 2019b) explores volatility co movement between top two Cryptocurrencies (Ether and Bitcoin) by applying Diagonal BEKK model, the focus of his study was only volatility dynamics of Bitcoin and Ether. The research finds indications that the market of digital currency is interdependent. Then he extended his work to leading cryptocurrencies. (Katsiampa, 2019a) studies Spillover impact of fluctuations in major digital currencies using BEKK-MGARCH technique by taking into consideration three leading digital currencies, including Bitcoin, Litecoin and Ether, and by using three pair-wise BEKK models for the Bitcoin-Litecoin, Litecoin-ether and Bitcoin-Ether pairs. The debate of volatility has not stopped there; (Yi, Xu, & Wang, 2018) studies volatility connectedness in the cryptocurrency market. The study investigates the relation between eight standard digital currencies for static and dynamic instability. The results show that their connectivity fluctuates cyclically and since the end of 2016 has shown an obvious upward trend.

Chu, Chan, Nadarajah, and Osterrieder (2017) uses GARCH model to seven digital currencies that were most common. The findings suggest that digital currencies like Bitcoin, Ethereum, Litecoin and several others exhibit fairly high volatility, particularly at the inter-daily prices. (Chu et al., 2017) suggest that such type of investment is ideal for investors seeking a way to invest or access technology markets in pursuit of risk.

Kim et al. (2016) uses comments of the user in digital cryptocurrencies forums to forecast volatility in Bitcoin, Ripple, Ethereum's regular prices and transactions, including positive outcomes, specifically for Bitcoin. (R. C. Phillips & Gorse, 2017) indicate that on many cryptocurrencies, secret Markov frameworks based on the views of novel social networking metrics provide foundation for profitable trade strategies. Katsiampa (2019a) examine the tail return behaviour of the main five digital currencies (Bitcoin, Ripple, Ethereum, Litecoin, Bitcoin Cash), utilizing extreme valuation estimation and calculating Valuation-at-Risk and Predicted Shortfall as volatility. The study considers Bitcoin Cash to be the most risky, whereas the low risky digital currencies are Bitcoin and Litecoin.

2.6 Comovement in Cryptocurrency

There are also many studies on comovement in stock market, metal market, commodity market and currency market. Earlier work studies comovement among cryptocurrencies and other assets, while some studies examine comovement between different digital currencies. For instance, Beneki, Koulis, Kyriazis, and Papadamou (2019) focus their studies on the relation among Bitcoin and Ethereum and define that correlations occurrs, for every cryptocurrency affecting another with a different ty-pe of influence over time. Wavelet methodologies are used by (Mensi, Rehman, Al-Yahyaee, Al-Jarrah, & Kang, 2019) to examine the comovement between major cryptocurrencies. Inspite of presence of comovement, the researchers note that for diversification objectives, mixed investments of various cryptocurrencies can be of interest. In addition to the study of commodity relations, Ji et al. (2019a) examine the connectivity of volatility and return in major cryptocurrencies, knowing that Bitcoin and Litecoin are at the forefront of return connectivity and the returns that are negative have a greater impact as compare to positive returns. In volatility case, Bitcoin is the most influential cryptocurrency. Multiple factors and channels that have been recently identified in the previous literature on the topic of intermarket interaction can play a significant role in linking the cryptocurrency market with commodity markets. The first of these is the linked information medium (Kodres & Pritsker, 2002), by which relations are made through the process of price discovery. The second one is the channel of risk premium by which a shock in one market can negatively impact the readiness of participants of the market to detain risk in every type of market (Acharya & Pedersen, 2005).

Popularity of cryptocurrencies is also important and except in the long run.

(Phillips & Gorse, 2018) examine whether the connection among the effects of internet and social media and the prices of many cryptocurrencies (Bitcoin, Ethereum, Monero and Litecoin) rely on the trading system (bubbles and certain events). Wavelet coherence is used by authors as a measure for co-moving among the price of cryptocurrency and the factors.

Alexakis and Apergis (1996) studies cointegration in foreign exchange market and found that in three currency markets, the concept of an effective foreign exchange market is present. Isa, Nasrul, Noh, and Mohamed (2018) studies cointegration and causality among the global economic factors and equity markets. In addition, using data from Brazil, Dutta (2018) explores cointegration and nonlinear causality among ethanol-related prices. Using cointegration and VECM (Vector Error Correction Model), (Manikandan, Mani, & Karthikeyan, 2018) studies relationship between Money, Output and Price Level in India. (Kwon & Shin, 1999) investigates causality and comovement among equity market Returns and macroeconomic indicators. There are few studies of long term relationship in the background of crptocurrencies. Conrad (2018) studies long- and short-term cryptocurrency volatility components through the application of GARCH-MIDAS analysis. Another study is conducted by Nguyen (2018) on co integrated cryptocurrency portfolios for statistical arbitrage. Nonetheless, there is rather limited literature on long term relationship within cryptocurrency markets. (Katsiampa, 2017) study is limited to just Bitcoin and Ether through the application of BEKK model. However, none of these studies have examined the long term comovement among the return of Bitcoin, Ripple, Litecoin, Bitshare, Monero, Dash, DogeCoin, Byte Coin, Digibyte and Monacoin through co integration analysis. This study examines the cointegration that is often detected in the behaviour of assets. It also identifies lead lag relationship between cryptocurrencies.

2.7 Hypotheses of the Study

Following hypotheses are developed:

H$_1$: There exists a long-term relationship between Crptocurrencies.

H_2: There exists short term relationship between Cryptocurrencies.

H_3: There exists lead lag relationship between Cryptocurrencies.

H_4: There exists adjustment speed among Cryptocurrencies.

Chapter 3

Research Methodology

This study is based on time series analysis to investigate long-term relationship between ten Cryptocurrencies. The presence of a cointegration relationship between variables, in addition, helps us to analyze causal links, namely the method of vector error correction. Moreover, to continue with methods of co-integration, combination of linear non-stationary series must be stationary. This study uses Augmented Dickey – Fuller (ADF) and Phillips – Perron (PP) tests to check the stationarity (P. C. Phillips & Perron, 1988; Dickey & Fuller, 1979). The cointegration method of Johansen is used to investigate the nature of a long-run relationship when it is observed that the series is integrated of same order (Johansen, 1988). Schwarz Information Criteria (SIC) is applied to assess the lag length criteria in the analysis of cointegration (Schwarz et al., 1978). The method of cointegration of Johansen relies on two statistics of maximum likelihood test, namely Max-Eigen and Trace (Johansen & Juselius, 1990). The outcomes of these tests show the presence and number of cointegrated vectors in the series. When the cointegration analysis shows the presence of cointegration relationships, a method for error correction model (VECM) is used to test short-run relationships (Granger, 1988) and to study lead lag relationship, Granger Causality test is used.
So, this study highlights the long term relationship among 10 cryptocurrencies through:

1. Descriptive statistics

2. Unit root test

3. Cointegration tests

4. Vector Error Correction Model

5. Granger causality test

3.1 Sample Distribution

In order to check, the cointegration among ten cryptocurrencies, historical data of the prices is needed. The data used in this research is the data of closing daily prices of the ten cryptocurrencies that is collected from Coinmarketcap, a website sharing information on numerous cryptocurrencies. The data is obtained over common periods of time, all starting from August 01, 2014 and ending on September 30, 2019. All prices are marked in U.S. dollars. The purpose behind this is to provide every cryptocurrency with as large samples as possible because the interest of the study is to test for cointegration (long run relationship) among cryptocurencies. So, cryptocurrencies have been short listed on the basis of data for the timeframe available and then on highest market capitalisation. The cryptocurrencies includes; Bitcoin, Ripple, Litecoin, Bitshare, Monero, Dash, Dogecoin, Bytecoin, Digibyte and Monacoin. These cryptocurrencies with market capitalization on 03 Oct, 2019 are shown below in table 3.1.

Table 3.1: Sample Details

Name	Symbol	Market Cap in USD	Sample Period
Bitcoin	BTC	$146,749,085,983	01 Aug, 2014 to 30 Sep, 2019
Ripple	XRP	$10,603,443,860	01 Aug, 2014 to 30 Sep, 2019
Litecoin	LTC	$3,487,518,742	01 Aug, 2014 to 30 Sep, 2019
Monero	XMR	$946,097,197	01 Aug, 2014 to 30 Sep, 2019
Dash	DASH	$628,352,351	01 Aug, 2014 to 30 Sep, 2019
Dogecoin	DOGE	$283,751,810	01 Aug, 2014 to 30 Sep, 2019
Digibyte	DGB	$90,850,283	01 Aug, 2014 to 30 Sep, 2019
Bitshare	BTS	$76,306,881	01 Aug, 2014 to 30 Sep, 2019
Bytecoin	BCN	$75,132,849	01 Aug, 2014 to 30 Sep, 2019
Monacoin	MONA	$76,356,792	01 Aug, 2014 to 30 Sep, 2019

3.2 Description of Cryptocurrency in the Study

This section explain the cryptocurrencies addressed in this study, which are BitCoin, Ripple, Litecoin, Bitshare, Monero, Dash, Dogecoin, Bytecoin, Digibyte and Monacoin.

3.2.1 BitCoin

Bitcoin (BTC) is a network of agreement that produces an entirely digital currency. It is a new payment system and the world's most used cryptocurrency. Bitcoin is a peer-to-peer payment channel operated by its users that does not allow any central authority to run. Bitcoin is fundamentally a computer record which is put away in an 'advanced wallet' application on a computer or cell phone. Individuals can send bitcoin to your computerized wallet, and in the same way you can send bitcoin to other individuals. In a public list called the blockchain, any single transaction is registered. The first bitcoin determination and verification of idea was issued in 2009 out of a mailing list made by Satoshi Nakamoto (Bitcoin.org, 2019). He elaborated it as: "An electronic cash form that is solely peer-to-peer will enable online payments that can be sent directly from one group to other group without passing through the instructions and permissions of a financial institution" (coinmarketcap.com).

This study uses the return for the historical closing daily prices of BitCoin for the period of 01 Aug, 2014 to 30 Sep, 2019.

$\mathrm{RBTC}_t = \mathrm{LN}\left(\frac{bitcoin_t}{bitcoin_{t-1}} \right)$

Where,

Ln represents the natural log,

bitcoin_t is the bitcoin price of day's' in term of dollar and bitcoin_(t-1) is the bitcoin price of day 't-1' in terms of dollar.

While log series are calculated by,

LBTC=LN(Bitcoin)

This study implies the same method to calculate return and log series for all cryptocurrencies that are observed in this study.

3.2.2 Ripple

Ripple is a cryptocurrency, a network and a corporation. The Ripple network's real cryptocurrency is named as XRP. Formed in San Francisco in 2012, Ripple uses the Ripple network to make world transfers cheaper and quicker (Bajpai, 2017). Ripple provides an alternative to SWIFT which operates with American and Santander Express financial institutions. Once a transaction takes place, fiat money is transformed to XRP and it can be bought and sold via the Ripple network and converted back to traditional currency.

