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Mean and Volatility Spillover From Bitcoin to Major Cryptocurrencies: An Evidence Through GARCH Based Models

by

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This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

CERTIFICATE OF APPROVAL

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Abstract

The purpose of this study is to examined the mean & volatility spillover from bitcoin to major crypto currencies. The study employed the daily data of ten crypto currencies from 2013 to 2019 that are selected on the base of market capitalization and longevity. Mean and volatility spillover is measured by using ARMA (1,1) GARCH (1,1)-M and asymmetric model of ARMA-TGARCH/EGARCH model from bitcoin to major crypto currencies. Moreover, the time-varying nature of conditional correlation is further investigated by using DCC-ADCC models for both aspects as well. The findings of the study conclude that there is volatility spillover from bitcoin to other crypto currencies except Monero and NEM. However, there is little evidence of mean spillover.The asymmetric model of GARCH provide the evidence of asymmetric nature of crypto currencies. Besides this, DCC GARCH also reveals the time-varying nature of conditional correlation. The results also show the presence of asymmetric behavior among different currencies. The study provides information to portfolio managers for assets allocation and risk diversification.

Keywords: Mean & Volatility Spillovers, ARMA-GARCH, ARMA-TGARCH, ARMA-EGARCH, DCC, ADCC and Crypto Currencies.

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Abbreviations

ADCC	Asymmetric Dynamic Conditional Correlation
ARMA	Auto-regressive Moving Averages
DCC	Dynamic Conditional Correlation
EMH	Efficient Market Hypothesis
GARCH	Generalized Auto-regressive Conditional Hetroskedasticity
GARCH-M	GARCH In Mean
MV-GARCH	Multivariate GARCH
VaR	Value at Risk

Chapter 1

Introduction

A crypto currency is a digital asset designed to work as a medium of exchange that uses cryptography to secure financial transactions, control the creation of additional units, and verify the transfer of assets. Crypto currencies and the technologies they use are changing the world. Crypto currency is decentralized as opposed to centralized digital currency and central banking systems.

The first coin constructed on blockchain technology is bitcoin by Nakamoto et al., (2008). It is considered as a market leader of Crypto-currency followed by Ethereum, Litecoin, etc. After bitcoin ethereum is considered as second major crypto-currency. Financial markets and media have been attracted by phenomena of crypto-currency in the current decade. Crypto-currency has a resemblance to some other assets such as bonds or equity. Crypto-currency attracts many users due to its decentralization and freedom (Joshi, Khatiwada, & Giri, 2018). Ammous (2018) argues that digital currency is the best alternative of cash and it considered as new form of currency. Baur, Hong and Lee (2018) argue that crypto-currency can be used as a medium of exchange or for investment tools. This phenomenon attracts many researchers to consider crypto-currency as their major subject. But crypto currency can not be considered as currency due to its instable nature. Every day it prices goes downward and upward. Due to opportunities and challenges, many policymakers and investors attracted to crypto-currency because of their hedging and speculative aspects. Crypto-currency should be treated more than novelty because of increasing demands and interest. Due to recent growth in crypto-currency, it is considered a separate class of assets. Crypto-currency has gained the attention of many investors and evolved with time. The most important feature of crypto-currency is that it is independent of any regulatory authority. Some important features of crypto-currency transactions are: these transactions are irreversibility, fast, unregulated and global. Crypto-currency allows the individual to make transactions without any involvement of any institute like banks and its also become the new asset class (Corbet, Lucey, Urquhart, & Yarovaya, 2019). According to Baur, Hong, & Lee (2018), the reason behind the popularity of crypto-currency is low transaction costs involved in dealing with crypto-currency. So people can buy anything with crypto-currency including illegal things. Foley, Karlsen & Putni (2019) examine that half of the users of bitcoin and quarter transactions of bitcoin involved illegal activities. Yermack (2015) argues that due to its volatile nature crypto-currency should be considered an asset rather than a currency.

According to Gajardo, Kristjanpoller and Minutolo (2018) Crypto-currency is becoming an important part of the financial market. People mostly consider their investment in crypto-currency as a speculative purpose so it should be considered as assets rather than currency (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). According to Ciaian and Rajcaniova (2018) prices of bitcoin and other currencies are independent because of the dominance of bitcoin in the market. Different studies have been done to measure those factors that are responsible for volatility in crypto-currency. The most important factor is the perception of people that how investor looks at the crypto-currency market. Any legal issue or scams may lead to a negative perception. To understand the economic and financial properties of crypto-currency is the major concern for many researchers. Many past studies have done in the context of bitcoin to research prices or return or many more characteristics of bitcoin. Some studies have been done that classify the crypto-currency as an investment (Baur et al., 2018; Glaser et al., 2014). The prices of bitcoin are also highlighted in some paper that includes (Brandvold, Molnr, Vagstad, & Valstad, 2015). This study purpose is to explain transmission of the mean and volatility from bitcoin to major crypto currencies. There is little literature about links in crypto-currencies. Because of the increasing interest in investment in crypto-currencies, people want to know more about this market.

Many studies explain different attributes of bitcoin such as (Cheah & Fry, 2015; Cheung, Roca, & Su, 2015; Fry & Cheah, 2016; Corbet et al., 2019) examine the bubbles in bitcoin. Thies and Molnr (2018) investigate the ups and downs of the return series of bitcoin. Brandvold et al., (2015); Corbet et al., (2019) & Kapar and Olmo (2019) study the bitcoin prices. Kurka (2019) investigates the relationship between crypto-currency and other asset class and finds that unconditional link between crypto currencies and assets class is insignificant. Further, it concludes that bitcoin can be used as a hedge to traditional assets class.

Tarblesi (2018) finds the volatility spillover among crypto-currency and widely traded assets class. The study finds no spillover among crypto-currency and other classes. Katsiampaa, Corbet, Lucey (2018) study the conditional correlation and conditional dynamic volatility among three pairs of crypto-currencies; bitcoin-ether, bitcoin-litecoin and ether-litecoin. They find that past shocks and volatility effects current conditional variance. The findings conclude that there is bidirectional shock transmission from bitcoin to ether and litecoin. Further, it concludes that there is a bidirectional volatility spillover from bitcoin to ether and bitcoin to litecoin. The absence of work in spillover effects within bitcoin markets is the main motive of this study. It focuses on volatility spillover, mean spillover, time-varying correlation and asymmetric behavior of correlation among crypto-currencies. This study also extends the previous literature by considering the broader market of crypto-currencies along with asymmetric behavior of volatility and correlation.

1.1 Theoretical Background

In the theoretical background, the most important theory is Market efficient theory. This theory is discussed by famous economist Fama (1970). Market efficient theory tells us to what extent market price shows all available information. If the market is efficient that means all information is transferred into prices and there are no over or undervalued security. Dyckman and Morse (1986) state that, "An efficient security market is a market if (a) the price of the traded security fully shows the all available information (b) these prices react immediately and in an un-bias form to new information". While on the other hand sometimes stock prices can mislead the investors and their decision making about stock portfolios. So market inefficiency breaks the efficient market hypothesis (Aumeboonsuke & Dryver, 2014). So there is no way to beat the market. Investors want to buy index funds those beliefs in this theory. There are multiple ways to gain market efficiency such as equilibrium, invisible hands and efficiency in a competitive market.

Fama states that there are three stages of market efficiency. The first one is a weak form that exhibits that past prices do not affect future, which rejects the major parameter of technical analysis that recommend investor to buy or sell the stock. So investors cant predict prices through past patterns. The consequence of weak form is that investors cant earn excess return through observing the past prices just because there is no relation between successive prices. Semi strong stage says that the market absorbs the new information so rapidly that investors cant take benefit from the up and down of the market by trading. The third strongest stage says that market presence exhibit both public and private information. Through different ways, market efficiency can be achieved for example by the invisible hand of competitive market and efficiency and equilibrium in a competitive market. The theory of market efficiency supports this study. This theory argues that information that reaches the market completely transfers into prices. So when investors forecast the prices of stocks by interpreting information that reaches the market. If investors forecast that prices will go upward in the future so they can easily manage the today cost to avoid any huge loss in the future.

1.2 Gap Analysis

Different studies have been done to measure volatility Spill-Over in different markets like the currency market, stock market and commodity market but little work is done in the context of the crypto-currency market. Katsiampaa et al., (2019) focus only on three pairs of crypto-currencies to measure volatility Spill-Over. This study is an extension work that will discuss major crypto-currencies having high market capitalization and longevity. This study not only explains the mean and volatility spill-over through ARMA-GARCH model but also explain asymmetric effect throug ARMA-TGARCH and ARMA-EGARCH, time-varying correlation and asymmetric behavior of correlation through DCC and ADCC. Due to the increase in the interest of investors in the crypto-currency market, this topic requires deeper investigation.

1.3 Research Questions

Research Question 1

Whether mean spill-over exists between Bitcoin and other crypto-currencies?

Research Question 2

Whether volatility spill-over exists between Bitcoin and other crypto-currencies?

Research Question 3

Whether asymmetric models better captures mean and volatility spillover?

Research Question 4

Whether time varying correlation exists between Bitcoin and other crypto-currencies?

Research Question 5

Whether asymmetric behavior of correlation exists between Bitcoin and other crypto-currencies?

1.4 Research Objectives

Research Objective 1

To investigate possibility of volatility spill-over between Bitcoin and other crypto-currencies through GARCH based model.