The Ripple transaction protocol, introduced in 2012 by David Schwartz, Authur Britto and Ryan Fugger, develops on distributive open source Encryption methods. Because of its primary objective, the Ripple cryptocurrency is quickly embraced by financial institutions to allow easy and safe global financial transactions without charges (Milutinović et al., 2018).

Registered to the Ripple Consensus Ledger, Ripple (XRP) is an individual virtual asset.XRP is indeed the most powerful transaction choice for financial institutions and liquidity suppliers pursuing global access, transparency and quick settlement finality with verified governance and the quickest verification of its kind (coinmarketcap.com).

The goal was to create a quick and cost-effective cryptocurrency while developing XRP. Within four seconds, transfers are processed and XRP performs 1,500 transactions in one second (Ripple 2019). XRP has been stated to be centralized as Ripple controls 60% of XRP (Göttfert, 2019).

XRP and Bitcoin's main difference is that XRP is not being mined. New XRP is routinely added into circulation (Schwartz 2017). Ripple has no blockchain. Rather, it utilizes the Ripple Protocol Consensus Algorithm (RPCA), a Ripple-designed technology (Cointelegraph).

3.2.3 Litecoin

Litecoin is a peer-to-peer digital currency developed by Charlie Lee (Former employee at Google). It is built on the basis of the BitCoin protocol, but different in use of hashing algorithm. Litecoin's idea is to make a cryptocurrency that could process transactions and payment quicker than Bitcoin. For Litecoin, producing a new block takes 2,5 minutes relative to Bitcoin's 10-minute verification period (Göttfert, 2019). Bitcoin and Litecoin are very similar technically, but Litecoin needs a different hashing algorithm than Bitcoin, named Scrypt. Litecoin utilizes the scrypt memory-intensive functional algorithm evidence. Scrypt permits such coins to be mined by consumer-grade hardware such as GPU (coinmarketcap.com). Litecoin miners earn 25 new coins per block. This volume is halved nearly every four years. The network aims at generating 84 million coins. Many updates are first introduced in Litecoin, such as the lightening network, and subsequently utilized by Bitcoin. Basically, lightening network means that it is possible to perform smaller payments outside the blockchain. This result in quicker transactions and lower transaction costs (Litecoin 2019).

3.2.4 Bitshares

Co-founder of EOS, Steemit, Cryptonomex and Dan Larimer developed Bitshares. Bitshares (BTS), previously referred as ProtoShares, is a decentralized peer-to-peer ledger and database that can offer collateralized smart coins such as bitAssets. Every - smart coin has at minimum 100% of its worth secured by the native currency of Bitshares, the BTS, that can be exchanged at a certain moment at a rate set by a reliable price stream. Bitshares also has a shared network of its own (coinmarketcap.com).

3.2.5 Monero

Monero (XMR) is a secret, stable and undetectable digital currency unveiled on 18 April 2014(coinmarketcap.com).Monero spends more on confidentiality than other Cryptocurrencies. Monero coins can't be followed backed to the blockchain and it is difficult to perceive what number of Monero coins a partner holds (Khatwani, 2018).

3.2.6 DASH

Dash was launched with zero pre mine coins on 18 January 2014. This uses 11 hashing algorithms. Dash lets you stay secret while you're transacting. Dash safeguards anonymity by using a technology created by the Dash group named DarkSend to anonymize payments that are generated over the web. DarkSend is backed by the Bitcoin payments CoinJoin campaign that is designed to anonymize. Payments are confidential through Dash and it cannot be detected in accordance with balance. Dash takes advantage of the power of its Masternode channel to support InstantX innovative technology. Users can utilize InstantX when transferring money, and in four seconds transfers will be complete (coinmarketcap.com).

3.2.7 Dogecoin

Based on popular Internet meme ”Doge” and its logo features a ShibaInu, Dogecoin (DOGE) is a Litecoin forked digital currency in Dec 2013. Dogecoin is used mainly as a tipping system for producing and circulating quality content on Twitter and Reddit. Dogecoin is founded by Oregon and Jackson Palmer from Sydney, Australia, Portland’s Billy Markus. Both conceived Dogecoin as a friendly, light-hearted digital currency that would draw more than the main Bitcoin market (coinmarketcap.com).

3.2.8 Bytecoin

Bytecoin (BCN) is founded in 2012 and is defined as an anonymous, distributed digital currency with an open source code. Bytecoin intends to be the foremost CryptoNote software project to be applied. The primary objective of the venture is to promote payments easily, secrecy and intractability. Bytecoin aims to get a 2-minute block time and flexible configurations intended to make mine simple. Its protection is allegedly attributed to the use of ring signatures to protect the identity of a recipient and unlink able domains to escape blockchain review. Recent updates to Bytecoin software entail publicly accessible deposits, Auditable Wallets that allegedly makes secrecy and Blockchain Gateways, a source of linking blockchain of Bytecoin with other blockchains (coinmarketcap.com).

3.2.9 Digibyte

The blockchain of Digibyte is created in 2013 and published with an open-source application by Jared Tate (Digibyte’s Creator & Founder) in January 2014. Digibyte (DGB) is a blockchain which focuses on cryptography, digital assets, transactions and encrypted communications software.Though dependent on Bitcoin, code adjustments allegedly enable enhanced features, along with, improved security, real time difficulty adjustment and 15second block duration. The purpose to design DigiAssets is to encourage the users to create Digibyte on top of the blockchain of Digibyte globally as a secondary platform to facilitate the tokens, digital identification, distributed issuing of resources, tokens and smart contracts (coinmarketcap.com).

3.2.10 Monacoin

Monacoin (MONA) is a peer-to-peer network of open source payments. Monacoin was known as "the first Japanese cryptocurrency" by its developers, the coin has become somewhat the national substitute of Japan to Bitcoin and Litecoin (coinmarketcap.com).

3.3 Econometric Model

The methods used in this research are discussed in this section. First, it explains the concept and process of cointegration. Then the unit root test of Dickey-Fuller is described, as well as the method of cointegration of Johansen, Vector Error Correction Model and the Granger Causality test.
(Engle & Granger, 1987) have developed a technique for evaluating time series data with the regression-based patterns. The study states that although there may be a significant correlation among two non-stationary time series that does not necessarily imply that a significant relationship exists among them. If on non-stationary time series statistical methods for stationary data are applied, this can lead to irrelevant relationships that are considered spurious. Stock and Watson (2015) describes cointegration as "when two or more variables of time series share an ordinary stochastic pattern". Cointegration techniques evaluate the time series that are non-stationary — processes whose means and variances differ over time. In simple words, the approach enables you to measure long-run parameters or equilibrium of unit root variables in systems (Rao, 2007). In addition, to measure long run relationship, cointegration technique a unique concept of statistics established by (Engle & Granger, 1987; Granger, 1988). Cointegration analysis has become a significant facet of the empirical analysis of economic time series

over the past several years. By using this approach, when a linear combination of the two is stationary, two variables are co-integrated, despite the fact that every variable is non-stationary. In specific, (a) In the same degree, the two variables should be embedded and (b) There should be a linear combination of the two factors integrated to a lesser degree than the individual factors. In simple words, although a set of variables is separately non-stationary, a linear composition of the series representing a fixed time series, since they are grouped in the same order individually (Vidyamurthy, 2004). This implies that a linear X_t and Y_t combination could form an I(0) and a stationarity process. Then, consider the model of regression linking the above mentioned variables:

$X_t = bY_t + u_t$.................... (3.1)

If X_t and Y_t are combined in different degrees, no parameter b will suit equation 3.1. A (long-term) relationship therefore suggests the above requirement (a). At the same moment, if there is no equilibrium relationship, a linear combination of the two relevant variables according to condition (b) above should not be predicted. In comparison, absence of Cointegration means that there is no longrun connection between the above factors. This study will use the cointegration test to measure the long term relationship among above mentioned cryptocurrencies. If these cryptocurrencies have long term relationship, they should be cointegrated. There are basically two steps involved in cointegration analysis. Firstly, to check the non-stationarity of the series unit-root test is applied and, If the results suggest that the first-differentiated set of variables are stationary, a corresponding test shall be conducted to ascertain whether such particular variables are co-integrated. Dickey and Fuller first developed the unit root hypothesis test (1979, 1981).

The assumption is made to evaluate time series using classical techniques such as normal least squares: the series that are time-independent their means and variances are constant (i.e. stationary processes). That presumption is not fulfilled by non-stationary time series so any hypothesis test results will be biased. These series must be evaluated using different techniques. Cointegration is one of these techniques. More precisely, cointegration is where the stationary $u_t=y_t$ - αx_t process can define two I(1) time $series_t$ and y_t.

3.3.1 Approaches and Statistical Test for Cointegration

Cointegration testing identifies long-term relationships among the variables sets. Three of the measures most common are:

1. Engle–Granger
2. Phillips–Ouliaris
3. Johansen test

These three methods are used in cointegration analysis. Johansen method is most widely used method. The Johansen procedure (1988, 1991) provides a convenient way of testing whether two or more series cointegrate, as long as the hypothesis that each variable has a unit root cannot be rejected. The Johansen method has several advantages over the two-stage approaches to cointegration of the (Engle & Granger, 1987). One disadvantage of the Engle and Granger test results from the fact that it includes a two-stage estimator, that means if any error occurs in the first stage is transmitted to the second stage. Another drawback is that, based on the variable chosen as the dependent variable, the findings are sensitive to the normalization adopted and may result in contradictory conclusions. By contrast, the results of the Johansen test are based on its eigenvalues and on estimates of matrix rank, obtained in a single stage, and are invariant to the choice of the selected variable for normalization. In addition, As Johansen test is a VAR-based methodology; there is less concern about the exogenous or endogenous explanatory variables. The cointegrating vectors may be subject to restrictions that are not possible with the Engle-Granger approach (Pereira, 2013).

3.3.2 Augmented Dickey-Fuller (ADF) Test

The ADF method is a root unit test that applies lagged terms to the Y variable to eliminate potential autocorrelation. The lag length criteria are decided on the base of Schwartz Bayesian Criterion (SBC) or the Akaike information criterion (AIC). The ADF test is as follow:

$\Delta X_t = \alpha + \beta T + \rho x_{(t-1)} + \sum_{i=1}^{m} \lambda i \Delta x_{(t-1)} + e_t$ .... (3.2)
Where:

x_t denotes the factor logarithm in time t, T is the time pattern, $\Delta x_{(t-1)}$ is $x_{(t-1)}$-$x_{(t-2)}$ and e_t is the error term. The null test is represented by α=0 and α<1 is as the alternative hypothesis. Refusing to accept the null would mean that x_t does not represent a unit root and is therefore stationary. This is achieved through evaluating the ADF results with a critical value at a defined level of significance (Asteriou and Hall 2016).