Research Objective 2

To forecast the mean Spill-Over among Bitcoin and other crypto-currencies through GARCH process.

Research Objective 3

To explore the time varying correlation between Bitcoin and other crypto-currencies.

Research Objective 4

To investigate the possibility of asymmetric behavior of correlation between Bitcoin and others crypt-currencies.

1.5 Significance of the Study

There are many studies that examine the mean and volatility across different markets, but very few found in the context of the crypto-currency market. The purpose of this study is to evaluate the mean and volatility spillover from bitcoin to major types of crypto-currency. The significance of this study can see from two perspectives: 1) from an investors point of view and 2) from an academic point of view.

The first one is that it is helpful to those stakeholders who deal with buying and selling in the crypto-currency market. It provides them insight about how fluctuations in bitcoin affect other currency so it helps them in deciding on investing in different crypto currencies. They may make a conscious decision about the future by forecasting the prices of different crypto-currencies. If they know how changes in bitcoin will affect the other currency, so they can avoid taking any risk in making an investment decision. This study is especially helpful for investors and managers whose major concerns is to invest in crypto-currency. It is also helpful for portfolio managers in diversifying the decision as uncorrelated and independent crypto-currencies can be grouped in a crypto-currency portfolio. From the point of view of portfolio diversification, this study will guide that currencies which have less spillover from bitcoin in that currencies there is more opportunity of portfolio diversification and currencies which have high spillover from bitcoin gives less opportunity of portfolio diversification.

Secondly, from an academic point of view, it extends the existing literature by studying time-varying correlation and asymmetric behavior of correlation of a broader set of crypto-currencies. It provides a clearer view of how mean and volatility transmits from bitcoin to major crypto-currencies and how the mechanism can be modeled through the GARCH process.

1.6 Organization of the Study

Chapter 1 consists of introduction, theoretical background, gap analysis, research question, research objectives, significance and plan of study. Chapter 2 contains the literature review and hypothesis of the study. Chapter 3 consists of a research methodology. Chapter 4 includes the analysis of data and results. Chapter 5 provides the limitations of the study and further direction.

Chapter 2

Literature Review

Financial markets are developing so rapidly. Their relationship with each other is the result of globalization. The players of these markets are conscious that how changes in one market affect the other markets. The mechanism of spillover between different markets is the major concern for researchers. Various studies have been done in this regard. The important studies include (Hamao, Masulis, & Ng, 1990; King & Wadhwani, 1990; Engle & Susmel, 1993; Karolyi, 1995; Lin, Engle, & Ito, 1994). But literature is all about the stock market, currency market, commodity market and equity market and very few studies on the crypto-currency market that is the focus of this study. As the crypto-currency is becoming a hot topic. Everyone is concerned about exploring the crypto-currency. Researchers are conscious about how mean and volatility transfer in the crypto-currency market.

Nakamoto et al., (2008) is the creator of Bitcoin. Firstly, Bitcoin is considered as electronic cash with an online payment system based on blockchain technology. Its role as currency has been criticized by many scholars like (Wu & Pandey, 2014; Baek & Elbeck, 2015; Dyhrberg, 2016; Blau, 2017) due to its unstable nature. An increase in bitcoin prices and its ups and down capture the attention of the economist. The literature on crypto-currency is getting enriched. The price of bitcoin is studied by many scholars like (Brandvold, Molnr, Vagstad, & Valstad, 2015; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Kapar & Olmo, 2019).

Bubble in crypto-currency is investigated by studies like (Cheah & Fry, 2015; Cheung, Roca, & Su, 2015; Fry & Cheah, 2016). Fluctuating return of bitcoin are studied by (Thies & Molnar, 2018). The crypto-currency is the hottest topic of 2017 and the reason behind this is increasing prices of bitcoin. Different studies have been done to discuss those factors that determined the price of crypto-currencies (Kristoufek, 2013; Dyhrberg, 2016). Factors that determined the price are demand-supply factors, investors behavior, global indicators, exchange rate, prices of coil or gold. Ali et al. (2014) also explore other factors that determine the price of crypto-currency that is: risk and return trade-off, transaction cost. With the development of the crypto-currency market; now it is considered as assets rather than currency (Blau, 2017; Dyhrberg, 2016; Baek & Elbeck, 2015). Bitcoin is a digital currency that attract many users because of its decentralization and freedom (Joshi, 2017).

Some investigations have been done for studying the characteristics of bitcoin. Grinberg (2011) shows that bitcoin has an edge over other currencies in making payments. However, Wu and Pandey (2014) finds that bitcoin havent basic currency attribute so it should be considered as illiquid assets. The nature of participant who participates in bitcoin system is discussed by (Glaser et al., 2014). It states that users trade on bitcoin with intention of speculative investments rather than for payment purposes. Yermack (2015) argues that bitcoin has similarity with speculative investments. It argues that due to its more volatile nature it is hardly considered as real currency. Letra and Santos (2016) examine the daily prices of bitcoin by using the GARCH model. The findings conclude that popularity does impact on prices of bitcoin and social media networks have some power of forecasting the prices of bitcoin.