3.3.3 Phillips-Perron'S (PP) Test

Phillips et al. (1990) and Phillips demonstrate that, under the null hypothesis in case of no cointegration, residual unit root tests related to the measured cointegrating residuals do not have the normal Dickey – Fuller distributions. The distribution of these experiments includes asymptotic ranges due to the spurious regression principle under the null hypothesis which depends on (1) the number of deterministic pattern terms and (2) the number of factors being evaluated for co-integration. Both distributions are recognized as the distributions of Phillips – Ouliaris and tabulated critical values.
The regression analysis includes the AR (1) form below:

$Y_t = \alpha_o + \alpha_1 Y_{t-1} + e_t$ .... (3.3)
Rejecting the null would mean that Y_t has no unit root and is stationary as a result. While the ADF test contributes lagged differentiated conditions for handling correlations of higher order, The Phillip Peron analysis adjusts the serial correlation coefficient $_1$ from the AR(1) regression in e_t.

3.3.4 Johansens (JOE) Test and Approach

Another test for cointegration is Johansen test; this makes it possible to combine more than one relationship of cointegration, unlike the method proposed by Engle

– Granger however this analysis is vulnerable to asymptotic conditions, i.e. large samples. The findings will not be accurate if the sample size is too limited in this case; Auto Regressive Distributed Lags (ARDL) should be used (Pesaran, Shin, & Smith, 2001)(David, 2014).

Auto regression of the vector (VAR) is important for comprehending the test of Johansen. A vector auto regression is a framework comprising of two or more than two regressions, whereby every variable regresses at n lags of the other variables and n lags of the variable itself. Every variable on a constant is regressed too. The following form can be used by a VAR system:

$\mathrm{Y}_t = \alpha + B_1\mathrm{Y}_{t-1} + B_2\mathrm{Y}_{t-2} + B_n\mathrm{Y}_{t-n} + e_t$ .... (3.4)

In this equation, Vector is represented by Y_t, $\beta_{(k)}$ functions as a j by j coefficients matrix, $= 1, 2, 3, 4, 5 \ldots,$, signifies j via one constant matrix and e_t symbolize the error terms. In case a model comprises several (three or more) parameters, there is an opportunity that more than one relationship will be cointegrated. As a general rule, cointergration can occur for at most n number of variables (n 1). Due to the application of VAR method, Johansen's methodology could identify multiple relationships of cointegrations. Contrary to the methodology of Engle and Granger, that can identify only single co-integrated relationship. According to Asteriou and Hall model (2016), Johansen's solution of derivation to detecting cointegration for a two-time series vector X_t=[Y_t,Z_t], is shown below:

$\mathrm{Y}_t = \pi_{11}\mathrm{Y}_{t-1} + \pi_{12}Z_{t-1} + e_1t$ .... (3.5)

$\mathrm{Z}_t = \pi_{21}\mathrm{Y}_{t-1} + \pi_{22}Z_{t-1} + e_2t$ .... (3.6)

Yt and Z_t & are now co-integrated, in the event that:

$\Delta Y_t = \alpha_1\ (\beta_1\mathrm{Y}_{t-1} + \beta_2\mathrm{Y}_{t-1}) + e_1t$ .... (3.7)

$\Delta Z_t = \alpha_2\ (\beta_1\mathrm{Y}_{t-1} + \beta_2\mathrm{Y}_{t-1}) + e_2t$ .... (3.8)

In equation 7, $\beta 1$ $Y_{(t-1)}$ + β_2 $Z_{(t-1)}$ is a stationarity process.
There are two ways to induce the measurements utilized to test whether the characteristic roots differentiate from zero. The first is the following:

λ_{max}(r,r+1)= -TIn(1-λ_{r+1}) .... (3.9)
In above equation T represents the observations and the n-r smallest squared canonical correlations is represented by $\lambda_{(r+1)}, \ldots, \lambda_n$
The second method is carried out by checking the likelihood ratio for the trace test of . In this case, the null means the number of cointegrated vectors is as high as possible (Asteriou and Hall 2016). Test statistics for the Trace test is as follow:

λ_{trace}= -T$\sum_{i=r+1}^{n} In(1-\lambda_{r+t})$.................... (3.10)

Both tests are used in this study in adopting the methodology of Johansen.

3.3.5 Vector Error Correction Model

In this study, if there is long-term cointegration then error correction term is used to catch the short-run variables deviation from their appropriate equilibrium values. Vector Error Correction Method (VECM) is based on the unrestricted autoregressive vector (VAR) method used to approximate time series that are non-stationary known as being co-integrated. Every variable is often a linear form of previous lags and previous lags of several other variables (Gujarati, 2009).
If there is long-term cointegration, the equation model will be restructured by adding a term of error correction to identify the short-run variables deviation from their appropriate equilibrium levels.
An error correction model (ECM) is one of the most widely used types of multiple time series methods of data in which the fundamental variables have such a long-run stochastic pattern, also identified as cointegration. ECMs are a theoretical method that is helpful for predicting the short- and long-term impacts of one time

series onto another time series. The word error-correction refers to the fact that the divergence of the last time span from such a long-run equilibrium, the error, impacts the dynamics of short-run.

$$\Delta Y_t = \alpha + \sum_{i=1}^{m} \beta \Delta X_{t-1} + \sum_{i=1}^{n} \delta \Delta Y_{t-1}) + \lambda_1 \text{ EC}_{t-1} + \epsilon_t \text{.....................} \quad (3.11)$$

$$\Delta X_t = \alpha + \sum_{i=1}^{1} \beta \Delta X_{t-1} + \sum_{i=1}^{p} \delta \Delta Y_{t-1}) + \lambda_2 \text{ EC}_{t-1} + \nu_t \text{.....................} \quad (3.12)$$

Where, Δ represents the operator of first difference, $\text{EC}_{(t-1)}$ shows the Error Term and Parameters to be measured include Δ, δ, and λ.

3.3.6 Granger Causality Test

Granger (1969) develops a fairly simple method that defines causality as: a variable y_t is said to be Granger-cause x_t, if x_t can be calculated with high accuracy through using past values of the y_t variable instead of using past values, all the other terms remain unchanged. The existence of cointegrating parameters, according to (Granger, 1988), suggests that the Granger causality should present in minimum one direction. A Granger variable affects rest of the variable if it tends to predict its possible future values. Granger causality analysis is based on the idea of predictability, time-based succession and implies the long-term stationarity of the price series. This checks the null hypothesis against the alternative hypothesis that the price series of the first cryptocurrency will not affect the price series of the second cryptocurrency.
For the case of two stationary variables x_t and y_t, the granger causality test present the following model.

$$y_t = \alpha_1 + \sum_{1-t}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} Y_j + Y_t -_j + \epsilon_{1t} \text{.....................} \quad (3.13)$$

$x_t = \alpha_2 + \sum_{1-t}^{n} \theta_i X_{t-i} + \sum_{j=1}^{m} \delta_j + Y_t -_j + \epsilon_{2t}$..................... (3.14)

Granger causality assists to ascertain unrestricted variables that are lagged in a given system by analysing interdependence among the various time series. This means that to ensure the available information on the previous values of x doesn't have a statistical effect on the current or potential value of y_t .

Chapter 4

Results

This chapter represents the result of the study to achieve the basic motive. The chapter starts by showing the behaviour of the data then descriptive statistics for all cryprocurrencies (Bitcoin, Litecoin, Bitshare, Ripple, Dash, Monero, Monacoin, Dogecoin, Digibyte and Bytecoin) are shown. After that Unit root tests are applied. Then, Results of the Johensen Cointgration are reported. Finally, results from Vector Error Correction Model, Granger Causality test are reported for the analysis of Short-term and leag lag relationships.

4.1 Non-Stationarity of Series

In finance research, seeing the behaviour of data is the first essential phase. The time series may be stationary or non- stationary. The log series of cryptocurrencies should be non-stationary for further cointegration analysis. For non-stationary time series, mean, standard deviation and auto correlation is not constant and indicates an increasing or decreasing trend with the passage of time. Graphs for the prices and return series for each digital currency (mentioned in chapter 3) are shown below:

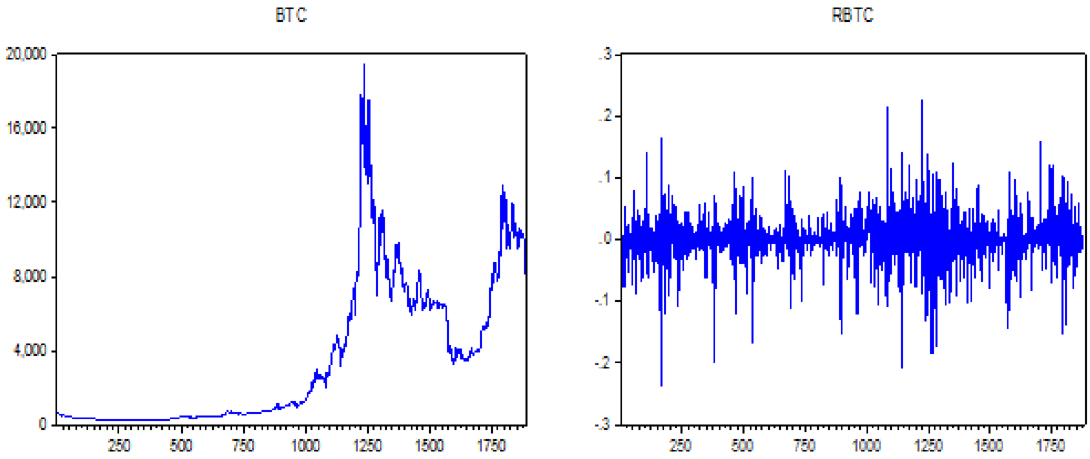

FIGURE 4.1: BTC and RBTC

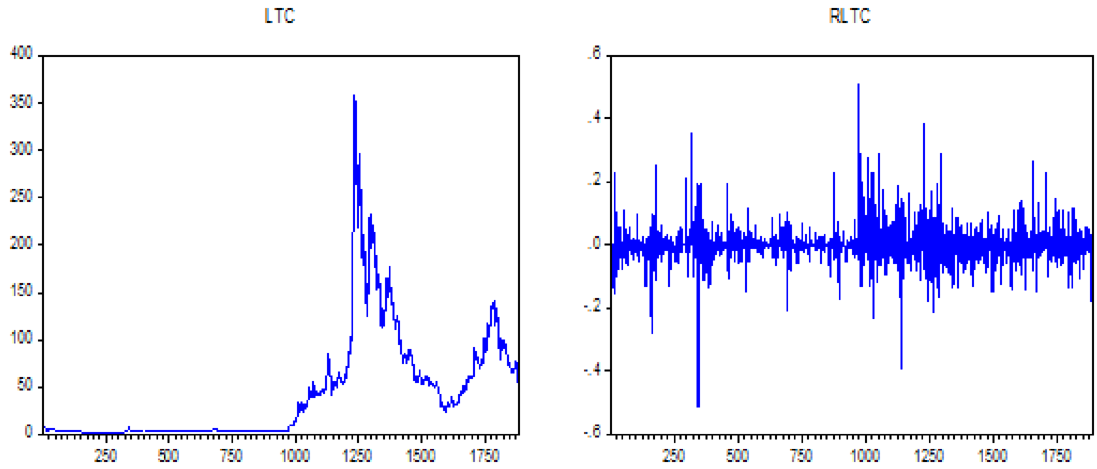

FIGURE 4.2: LTC and RLTC

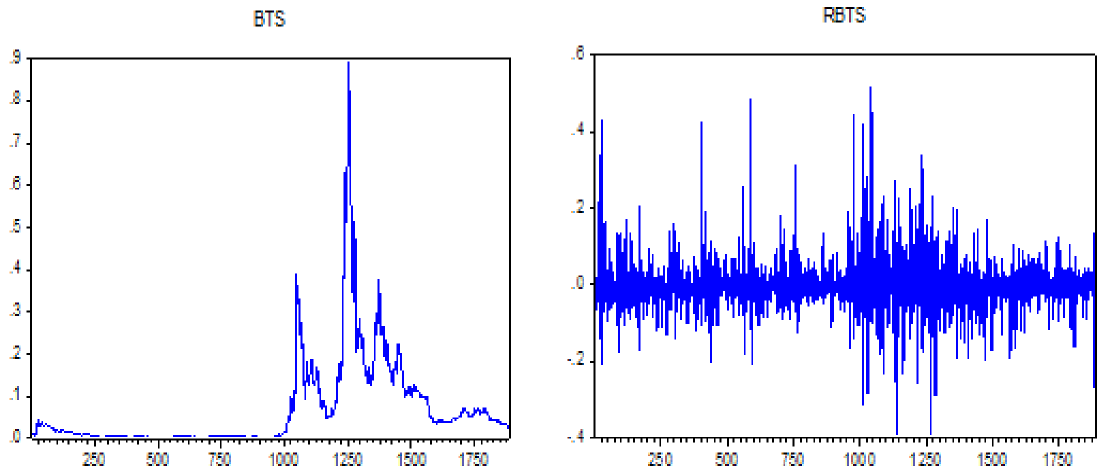

FIGURE 4.3: BTS and RBTS

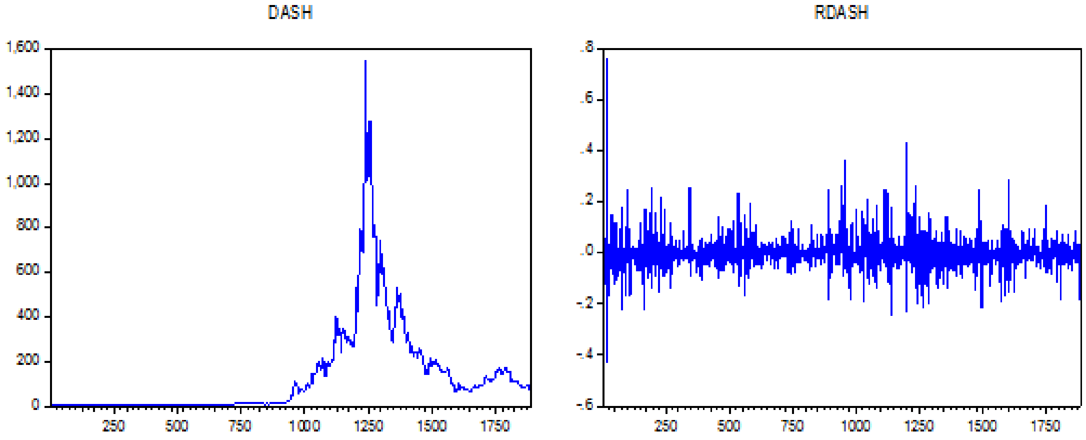

FIGURE 4.4: DASH and RDASH

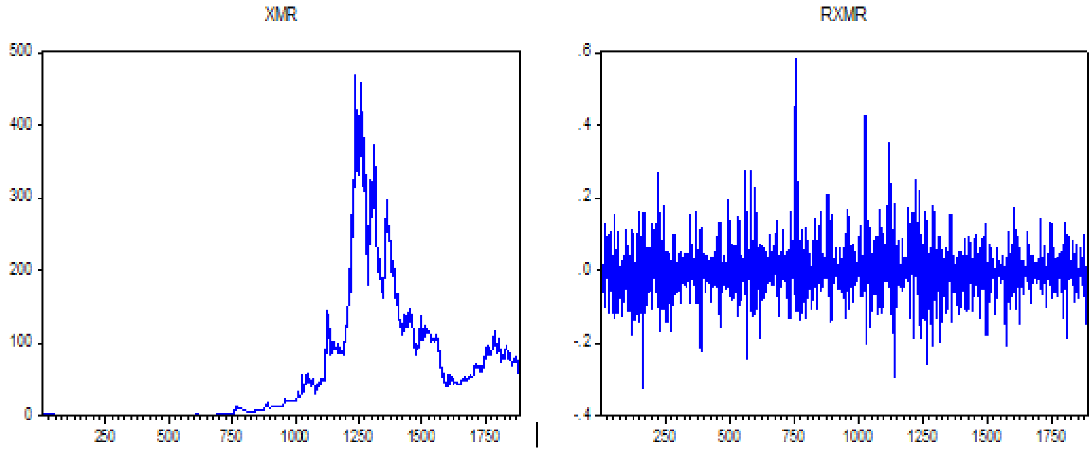

FIGURE 4.5: XMR and RXMR

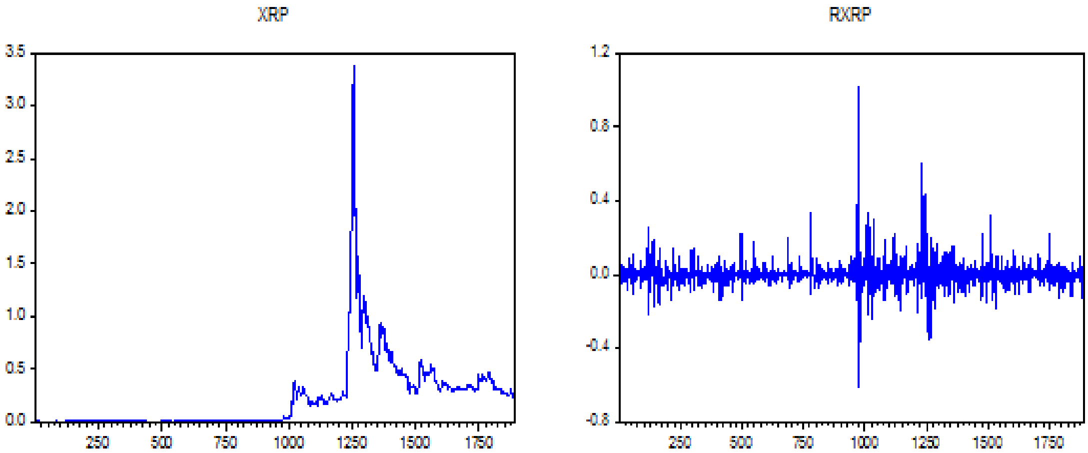

FIGURE 4.6: XRP and RXRP

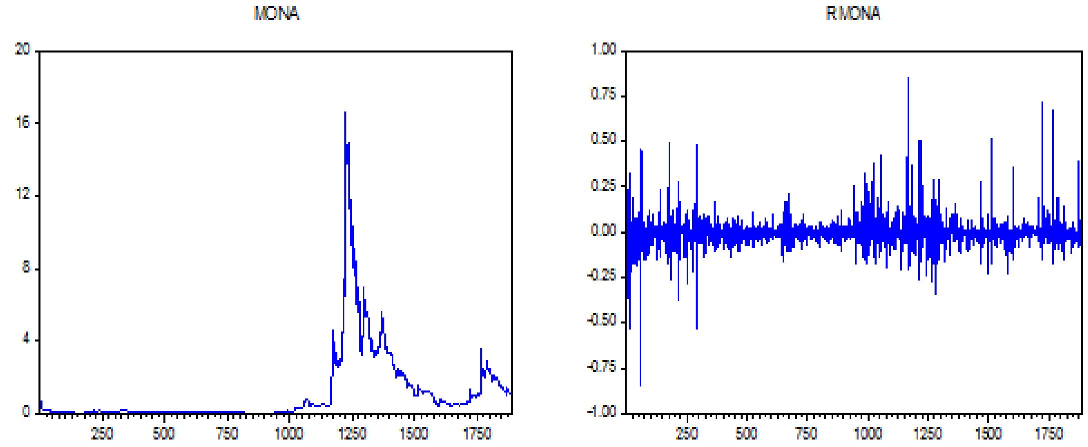

FIGURE 4.7: MONA and RMONA

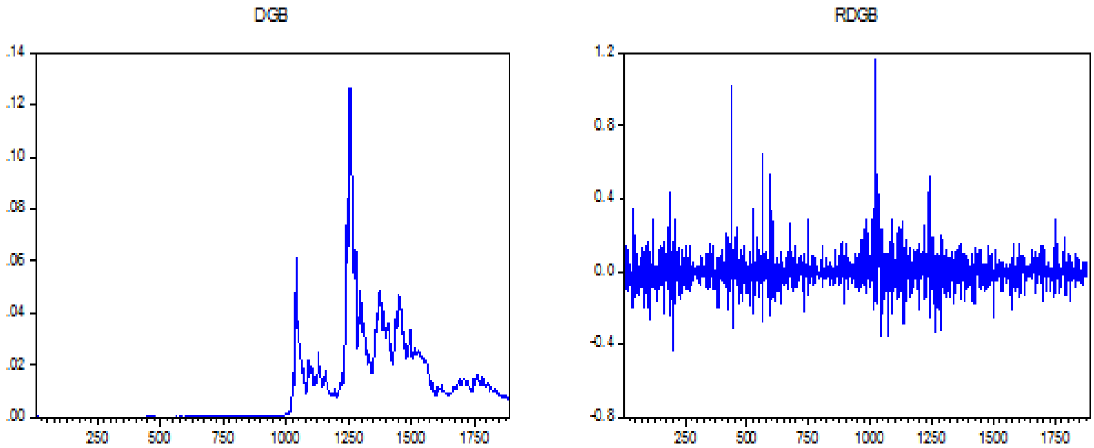

FIGURE 4.8: DGB and RDGB

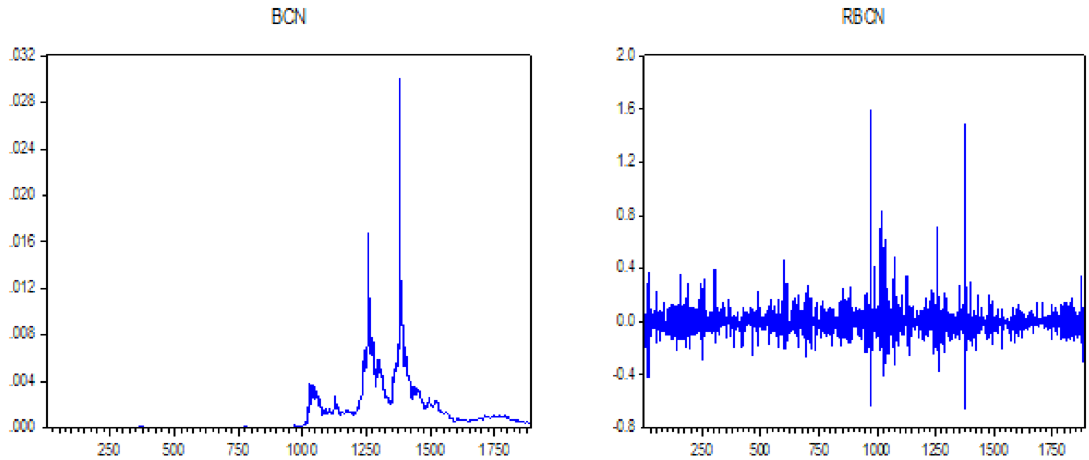

FIGURE 4.9: BCN and RBCN

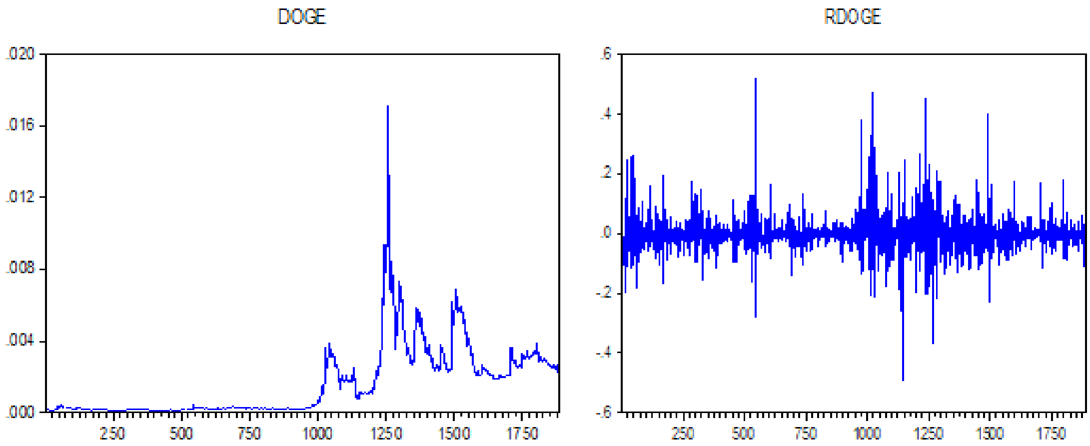

FIGURE 4.10: DOGE and RDOGE

4.2 Descriptive Statistics

The second step is to analyze the characteristics of each series using descriptive statistics. **Table: 4.1** reveals the descriptive statistics of returns of cryptocurrencies i.e., Bitcoin, Ripple, Litecoin, Bitshare, Monero, Dash, Dogecoin, Bytecoin, Digibyte and Monacoin.

Table: 4.1, includes Mean, Median, Standard Deviation, Skeweness and kurtosis. Furthermore, Maximum & Minimum average results are also reported for the distribution of returns.

TABLE 4.1: Descriptive Statistics

Variables	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis
RBTC	0.0014	0.0387	0.2251	-0.2376	-0.3142	8.2111
RBTS	0.0006	0.0742	0.52	-0.3917	0.9587	10.8051
RLTC	0.0011	0.058	0.5103	-0.5139	0.7005	16.1173
RXMR	0.0016	0.0671	0.5846	-0.3254	0.7994	9.7797
RXRP	0.002	0.0669	1.0274	-0.6163	2.9336	45.7581
RDASH	0.0013	0.0629	0.7682	-0.4269	1.3362	19.6319
RMONA	0.0002	0.0895	0.8522	-0.847	1.2229	24.2294
RDGB	0.0018	0.0951	1.1656	-0.4304	2.3727	26.1464
RDOGE	0.0013	0.0627	0.5183	-0.4929	1.0061	15.0417
RBCN	0.0015	0.1101	1.5978	-0.6571	3.6009	49.9658

The mean value determines every crypto currency's average return. The negative mean value indicates negative average returns from these cryptocurrencies.

Bitshares and Monacoin show the lowest average returns of 0.0006 and 0.0002, respectively. Ripple tops the sample with 0.0020 in terms of the maximum mean return value, followed by Digibyte, Monero, Bytecoin, Bitcoin, Dash, Dogecoin and Litecoin with 0.0018, 0.0016, 0.0015, 0.0014, 0.0013, 0.0013 and 0.0011 respectively.

The standard deviation indicates the risk of investment in these cryptocurrency. The descriptive statistics reveal that Bytecoin is the most risky cryptocurrency from the sample with a standard deviation of 0.1101 followed by Digibyte and Monacoin with standard deviations of 0.0951 and 0.0895 respectively. The two least risky cryptocurrency in the sample are Bitcoin and Litecoin with standard deviations of 0.0387 and 0.0580 respectively. Bitshares, Monero, Ripple, Dash, Dogecoin shows standard deviation of 0.0742, 0.0671, 0.0669, 0.0629 and 0.0627 respectively.

Ideally, there should also be high returns when there is high risk. However, the descriptive statistics indicate an inefficient connection between risks and average returns of cryptocurrencies in the sample.

Skewness tells of data's asymmetrical behaviour. Skewness values of Litecoin, Bitshare, Monero, Ripple, Dash, Dogecoin, Bytecoin, Digibyte and Monacoin show positive skewness, meaning that the mean here goes beyond the mode, however BitCoin only shows negative skewedness, meaning that the mean is less than mode. The negative skew trend shows the steady depreciation in the returns of BitCoin i.e. Bitcoin's price dropped by about 65% in the 2018 cryptocurrency clash (from 6 January to 6 February 2018 during the month).

Kurtosis indicates the tailedness of probability distribution. For all cryptocurrencies, the value of kurtosis is greater than 3, which means that all series of cryptocurrencies are leptokurtic i.e. fat tails and are extremely affected with cryptocurrency market bubbles. In this sample, Bytecoin is the most leptokurtic cryptocurrency with a kurtosis value of 49.9658 followed by Ripple's value of 45.7581.