Briere, Oosterlinck and Szafarz (2015) present the first look of bitcoin as a diversification tool. Most researchers argue that due to its negative correlation with stock indices it gives high diversification. Gangwal (2016) also argues that by the addition of bitcoin in portfolio it can achieve high diversification through mean-variance analysis. Dyhrberg (2016) discusses the financial abilities of bitcoin using the GARCH model and concludes that bitcoin has some similarity with gold and dollar having hedging capability and can use as a medium of exchange.

Whelan (2013) argues that bitcoin and dollar are the same but there is only a little difference which is that the dollar is backed by the government and bitcoin is not backed by the government. Baur et al., (2018) using the same econometric model of Dyhrberg (2016) argues that bitcoin shows different return volatility as compared to gold and dollar. Bouri, Molnar, Azzi, Roubaud and Hagfors (2017) explain the relationship of bitcoin and other commodities as diversifier and hedger through DCC-GARCH. It shows that bitcoin is a strong hedge against the movement of commodity indices. If we study the bitcoin price crash in the 2013 study reveals that bitcoin properties like hedging and diversification are reported only in the pre-crash period. Volatility in prices of crypto-currency has been studied by (Katsiampa, 2017; Ardia, Bluteau, & Rede, 2019; Phillip, Chan, & Peiris, 2018; Baur & Dimpfl, 2018; Chaim & Laurini, 2018; Troster, Tiwari, Shahbaz, & Macedo, 2018). Many studies have been done to investigate volatility spillover in the stock market and commodity market by using Diebold and Yilmaz (2009) methodology. Very few studies have been found that investigate the volatility spillover among the crypto-currency market.

Trabelsi (2018) investigates the volatility spillover among crypto-currency and other assets class include traditional assets class. Stock index, commodity index such as gold oil through spillover index approach and variance decomposition network. The findings conclude that there is no spillover exist between the crypto-currency market and assets class. Ardia, Bluteau and Ruede (2019) investigate the changes in the volatility dynamics of bitcoin in the long run. It applies the MSGRACH model and concludes that there is regime change in volatility. It further concludes that MSGARCH is best for calculating VAR. Klashorst (2018) investigates volatility spillover among the crypto-currency and equity market by using two stock indices and five major crypto-currencies for his data sample. The findings conclude that there is only volatility spillover from the equity market to the crypto-currency market. There is no leverage effect in the return of crypto-currency. Further, he concludes that there is no time-varying correlation between the equity market and the crypto-currency. In last he finds that the past return negatively affects the current return of bitcoin and stock indices.

Katsiampa et al., (2018) investigates the conditional dynamic volatility and conditional correlation among crypto-currencies having high market capitalization. The study finds that past shocks and volatility affect current conditional variance. The absence of work in spillover effects within bitcoin markets is the main motive of this study .it will focus on volatility spillover, mean spillover, time a varying correlation and asymmetric behavior of correlation among crypto-currencies. Urquhrat (2017) examines the bitcoin volatility by applying the GARCH model. The study concludes that there is no leverage effect in bitcoin and finds no evidence about which model is better i.e. GARCH or HAR. Stavroyiannis and Bablos (2017) examine the dynamic characteristics of bitcoin and SP 500 indexes of the U.S stock market by using uni-variate and multivariate GARCH models and VAR. The study investigates bitcoin its classification as a hedge or diversifier. It concludes that bitcoin has not any characteristics of hedge or diversifier. Cermak (2017) examines whether bitcoin can be used as an alternative for fiat currencies. The findings conclude that bitcoin can be used as an alternative of fiat currencies in China, the U.S and the European Union but not in japan.

Bouoiyour and Selmi (2017) examine the changings in bitcoin price by using a GARCH model for the time frame of 2010 to 2015. It concludes that in the first half of 2015 there is a decrease in volatility. Bouri, Azzi and Dyhrberg (2016) investigate the bitcoin return and volatility changes. The findings conclude that there is no asymmetric volatility in bitcoin. The study further concludes that before the price crash of 2013 negative shocks create less conditional volatility. Katsiampa (2017) estimates the volatility of bitcoin prices by using different GARCH models GARCH, EGARCH, TGARCH, Asymmetric Power ARCH (APARCH), Component GARCH (CGARCH) and Asymmetric Component GARCH (ACGARCH). It investigates that which model of GARCH explain best about volatility of bitcoin prices by using the daily prices of bitcoin from the time frame of 2010 to 2016. The findings conclude that bitcoin prices are so speculative. However, it is concluded that the best model is the ARA-CGARCH model. Chu, Chan, Nadarajah and Osterrieder (2017) apply the: SGARCH, EGARCH, GJRGARCH, APARCH, IGARCH, CSGARCH, GARCH, TGARCH, AVGARCH, NGARCH, NAGARCH and ALLGARCH models to seven crypto-currencies to check goodness of fit of models. The findings conclude that among all of the GARCH type models fitted, the IGARCH and GJARGARCH model provides the best results for larger crypto-currencies. Dyherberg (2016) examines the capabilities of bitcoin by using asymmetric GARCH models and concludes that bitcoin can be used as a hedge against stocks.

Conrad, Custovic and Ghysels (2018) examine the short and long term part of the volatility of crypto-currencies by using the GARCH-MIDAS model. It considers the stock market of the USA as it is the main cause of volatility in prices of bitcoin and concludes that the US stock market effect positively on long term volatility of bitcoin. It further concludes that positive relationship exist between the long-run volatility of bitcoin and Baltic dry index. Al- Khazali, Bouri, Roubaud and Zoubi (2017) examine the effect of positive and negative news on bitcoin and gold by using GARCH models. it uses the time frame of 2010 t 2017. The findings conclude that return and volatility dont react in the same order. It further concludes that there is asymmetric effect and gold and bitcoin dont react the same to positive and negative news. Yi, Xu and Wang (2018) investigate the volatility connection of eight crypto-currencies at both static and dynamic levels by using the spillover index approach. The findings conclude that there is a volatility interconnection in eight crypto-currencies of data samples

Bouri, Das, Gupta and Roubaud (2018) examine the return and volatility spillover among the largest crypto-currency and four types of assets class including equities, stocks, commodities, currencies and bonds by using the VAR-GARCH in mean model for the time frame of 2010 to 2017. The findings conclude that there is volatility spillover from all these assets class to bitcoin market. The significance of spillover shows that there is the least volatility transmit from bitcoin to these assets classes. Yaya, Ogbonna and Olubsoye (2018) examine the dependency of prices of bitcoin on other crypto-currencies by applying the fractional integrational approach for persistence. The findings conclude that there is a high persistence of shocks after the crash period. Adjepong, Alagidede and Akosah (2019) examine the coherency and volatility spillover in seven top leading crypto-currencies for the time frame from 2014 to 2018 by applying the Wavelet-based method. The findings conclude that volatility linkage among crypto-currency is very sensitive to the trading cycle.

Qarni, Gulzar, Fatima, Khan and Shafi (2019) examine the volatility spillover between U.S bitcoin and different financial markets for the time frame from 2010 to 2017. The methodology including Diebold and Yilmaz methodology (2012), Volatility spillover approach, Barunik, Kocenda and Vacha (2017) spillover asymmetric measure and Barunik and Krehlik (2018) frequent connectedness. The findings conclude that volatility spillover is asymmetric in nature. There is a low level of contagion and integration. Fluctuation in bitcoin has no impact on US financial markets. Walther, Bouri and Klein (2019) examine the volatility of the top five crypto-currency choose based on high market capitalization. The study investigates the volatility at daily, weekly and monthly level by using GARCH-MIDAS model and concludes that global economic activity is the main cause of volatility in the crypto-currency market.

Charfeddine and Maouchi (2019) examine the relationship between cryptocurrencies and other financial securities and commodities. The study uses time-varying approaches and bi-variate dynamic conditional correlation GARCH models. The results conclude that the correlation between crypto-currency and these financial securities is weak. It further concludes that any shocks can be sensitive to the relation between crypto-currency and financial securities. Zieba, Kokoszyczynski and Sledziewska (2019) investigate the level to which bitcoin and other crypto-currencies are dependent on each other. It uses the MST model and VAR model and concludes that changes in prices of bitcoin don't affect other prices of other crypto-currencies.

Ji, Bouri, Lau and Robaud (2019) examine the return and volatility spillover in the top six largest crypto-currencies for the time frame 2015 to 2018 by using Debold and Yilmaz method. The findings conclude that there is mostly return spillover from litecoin and bitcoin to other crypto-currencies. Positive return is less strong as compared to negative ones. There is a transfer of negative return shock in ripple and ethereum. Moreover, there is a high volatility spillover in bitcoin. Kotmous (2018) examines the relation between 18 major crypto-currencies by using vector auto-regression and variance decomposition. The study concludes that there is return and volatility spillover from bitcoin to other major crypto-currencies and it increases with time. There are prickles in spillover during any major news.