For each cryptocurrency, the minimum and maximum return earned per day is reported by Minimum and Maximum. For instance, average return per day for

Bitcoin (BTC) is (0.14%), minimum return earned per day is (23.76%) and maximum return earned per day is (22.51%). Bitshares (BTS) average return per day is (0.06%), minimum returned earned per day is (39.17%) and maximum return earned per day is (52%). Average return per day for Litecoin (LTC) is (0.11%), minimum return earned per day is (51.39%) and maximum return earned per day is (51.03%) and so on.

4.3 Unit Root Test

The next step is the use of unit root to determine the stationarity of the series. The results of the unit root test used to identify the order of integration between time series data by using Augmented Dicky- Fuller are reported in Table 4.2. The Augmented Dicky-Fuller and Phillip-Perron test are used at the level and first difference. Results indicate that BTC, BTS, LTC, XMR, XRP, DASH, MONA, DGB, DOGE and BCN have Unit Root meaning that non-stationary at level however, first difference of the series that are logarithmic transformed are stationary. The chi-squared likelihood is statistical significant at 5% level (Fisher and Chie square statistics) and all the t-values corresponding with the model parameters are higher than 1.96 (Hair et al., 2006).

TABLE 4.2: Unit Root Analysis - Augmented Dicky-Fuller Test

	Level t-statistic	**level p-value**	**Ist Diff t- statistics**	**Ist Diff p-value**	**Decision**
L BTC	-2.197	0.49	-43.119	0	I(1)
L BTS	-1.238	0.66	-27.644	0	I(1)
L LTC	-2.012	0.594	-42.467	0	I(1)
L XMR	-0.53	0.883	-44.189	0.0001	I(1)
L XRP	-0.968	0.767	-27.463	0	I(1)
L DASH	-0.851	0.804	-45.018	0.0001	I(1)
L DOGE	-1.005	0.754	-41.045	0	I(1)
LMONA	-2.601	0.28	-43.131	0	I(1)
L BCN	-1.185	0.683	-51.603	0.0001	I(1)
L DGB	-0.894	0.791	-43.234	0	I(1)

Furthermore, **Table: 4.3**, reveals the results of Phillip-Perron test that is applied on both first difference and level. Finding of this test also shows that series are integrated of same order. In simple words, all log series of cryptocurrencies (observed in this study) are non-stationary at level and stationary at first- difference. Thus, it can comfortably be said that all log series are I (1) means integrated of Order one. It is worth noting that under the assumption of no trend and constant trend the findings are robust.

Table 4.3: Unit Root Analysis - Phillip-Perron Test

	Level t-statistic	**level p-value**	**Ist Diff t- statistics**	**Ist Diff p-value**	**Decision**
L BTC	-2.217	0.479	-43.132	0	I(1)
L BTS	-1.253	0.653	-41.768	0	I(1)
L LTC	-2.072	0.561	-42.511	0	I(1)
L XMR	-0.597	0.869	-44.353	0.0001	I(1)
L XRP	-1.06	0.734	-44.275	0.0001	I(1)
LDASH	-0.841	0.807	-45.003	0.0001	I(1)
LDOGE	-1.04	0.741	-41.156	0	I(1)
MONA	-2.612	0.275	-43.14	0	I(1)
L BCN	-1.165	0.691	-51.946	0.0001	I(1)
L DGB	-0.944	0.774	-43.306	0	I(1)

This study may now carry out a cointegration analysis after meeting these basic requirements. The Johansen and Juselius (1990) method and test for maximum likelihood-based (Johansen, 1988; Johansen & Juselius, 1990) is applied to identify the existence of cointegrating equations in a set of time series that are non-stationary.

4.4 Lag Length Selection

The next step consists of choosing the parameters for the lag length for which the result is shown in **Table: 4.4**. To select the lag length criteria VAR test is applied, and results indicate that AIC, LR, FPE and HQ all select different lags however, SC selects 1 lag. In this study, SC criteria is adopted and one lag is therefore used.