Baur and Dimpfl (2018) investigate the asymmetric volatility of 20 largest crypto-currencies by using the TGARCH model. The study concludes that negative shocks create less volatility as compared to positive shocks. Symitsi and Chalvatsiz (2018) examine the spillover from bitcoin to energy and technology companies by using the VAR-GARCH model. The study concludes that there is a return spillover from energy and technology companies to bitcoin. There is short term volatility transmit from technology companies to bitcoin. There is long term volatility from bitcoin to fossils fuels. There is negative shock transmit from bitcoin to stock indices and stock indices to bitcoin. The correlation between bitcoin and stock indices is low that gives the advantage of portfolio. Mighri and Alsaggaf (2019) examine volatility spillover and conditional correlation by applying a multivariate GARCH model. The findings conclude that volatility spillover exists in crypto-currency and the DCC GARACH model is best for measuring the conditional correlation. Guesmi, Saadi, Abid and Sadi (2019) examine the volatility spillover between bitcoin and financial indicators by applying a multivariate GARCH model. The findings conclude that there is a significant return and volatility spillover exists between bitcoin and financial indicators.

Liu and Serletis (2019) examine the return and volatility spillover among the crypto-currency market and across with other financial market by applying the GARCH in Mean model. The findings conclude that there is return and volatility spillover among crypto-currencies and also form the crypto-currency market to other financial markets. Vardar and Aydogan (2019) explore return and volatility spillover between bitcoin and other assets like stock and bond in turkey by using the time frame from July 2010 to June 2018 by applying VAR-GARCH in mean with BEKK model. The study concludes that there are return and volatility spillover between bitcoin and other assets class except for the US dollar. Kumar and Anandarao (2019) examine the volatility spillover among four leading crypto-currencies: bitcoin, ethereum, ripple and litecoin for the time frame of August 2015 to Jan 2018 by using I-GARCH and DCC model. The study concludes that there is volatility spillover from bitcoin to ethereum and litecoin. Moreover, the findings conclude that all crypto-currency is affected by fluctuation in bitcoin. Miglietti, Kubosova and Skulanova (2019) examine the volatility of bitcoin, litecoin and euro for the time frame of Jan 2014 to December 2017 by using Dickey-Fuller test and Akaike information criteria. The study concludes that litecoin is high volatile as compared to bitcoin and euro and bitcoin is volatile as compared to the euro.

Katsiampa (2018) examines the volatility between bitcoin and ether. He used a bi-variate diagonal BEKK model and findings conclude that there is inter dependency between bitcoin and ether. Moreover, it is concluded that to any new and important news conditional volatility and correlation of above these two crypto-currencies have a response. Finally, ether can be used as a hedge. Kyriazis, Dasskalou, Arampatizs and papaaioannou (2019) examine the volatility of the crypto-currency market for the time frame of Jan 2018 to Sep 2018 by using ARCH, GARCH and DCC-GARCH model. The findings conclude that mostly crypto-currency is affected by highly capitalize crypto-currencies such as bitcoin, ethereum and ripple. Zieba, Sledziewska and Kokoszczynski (2019) examine the inter dependency of crypto-currency of each other especially on bitcoin by using MST and VAR method. The study concludes that bitcoin price changed isnt affected by other crypto-currencies.

Beneki, Koulis, Papadamou and Kyriazis (2019) investigate the volatility spillover between bitcoin and ethereum. it uses the BEKK-GARCH model and VAR model. The findings conclude that there is volatility spillover from ethereum to bitcoin but not from bitcoin to ethereum. There is a positive response of bitcoin volatility on positive volatility shocks on ethereum return. Yaya, Ogbonna and Mudida (2019) examine the volatility persistence in twelve crypto-currencies during pre-crash and post-crash period through applying fractional integration methods. The findings conclude that persistence of volatility exists only for a short period.

Cobert et al., (2019) examines the dynamics of conditional volatility and co-movement of their volatility. The study uses the daily closing prices of bitcoin, ether and litecoin for the time frame of 2015 to 2018 and applied diagonal BEKK and asymmetric diagonal BEKK model. The study concludes that past conditional volatility and past squared error have a significant impact on all conditional variances. Further, the findings conclude that there is a high persistence of volatility in all crypto-currencies. There is a strong interdependence between crypto-currencies. The asymmetric diagonal BEKK model is best as compared to others. Conditional volatility of return of will the crypto-currency is affected by the asymmetric effect of positive and negative news. There is a time-varying conditional correlation that exists in crypto-currencies.

Different studies have been done to study the mean and volatility spillover in the stock exchange market. The investors want to know the mechanism of how mean and volatility transmitted into stock exchange from a different market so that they can make a wise decision about investing in the stock market. Choi, Fang and Fu (2010) examine the volatility between foreign exchange and stock market in Indian and New Zealand. It finds significant asymmetric volatility. Filis, Degiannakis and Floros (2011) study the time-varying correlation between the stock market and oil prices in the USA, Germany, and Netherlands. The study uses the DCC-GARCH models and concludes that there is a negative relation in oil prices and stock market returns. Xiao and Dhesi (2010) examine the volatility spillover of four indices by using BEKK and DCC models. The study finds a significant volatility link between U.S and Europe markets.

Bonga and Hoveni (2011) examine volatility spillover between the South Africa equity market and the foreign exchange market by using the EGARCH model. The study concludes that only unidirectional volatility spillover exists from the equity market to the foreign exchange market. Joshi (2011) studies the mean and volatility spillover between the Asian stock market by applying the GARCH-BEKK model and finds that bidirectional return spillover. Chittedi (2012) examines the relationship between oil prices and the stock market in India through the ARDL approach. The findings conclude stock prices have an impact on oil prices in India. Guesmi and fattoum (2014) study the volatility and asymmetric relationship between oil and stock markets by using the DCC-GARCH model and conclude that oil prices have a huge effect on the stock market.

Lin, Wesseh and Appiah (2014) examine the volatility spillover between the oil market and stock market in Ghana and Nigeria and state that strong volatility spillover exists in the Nigeria stock market. Andrikopoulos, Samitas and Kougepsakis (2014) examine the arrangement of volatility spillover between currency and stock market for European companies. The study concludes that bidirectional asymmetric volatility exists between the stock market and the currency market. Bouri (2015) examines that mean and conditional variance by using the ARMAX-GARCH model. The study focuses on how the financial crisis of 2008 affect the volatility spillover between the oil market and the stock market. It concludes that there is a significant impact of oil prices on the stock market. Khalfaoui, Boutahar and Boubaker (2015) examine the spillover between oil prices and the stock market by using the BEKK-GARCH technique. The study finds that spillover exists between oil prices and the stock market. Mozumder, De Vita, Kyaw and Larking (2015) explore the volatility spillover between stock prices and exchange rates and conclude that volatility spillover exists. Bad news has more impact on the market as compared to good news. Xiong and han (2015) study the volatility spillover between foreign exchange and stock market and find there is a negative spillover between these two markets.

Boldanov, Degiannakis and Filis (2016) study the time-varying correlation between oil prices and stock market volatility by using the BEKK model. The study uses six major countries that import and export oil. The study finds that the correlation between stock and oil market changes with time. Further, it concludes that there is a time-varying correlation between oil importing and exporting countries. Tian and Hamori (2016) study the transmission of the financial shocks across different markets like equity, bond and equity market and suggest that volatility spillover fluctuates over the period. Mwambuli, Xianzhi and Kisava (2016) examine the symmetric volatility spillover between the stock market and stock exchange market in Turkey and conclude that asymmetric volatility exists between these two markets. It further finds that significant asymmetric volatility exists between these two markets.

Ping, Ziyi, Tianna and Qingchao (2018) examine volatility spillover of fuel oil spot, fuel oil furniture an energy stock market in china by using the DCC-GARCH model and VAR-BEKK-GARCH models. It finds that correlations among these markets are low as compared to US markets. Secondly, it concludes that there are bilateral volatility spillover effects between fuel oil spot and futures, fuel oil spot and energy stocks, while there is a unidirectional effect from the energy stock market to fuel oil futures market. Hung (2019) studies the mean and volatility spillover between china and south Asian stock markets by using GARCH-BEKK models. The study suggests that volatility in the Chinese stock market has an impact on other markets. Morales and Sosvilla (2018) examine volatility spillover between foreign exchange and stock market in seven economies which are the major part of foreign exchange transactions by using CGARCH and SVAR. The study concludes that some elements which include permanent and temporary both of variance show peaks volatility during economic and financial uncertainty. After the crisis period, long term volatility is greater than the short term. During the post period of financial crisis inter and intra-spillover increase. Stock markets trigger the short and long term volatility but only before the periods of crisis. Foreign exchange plays a very vital role in increasing the short term volatility. Khalfaoui, Sarwar and Tiwari (2019) examine the volatility spillover between the oil market and the stock market of oil exporting-importing countries by using DCC and CDCC models. The study concludes that oil-importing countries are affected by the lagged oil process, and there is no evidence of inter dependency between the stock market of these countries. Further, it concludes past volatility shocks in the oil market and stock market effect the current volatility in these markets.