TABLE 4.4: Stats for the Lag Order Selection

Lag	LogL	FPE	AIC	SC	HQ
0	-13675.8	1.00e-06	14.56709	14.59657	14.57795
1	26118.32	4.49e-25	-27.6832	-27.35892*	-27.56372*

4.5 Multivariate Cointegration

The null hypothesis of r cointegrating vectors is tested against the proxy of r or maybe more vectors of cointegration with trace and Maximum Eigenvalue statistics. Multivariate testing for cointegration is applied on the entire sample period and the findings are shown in table 4.5 and 4.6. Trace test indicates 1 cointegrat-

TABLE 4.5: Multivariate Cointegration Analysis - Trace Statistic

Hypothesized No. of CE(s)	Eigen value	Trace Statistic	Critical Value0.05	Prob.
None *	0.04	274.657	251.265	0.003
At most 1	0.027	198.496	208.437	0.135
At most 2	0.021	146.62	169.599	0.415
At most 3	0.018	106.443	134.678	0.65
At most 4	0.015	72.721	103.847	0.84
At most 5	0.009	43.477	76.973	0.97
At most 6	0.007	25.532	54.079	0.983
At most 7	0.003	11.519	35.193	0.995
At most 8	0.002	5.942	20.262	0.952
At most 9	0.001	2.253	9.165	0.727

ing eqn (s) at the 0.05 level *denotes rejection of the hypothesis at the 0.05 level. **Table: 4.5**, shows the result of trace test that identifies the existence of one equation of cointegration at the = 0.05. The results thus provide evidence of a long-term relationship among cryptocurrencies. Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level.

Table 4.6: Multivariate Cointegration Analysis – Maximum Eigenvalue

Hypothesized No. of CE(s)	**Eigen value**	**Max-Eigen Statistic**	**Critical Value 0.05**	**Prob.**
None *	0.04	76.162	65.3	0.003
At most 1	0.027	51.876	59.24	0.221
At most 2	0.021	40.177	53.188	0.534
At most 3	0.018	33.722	47.079	0.598
At most 4	0.015	29.244	40.957	0.534
At most 5	0.009	17.945	34.806	0.918
At most 6	0.007	14.013	28.588	0.879
At most 7	0.003	5.576	22.3	0.997
At most 8	0.002	3.689	15.892	0.971
At most 9	0.001	2.253	9.165	0.727

Table: 4.6, shows the result of maximum Eigenvalue test that identifies the existence of one equation of cointegration at the $= 0.05$. The result thus also provides evidence of a long-term relationship among cryptocurrencies.

4.6 Vector Error Correction Model

If in the cointegration analysis the variables have a cointegrating parameter, the Vector Error Correction Method (VECM) may be used.

The VECM method integrates the simulation of a short-term dynamic specification along with long-term relationship of cointegration and determines the change of the equilibrium and the rate of adjustment.

Table: 4.7, show the results of Vector Error Correction Model, for the short term relationships the t-statistics for the Bitcoin is insignificant which means that there is no relation between current and previous daily return of Bitcoin. One cannot predict the return by using the previous day return and so on. Result of Monacoin shows significant t-stats that means in short run Monacoin has an effect on Bitcoin. Result also indicates short term relationship of Bitcoin and DASH with Bitshares. In short run, Ripple and Bitcoin has an impact on DASH. Furthermore, Ripple and DASH have a short-run impact on Monero.

Table 4.7: Vector Error Correction Model

Error Correction:	D(LBTC)	D(LBTS)	D(LLTC)	D(LDASH)	D(LXMR)	D(LXRP)	D(LDOGE)	D(LMONA)	D(LDGB)	D(LBCN)
CointEq1	-0.004	-0.006	-0.004	-0.002	-0.009	-0.017	-0.004	-0.011	-0.018	-0.026
	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.004	-0.005
	[-2.14219]	[-1.84895]	[-1.72557]	[-0.75548]	[-2.88735]	[-6.01410]	[-1.39234]	[-2.80001]	[-4.43567]	[-5.48101]
D(LBTC(-1))	0.008	-0.251	0.01	-0.148	0.002	-0.203	-0.136	-0.067	-0.072	0.125
	-0.034	-0.065	-0.051	-0.055	-0.059	-0.058	-0.055	-0.077	-0.083	-0.093
	[0.22482]	[-3.88136]	[0.19817]	[-2.68963]	[0.03671]	[-3.51009]	[-2.48497]	[-0.86363]	[-0.86912]	[1.33693]
D(LBTS(-1))	0.022	0.038	0.01	0.027	-0.003	-0.026	0.043	0.041	0.013	0.123
	-0.015	-0.029	-0.023	-0.025	-0.026	-0.026	-0.025	-0.035	-0.037	-0.042
	[1.44982]	[1.31489]	[0.44023]	[1.10868]	[-0.09904]	[-1.00781]	[1.74343]	[1.17749]	[0.36165]	[2.94495]
D(LLTC(-1))	-0.021	0.066	-0.006	0.054	-0.051	0.091	0.001	0.031	-0.092	-0.126
	-0.021	-0.04	-0.031	-0.034	-0.036	-0.035	-0.033	-0.047	-0.051	-0.057
	[-1.01844]	[1.66909]	[-0.18898]	[1.59525]	[-1.41282]	[2.58069]	[0.01690]	[0.66367]	[-1.82797]	[-2.20279]
D(LDASH(-1))	-0.015	0.071	0.013	-0.028	0.067	0.034	0.036	0.048	0.043	-0.036
	-0.017	-0.033	-0.026	-0.028	-0.03	-0.029	-0.028	-0.039	-0.042	-0.047
	[-0.84853]	[2.16914]	[0.51963]	[-1.01616]	[2.28144]	[1.16598]	[1.29194]	[1.24582]	[1.02433]	[-0.77339]
D(LXMR(-1))	0.011	0.036	0.031	0.037	-0.025	0.014	0.002	-0.004	-0.039	-0.033
	-0.017	-0.031	-0.025	-0.027	-0.028	-0.028	-0.027	-0.037	-0.04	-0.045
	[0.64429]	[1.14477]	[1.24711]	[1.40291]	[-0.87328]	[0.48425]	[0.08059]	[-0.10030]	[-0.97747]	[-0.72490]
D(LXRP(-1))	-0.026	0.008	0.001	-0.076	-0.075	-0.015	-0.052	-0.026	0.088	0.006
	-0.016	-0.03	-0.023	-0.025	-0.027	-0.027	-0.025	-0.035	-0.038	-0.043
	[-1.68734]	[0.27690]	[0.03883]	[-2.99726]	[-2.78267]	[-0.57878]	[-2.06987]	[-0.73577]	[2.31388]	[0.14280]
D(LDOGE(-1))	-0.006	0.001	0	0.003	0.027	-0.01	0.041	-0.058	-0.001	0.028
	-0.019	-0.036	-0.028	-0.03	-0.032	-0.032	-0.03	-0.043	-0.046	-0.052
	[-0.30112]	[0.02522]	[0.01509]	[0.10657]	[0.84958]	[-0.30268]	[1.36858]	[-1.35671]	[-0.02253]	[0.55130]
D(LMONA(-1))	0.021	0.024	0.0003	-0.008	0.011	0.007	-0.0003	0.015	-0.024	-0.044
	-0.01	-0.02	-0.0156	-0.017	-0.018	-0.018	-0.0168	-0.024	-0.025	-0.029
	[2.03181]	[1.21243]	[0.01745]	[-0.48009]	[0.58768]	[0.40012]	[-0.02072]	[0.61994]	[-0.95556]	[-1.52439]
D(LDGB(-1))	-0.001	-0.021	-0.003	-0.009	-0.009	0.008	0.04	-0.004	0.006	0.133
	-0.011	-0.021	-0.016	-0.017	-0.019	-0.018	-0.017	-0.024	-0.026	-0.03
	[-0.12280]	[-1.00485]	[-0.19610]	[-0.49614]	[-0.47148]	[0.41243]	[2.29930]	[-0.14992]	[0.22840]	[4.50552]
D(LBCN(-1))	0.008	0.033	-0.011	0.022	0.022	0.041	0.024	0.039	0.015	-0.22
	-0.009	-0.017	-0.014	-0.015	-0.016	-0.015	-0.015	-0.021	-0.022	-0.025
	[0.82872]	[1.92109]	[-0.84346]	[1.48544]	[1.37646]	[2.66566]	[1.67540]	[1.89182]	[0.67490]	[-8.83874]
C	0.002	0.001	0.001	0.002	0.002	0.002	0.001	0.0006	0.002	0.002
	-0.001	-0.002	-0.001	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.003
	[1.62417]	[0.37653]	[0.74522]	[1.09274]	[1.13965]	[1.41734]	[0.93863]	[0.31814]	[0.85966]	[0.63933]

Findings also indicate a short- run relationship of Bitcoin, Litecoin and Bytecoin with Ripple. Similarly, Digibyte, Ripple and Bitcoin have a relationship with Dogecoin in short run. In short run Ripple has an impact on Digibyte. Finally, Bitshares, Litecoin and Digibyte have impact on Bytecoin in short-run. Results clearly show there is no impact of Monero and Dogecoin on cryptocurrencies in short run.

Vector Error Correction model, (VEC) is applied to explore the short – term disequilibrium of the series and its adjustment. In simple words, Error Correction Model means when the series (two or more) moving together in long-run but suddenly, disequilibrium arises among them that disturbs the cointegrated relationship. Thus, there should be a correction of this disequilibrium that is for short-run, is addressed through Error correction term. The ECM (–1) coefficient suggests how much of the short-run disequilibrium is eliminated in one period.

Results for the adjustment speed of all cryptocurrencies (observed in this study) are shown in Table 4.8.

TABLE 4.8: Adjustment Speed

Cryptocurrencies	**Adjustment Speed**	**t-statistics**
D(LBTC)	-0.004	[-2.14219]
D(LBTS)	-0.006	[-1.84895]
D(LLTC)	-0.004	[-1.72557]
D(LDASH)	-0.002	[-0.75548]
D(LXMR)	-0.009	[-2.88735]
D(LXRP)	-0.017	[-6.01410]
D(LDOGE)	-0.004	[-1.39234]
D(LMONA)	-0.011	[-2.80001]
D(LDGB)	-0.018	[-4.43567]
D(LBCN)	-0.026	[-5.48101]

Results show that coefficient of the six out of ten cryptocurrencies namely; bitcoin, monero, ripple, monacoin, digibyte and bytecoin seem to be significant, with t-values above 1.96, meaning that disequilibrium exists in the short run. Furthermore, as expected in above mentioned six cryptocurrencies, error correction terms (ECT) seem statistical significant along with negative signs in accordance to the ECM theory. Significance means that disequilibrium occurs in the short run and negative signs shows it has been adjusted. Bitcoin model appears to be correcting 0.4 percent of its prior period's disequilibrium in the way merging its level of long-run and so on. The adjustment speed of all six cryptocurrencies is very low.

Bytecoin correction speed is comparatively higher than monero, ripple, monacoin and digibyte i.e., 2.6 percent.

4.7 Granger Causality Test

This study uses the Granger Causality method to analyze the short-term effects of the cointegrated series. This test enables us about the lead lag relationship across the different cryptocurrencies.

Table: 4.9, summarizes the findings obtained for granger causality test applied at one lag. Results show bidirectional causality is detected between Bytecoin and Ripple. Results also indicate that there are unidirectional relationships for the pairs (BitCoin, Dash/ Monacoin, BitCoin/ BitCoin, Bytecoin/ Dash, Bitshares/ Bitshares, Bytecoin/ Dash, Monero/ Ripple, Dash/ Ripple, Monero/ Ripple, Digibyte/ Bytecoin, Ripple/ Ripple, Bytecoin/ Digibyte, Dogecoin/ Dogecoin, Bytecoin and Digibyte, Bytecoin). This relationship means that the effect of shocks on one cryptocurrency is more intense on the other cryptocurrency.

In simple words, where the p value is significant at the 0.05 significance level, it can be said that there is a lead lag relationship between cryptocurrencies. Cryptocurrencies that have lead- lag relationship are dicussed below:

Results indicate that relationship between Bitcoin and DASH is significant it means there is a lead lag relationship among them. Lead lag relationship tells us about the movement of cryptocurrencies that which series moves first or later. Here, Bitcoin moves first and DASH follows the Bitcoin.

Monacoin are also Granger-causing Bitcoin. It indicates lead lag relationship among them. Monacoin leads and Bitcoin follows. Results also show a significant relationship among Bitcoin and Bytecoin. Bitcoin moves first and Bytecoin follows Bitcoin. Furthermore, there is a significant relationship among DASH and Bitshares, that means DASH leads and Bitshares follows. Bitshares Granger-causing Bytecoin that means Bitshares leads and Bytecoin follows. DASH Granger-causing Monero that shows DASH moves first and Monero follows DASH.

Table 4.9: Granger Causality Test

Null Hypothesis:	**Obs.**	**F-Statistic**	**Prob.**
D(LBTS) does not Granger Cause D(LBTC)	1885	0.876	0.349
D(LBTC) does not Granger Cause D(LBTS)		3.416	0.065
D(LLTC) does not Granger Cause D(LBTC)	1885	0.69	0.406
D(LBTC) does not Granger Cause D(LLTC)		0.526	0.468
D(LDASH) does not Granger Cause D(LBTC)	1885	0.239	0.625
D(LBTC) does not Granger Cause D(LDASH)		3.92	0.048
D(LXMR) does not Granger Cause D(LBTC)	1885	0.292	0.589
D(LBTC) does not Granger Cause D(LXMR)		0.011	0.916
D(LXRP) does not Granger Cause D(LBTC)	1885	1.103	0.294
D(LBTC) does not Granger Cause D(LXRP)		3.25	0.072
D(LMONA) does not Granger Cause D(LBTC)	1885	4.051	0.044
D(LBTC) does not Granger Cause D(LMONA)		0.004	0.949
D(LDOGE) does not Granger Cause D(LBTC)	1885	0.063	0.802
D(LBTC) does not Granger Cause D(LDOGE)		2.364	0.124
D(LDGB) does not Granger Cause D(LBTC)	1885	0.029	0.866
D(LBTC) does not Granger Cause D(LDGB)		3.052	0.081
D(LBCN) does not Granger Cause D(LBTC)	1885	0.469	0.493
D(LBTC) does not Granger Cause D(LBCN)		4.836	0.028
D(LLTC) does not Granger Cause D(LBTS)	1885	1.609	0.205
D(LBTS) does not Granger Cause D(LLTC)		0.678	0.411
D(LDASH) does not Granger Cause D(LBTS)	1885	4.517	0.034
D(LBTS) does not Granger Cause D(LDASH)		0.003	0.954
D(LXMR) does not Granger Cause D(LBTS)	1885	1.123	0.289
D(LBTS) does not Granger Cause D(LXMR)		0.302	0.583
D(LXRP) does not Granger Cause D(LBTS)	1885	0.733	0.392
D(LBTS) does not Granger Cause D(LXRP)		0.895	0.344
D(LMONA) does not Granger Cause D(LBTS)	1885	1.407	0.236
D(LBTS) does not Granger Cause D(LMONA)		1.084	0.298
D(LDOGE) does not Granger Cause D(LBTS)	1885	0.107	0.743
D(LBTS) does not Granger Cause D(LDOGE)		2.257	0.133
D(LDGB) does not Granger Cause D(LBTS)	1885	0.317	0.574
D(LBTS) does not Granger Cause D(LDGB)		0.041	0.839
D(LBCN) does not Granger Cause D(LBTS)	1885	2.126	0.145
D(LBTS) does not Granger Cause D(LBCN)		20.393	0
D(LDASH) does not Granger Cause D(LLTC)	1885	1.406	0.236
D(LLTC) does not Granger Cause D(LDASH)		0.139	0.709
D(LXMR) does not Granger Cause D(LLTC)	1885	2.767	0.096
D(LLTC) does not Granger Cause D(LXMR)		0.729	0.393
D(LXRP) does not Granger Cause D(LLTC)	1885	0.413	0.521
D(LLTC) does not Granger Cause D(LXRP)		3.153	0.076
D(LMONA) does not Granger Cause D(LLTC)	1885	0.09	0.764
D(LLTC) does not Granger Cause D(LMONA)		0.824	0.364

Continued Table 4.8: Granger Causality Test

D(LDOGE) does not Granger Cause D(LLTC)	1885	0.149	0.7
D(LLTC) does not Granger Cause D(LDOGE)		0.117	0.733
D(LDGB) does not Granger Cause D(LLTC)	1885	0.02	0.889
D(LLTC) does not Granger Cause D(LDGB)		3.109	0.078
D(LBCN) does not Granger Cause D(LLTC)	1885	0.397	0.529
D(LLTC) does not Granger Cause D(LBCN)		0.246	0.62
D(LXMR) does not Granger Cause D(LDASH)	1885	0.266	0.606
D(LDASH) does not Granger Cause D(LXMR)		5.149	0.023
D(LXRP) does not Granger Cause D(LDASH)	1885	6.869	0.009
D(LDASH) does not Granger Cause D(LXRP)		1.793	0.181
D(LMONA) does not Granger Cause D(LDASH)	1885	0.635	0.426
D(LDASH) does not Granger Cause D(LMONA)		2.363	0.124
D(LDOGE) does not Granger Cause D(LDASH)	1885	0.211	0.646
D(LDASH) does not Granger Cause D(LDOGE)		1.178	0.278
D(LDGB) does not Granger Cause D(LDASH)	1885	0.411	0.522
D(LDASH) does not Granger Cause D(LDGB)		0.107	0.744
D(LBCN) does not Granger Cause D(LDASH)	1885	0.641	0.424
D(LDASH) does not Granger Cause D(LBCN)		1.163	0.281
D(LXRP) does not Granger Cause D(LXMR)	1885	5.107	0.024
D(LXMR) does not Granger Cause D(LXRP)		0.08	0.777
D(LMONA) does not Granger Cause D(LXMR)	1885	0.419	0.517
D(LXMR) does not Granger Cause D(LMONA)		0.213	0.644
D(LDOGE) does not Granger Cause D(LXMR)	1885	0.162	0.687
D(LXMR) does not Granger Cause D(LDOGE)		0.005	0.945
D(LDGB) does not Granger Cause D(LXMR)	1885	0.055	0.814
D(LXMR) does not Granger Cause D(LDGB)		1.571	0.21
D(LBCN) does not Granger Cause D(LXMR)	1885	1.305	0.253
D(LXMR) does not Granger Cause D(LBCN)		1.362	0.243
D(LMONA) does not Granger Cause D(LXRP)	1885	0.201	0.654
D(LXRP) does not Granger Cause D(LMONA)		0.011	0.915
D(LDOGE) does not Granger Cause D(LXRP)	1885	0	0.99
D(LXRP) does not Granger Cause D(LDOGE)		1.631	0.202
D(LDGB) does not Granger Cause D(LXRP)	1885	0.285	0.594
D(LXRP) does not Granger Cause D(LDGB)		5.804	0.016
D(LBCN) does not Granger Cause D(LXRP)	1885	4.38	0.037
D(LXRP) does not Granger Cause D(LBCN)		7.655	0.006
D(LDOGE) does not Granger Cause D(LMONA)	1885	0.092	0.762
D(LMONA) does not Granger Cause D(LDOGE)		0.003	0.953
D(LDGB) does not Granger Cause D(LMONA)	1885	0.155	0.694
D(LMONA) does not Granger Cause D(LDGB)		1.186	0.276
D(LBCN) does not Granger Cause D(LMONA)	1885	2.858	0.091
D(LMONA) does not Granger Cause D(LBCN)		0.23	0.631
D(LDGB) does not Granger Cause D(LDOGE)	1885	6.46	0.011
D(LDOGE) does not Granger Cause D(LDGB)		0.039	0.844
D(LBCN) does not Granger Cause D(LDOGE)	1885	3.077	0.08
D(LDOGE) does not Granger Cause D(LBCN)		8.269	0.004
D(LBCN) does not Granger Cause D(LDGB)	1885	0.028	0.867
D(LDGB) does not Granger Cause D(LBCN)		32.318	0.000

In addition, results indicate significant relationship among Ripple and DASH it means there is a lead lag relationship between them in which, Ripple leads and DASH follows. Ripple also Granger-causing Monero that shows Ripple leads and Monero follows. Similarly, there is a lead-lag relationship between, Ripple, Digibyte/ Bytecoin, Ripple/ Ripple, Bytecoin/ Digibyte, Dogecoin/ Dogecoin, Bytecoin and Digibyte, Bytecoin. First cryptocurrency leads and second follows.
The pairs where the p value is insignificant it means there is no relationship among these. For example, relationship of Bitshares and Bitcoin is insignificant that means there is no lead lag relationship that shows changes in the Bitshares have no relationship with the changes in BitCoin and so on.

Chapter 5

Discussion and Conclusion

5.1 Conclusion

Cryptocurrency is a research area that is relatively unexplored. Virtual currencies have been a new phenomenon on financial markets globally for about a decade. Cryptocurrencies operate outside of centralized financial institutions by offering alternative money. Though providing a less expensive solution to traditional currencies in contexts of transaction fees, virtual currency markets and its prices are growing much more recklessly and fluctuating far greater than conventional currencies.

Only a few studies on the long-term relationship among cryptocurrencies have been published. The present study aims to address this gap in knowledge by exploring long-term as well as the short-term relationship. It further examines the presence of lead lag relationship between cryptocurrencies including Bitcoin during sample time frame. The cryptocurrencies that are studied include; Bitcoin, Litecoin, Bitshare, Dash, Ripple, Monero, Monacoin, Dogecoin, Digibyte and Bytecoin.

In general, this study investigates three hypothesis related to above mentioned cryptocurrencies. Hypothesis 1 states the crptocurrencies have a long-term relationship. Hypothesis 2 states that there exists short-term relationship among cryptocurrencies. Hypothesis 3 implies that above mentioned crptocurrencies has a lead lag relationship. Hypothesis 4 implies that there exists adjustment speed among Cryptocurrencies.

To test these hypothesis, this study applies (Johansen & Juselius, 1990) multivariate cointegration method, Vector Error Correction Model (VECM) and Granger causality test (1987) on closing prices of ten virtual currencies (BitCoin + nine altcoins) for the period between August 2014 and September 2019.

First of all, stationarity of each series is tested. All the graphical representation of each cryptocurrency price series exhibits non stationary behaviour. The Augmented Dickey-Fuller (ADF) test and a Phillips-Perron (PP) unit root test are also used to ensure the stationarity of series. Both ADF and PP test are applied on level and first difference with the assumption of no trend and constant trend. The analysis of the Augmented Dickey-Fuller test shows that all cryptocurrencies have a unit root indicating that the data is non-stationary. The same results are yielded by the Phillips-Perron test.

A Johansen cointegration test is applied after verifying the data is integrated of same order. Secondly, the lags length is selected using the Schwarz Information Criterion (SC). Trace and Maximum Eigenvalue test shows cointegration among sample cryptocurrencies. In the johansen cointegration test, this study reports the Trace statistics that indicates one cointegration at the significance level (0.05). It suggests that in the time period being studied, there is a co-integrating relationship among Bitcoin, Litecoin, Bitshares, Monero, Ripple, Dash, Monacoin, Dogecoin, Digibyte and Bytecoin. The results are consistent with prior studies on cointegration between cryptocurrencies by (Ciaian et al., 2018; Van Den Broek & Sharif, 2018; Leung & Nguyen, 2019).

A Vector Error Correction Model (VECM) is used to measure the short-run relationship among the cointegrated time series. The VECM used the same number of lags as used in Johansen test. Vector Error Correction Model show results in two parts. The first part estimates the long term relationship and the second part shows the short term relationship. This study reports only short-term result that shows there is short term relationship among various cryptocurrencies on the basis of t-stats significant at > 1.96. Prominently, in short run bitcoin is related with bitshare, dash, ripple and dogecoin. Furthermore, in short run, dash has in impact on Bitshares and Monero. Ripple is also correlated with dash, monero, dogecoin and digibyte in short-run.

Error correction model also estimates the adjustment or correction speed of all cryptocurrencies. It states that the short term disequilibrium may arise from long run relationships. Findings of this test show that bitcoin, monero, ripple, monacoin, digibyte and bytecoin's model correction term is statistically negatively significant (t-value 1.96) in compliance with Error Correction concept. Adjusted speed of all models is very slow. BTC represents the slowest or negligible correction speed among all cryptocurrencies that is 0.4% and fastest adjustment speed among these cryptocurrencies is of Bytecoin that is 2.6% meaning that 2.6% of disequilibrium is adjusted in one period with a very slow speed. Adjustment speed of Monero, Ripple, Monacoin and Digibyte are 0.9%, 1.7%, 1.1% and 1.8% respectively.

Granger causality method examines the lead lag relationship among Bitcoin, Litecoin, Bitshares, Monero, Ripple, Dash, Monacoin, Dogecoin, Digibyte and Bytecoin. In this study, this test is applied to identify that which cryptocurrency moves first and its follower (lead lag relationship). The study suggests the evidence of the presence of uni-directional causality among many pairs of cryptocurrencies namely, (BitCoin, Dash/ Monacoin, BitCoin/ BitCoin, Bytecoin/ Dash, Bitshares/ Bitshares, Bytecoin/ Dash, Monero/ Ripple, Dash/ Ripple, Monero/ Ripple, Digibyte/ Bytecoin, Ripple/ Ripple, Bytecoin/Digibyte, Dogecoin/ Dogecoin, Bytecoin and Digibyte, Bytecoin).meaning that there exists a lead lag relationship among above mentioned pairs of cryptocurrencies. It shows that in one pair, for instance (Bitcoin and Dash), means that changes in Bitcoin can granger causes Dash and so on. There is bidirectional relationship for the cryptocurrency pair Bytecoin and Ripple.

5.2 Recommendation

As cryptocurrency market keeps growing with new exchanges and new coins, understanding of co-integration between cryptocurrencies along with adjustment speed is very essential for individual investors, crypto-fund managers.

Investors may be able to determine how to operate in the crypto-currency market plus it will help the crypto investors to diversify portfolio. As, Bitcoin is co-integrated with nine other cryptocurrencies, it indicates there is a long-run relationship among them. Investors can use this to make strategic investment decisions. The investment strategy attempts to identify certain assets with similar price changes or movements that can be used by investors when the assets are integrated.

The findings of this study suggest that empirical evidence of Bitcoin, Bitshares, Litecoin, Dash, Monero, Ripple, Monacoin, Digibyte, Dogecoin and Bytecoin co-integration is valuable not only for digital currency users and potential investors, but it also presents a fascinating laboratory for short- and long-term cryptocurrencies study. Adjustment speed will help the crypto investors to know if there is a long-run equilibrium deviation investors may operate on it in the expectation that it will revert to the long-run equilibrium. This may assist crypto-investors to make a wise investment decision while investing in crypto-market.

5.3 Limitations and Future Directions

Further study may explore if there is a co-integrating relationship between different cryptocurrencies, as there may be several other cryptocurrency than Bitcoin that has an effect on alternative coin prices. In addition, the historical data used in this study is the daily closing price, but further research may investigate hourly prices. It could result an interesting feature on the relationship among cryptocurrencies.

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Appendix-A

Bitcoin Legality

	Name	BTC Legality	Classification		Name	BTC Legality	Clasification
1	Afghanistan	Illegal	Currency	**59**	Lebanon	Legal	No Information
2	Aland Islands	Legal	Currency	**60**	Liberland	Legal	Currency
3	Algeria	Illegal	Currency	**61**	Libyan Arab Jamahiriya	Legal	Money
4	American Samoa	Restricted	Commodity	**62**	Liechtenstein	Legal	Currency
5	Andorra	Neutral / Alegal	No Information	**63**	Lithuania	Legal	Currency
6	Argentina	Neutral / Alegal	Property	**64**	Luxembourg	Legal	Currency
7	Australia	Legal	Currency	**65**	Malaysia	Neutral / Alegal	No Classification
8	Austria	Legal	Currency	**66**	Maldives	Neutral / Alegal	No Information
9	Azerbaijan	Legal	Currency	**67**	Malta	Legal	Currency
10	Bangladesh	Illegal	No Information	**68**	Mauritius	Neutral / Alegal	No Classification
11	Barbados	Neutral / Alegal	No Information	**69**	Mexico	Restricted	Currency
12	Belarus	Legal	No Information	**70**	Monaco	Legal	Currency
13	Belgium	Legal	Currency	**71**	Mongolia	Legal	No Information
14	Bolivia	Illegal	No Information	**72**	Morocco	Illegal	No Information
15	Brazil	Legal	Commodity	**73**	Nepal	Restricted	No Classification

16	Brunei Darussalam	Legal	Currency	**74**	Netherlands	Legal	Commodity
17	Bulgaria	Legal	Currency	**75**	New Zealand	Legal	Commodity
18	Canada	Legal	Barter Good	**76**	Nicaragua	Legal	No Information
19	Chile	Legal	No Information	**77**	Nigeria	Neutral / Alegal	Currency
20	China	Restricted	Commodity	**78**	Northern Mariana Islands	Legal	Commodity
21	Colombia	Neutral / Alegal	No Classification	**79**	Norway	Legal	Commodity
22	Congo	Legal	No Information	**80**	Pakistan	Neutral / Alegal	No Classification
23	Costa Rica	Legal	Currency	**81**	Paraguay	Neutral / Alegal	No Classification
24	Croatia	Legal	Currency	**82**	Peru	Neutral / Alegal	No Classification
25	Cuba	Legal	Currency	**83**	Philippines	Legal	Barter Good
26	Cyprus	Legal	Currency	**84**	Poland	Legal	Property
27	Czech Republic	Legal	Currency	**85**	Portugal	Legal	No Classification
28	Denmark	Legal	Currency	**86**	Republic of Macedonia	Illegal	No Information
29	Ecuador	Illegal	No Information	**87**	Reunion	Legal	Commodity
30	Egypt	Restricted	Commodity	**88**	Romania	Legal	Currency
31	Estonia	Legal	Currency	**89**	Russian Federation	Illegal	Currency
32	Finland	Legal	Currency	**90**	San Marino	Legal	Currency
33	France	Legal	Commodity	**91**	Saudi Arabia	Restricted	No Information
34	Gabon	Neutral / Alegal	No Information	**92**	Serbia	Legal	No Information
35	Georgia	Legal	No Classification	**93**	Singapore	Legal	Currency
36	Germany	Legal	Barter Good	**94**	Slovakia	Legal	Currency
37	Greece	Legal	Currency	**95**	Slovenia	Legal	Currency
38	Hong Kong	Legal	Commodity	**96**	South Africa	Legal	Currency
39	Hungary	Legal	Currency	**97**	South Korea	Legal	No Classification
40	Iceland	Legal	Currency	**98**	Spain	Legal	Currency
41	India	Neutral / Alegal	Commodity	**99**	Svalbard and Jan Mayen	Legal	Commodity
42	Indonesia	Neutral / Alegal	Commodity	**100**	Sweden	Legal	Commodity

43	Iran	Legal	No Classification	**101**	Switzerland	Legal	Currency
44	Iraq	Legal	No Information	**102**	Taiwan	Legal	No Information
45	Ireland	Legal	Currency	**103**	Thailand	Legal	Commodity
46	Isle of Man	Legal	No Information	**104**	Tunisia	Neutral / Alegal	No Classification
47	Israel	Legal	Commodity	**105**	Turkey	Legal	Commodity
48	Italy	Legal	Currency	**106**	Ukraine	Legal	Currency
49	Japan	Legal	Currency	**107**	United Arab Emirates	Legal	Currency
50	Jersey	Legal	Currency	**108**	United Kingdom	Legal	Currency
51	Jordan	Neutral / Alegal	No Classification	**109**	United States of America	Legal	Property
52	Kazakhstan	Neutral / Alegal	Currency	**110**	Uruguay	Neutral / Alegal	Property
53	Kenya	Neutral / Alegal	No Classification	**111**	Uzbekistan	Legal	Currency
54	Kosovo	Neutral / Alegal	No Information	**112**	Venezuela	Neutral / Alegal	Commodity
55	Kuwait	Legal	No Information	**113**	Viet Nam	Neutral / Alegal	Property
56	Kyrgyzstan	Neutral / Alegal	Currency	**114**	Zambia	Restricted	No Information
57	Latvia	Legal	Currency	**115**	Zimbabwe	Legal	Commodity