Qarni and Gulzar (2018) examine the return volatility spillover between the stock market of China. it concludes that return spillover is high as compared to volatility spillover. Hu, Hu and Ning (2018) examine the return and volatility spillover between stock indices of IT technology in the Asia area. The study uses the time frame of 1998 to 2017 and applies the approach of Diebold and Yilmaz. The findings conclude that return and volatility usually arise from the United States, whereas other countries receive this spillover from the United States. Arouri, Jouini and Nguyen (2012) estimate the volatility spillover between oil and stock markets of Europe by using the VAR-GARCH model and find significant volatility spillover between these two markets. Zhou, Zhang and Zhang (2012) examine the volatility direction among Chinese and world equity markets and find that Chinese markets have a positive effect on all other markets. Sakthivel, Bodkhe and Kamaiah (2012) estimate the volatility and correlation between stock markets of USA, India, UK, Japan and Australia and find that volatility transfer from USA to India and India to USA and from Japan and the United Kingdom to India. It further finds long-run co-integration. The most dominate market is the USA stock market which influences all other markets. Abbas, Khan, and Shah (2013) estimate the volatility spillover between equity markets of China, Pakistan, Sri Lanka and India and find the volatility spillover among those countries having good trade terms but they also find some volatility among those who havent such terms.

Yasvas and Dedi (2016) estimate the return and volatility spillover between equity markets of China, Russia, Germany, United Kingdom by using MARMA, GARCH in mean, EGARCH models. The study finds the co-movement among these markets. Russia and turkey market show high volatility than UK and Chinese markets. Xu, Taylor and Lu (2018) examine the volatility spillover in the equity market during and after the global financial crisis. The findings conclude that volatility is independent in the case of equity markets. Different studies have been done for mean and volatility spillover in the currency market. The currency market also includes the foreign exchange market. The exchange rate is the value of the currency of one country in terms of the currency of other countries. The fluctuation in currency is on a daily basis. There are many reasons behind it. Some theories suggest there is lead and lag relationship between the currency market and the stock market. Fedrova and Saleem (2009) examine the transmission of volatility between the currency market and the stock exchange market in Eastern Europe. This study is done in three stages. At first, it evaluates the relationship between European equity markets and Russia secondly it estimates the relation between the currency market of different regions of Europe. In last it estimates the dependency level between equity markets and Eastern Europe and Russia by using the GARCH-BEKK model. It finds that return and volatility spillover in the equity market as well as in the currency market. Further, it is concluded that volatility transfers only from currency to the stock market. Bubak, Kocenda and Zikes (2011) examine the volatility spillover in European foreign exchange markets. The study finds a significant volatility spillover between these markets. Morales (2008) estimates the volatility spillover between stock return and exchange rate of the Czech Republic, Hungary, Poland and Slovakia for the time frame 1999-2006. The findings conclude that there is no volatility spillover exist in these countries. Gosh (2014) examines the volatility spillover in the foreign exchange market in India. The study finds the asymmetric volatility spillover from different markets to Indian foreign exchange markets. But this volatility decrease after the financial crisis period. Antonakakis and Kizys (2015) examine the dynamic spillover between the currency market and commodity markets and find that spillover exists between these two markets.

Ji and Fan (2012) examine the volatility spillover between the non-energy commodity market and the oil market by using the EGARCH model. The findings conclude that there is volatility spillover from the oil market to the commodity market. Nazlioglu, Erdem and Soytas (2013) investigate the volatility movement between oil and agriculture markets by applying causality tests. The findings conclude that volatility spillover changes with time. Haixia and Shiping (2013) estimate volatility spillover between crude oil agriculture markets of china by using EGARCH and BEKK-MVGARCH model. The findings conclude that oil and corn are the major receiver of the ARCH effect. Mensi, Beljid, Boubaker and Managi (2013) examine the correlation and volatility spillover between commodity and stock markets by applying the VAR-GARCH model and find the significant volatility between stock exchange and commodity markets. The study concludes that there is the highest conditional correlation among SP index 500 and gold index and SP 500 and WTI index. Ismail and Jabeen (2015) examine the return and volatility transmission between food and agriculture commodities by using different models of GARCH. The findings conclude that if the price of one commodity change it affect the price of another commodity. The study of Jebabli, Arouri and Teulon (2014) conclude that volatility spillovers significantly increase during the period of crises by using the VAR model.

Beckmann and Czudaj (2014) examine the volatility spillover by applying the GARCH-M model and VAR model in the agriculture market. The study finds significant volatility in the agriculture market. Kang, Mciver and Yoon (2017) examine the dynamic volatility spillover between crude oil, precious metals and agricultural commodity futures market by applying the DECO-GARCH model. The study finds bidirectional return and volatility transmission among the futures commodity market. The study concludes that gold and silver are transferring information to other commodity markets. Kanchna et al., (2017) examines the price and volatility spillover between spot and future market of black pepper. He finds that there is a high persistence of volatility in the spot market. He finds the bidirectional volatility. He also finds a co-integration relation between the spot and futures markets. Yousaf and Ahmed (2019) estimate the mean spillover in Latin American stock exchange markets by using GARCH in mean model and find that there is mean spillover from US markets to Latin American stock market.

Maitra and Dawar (2019) examine the return and volatility spillover between commodity future, stock market and exchange rate and find that return spillover exists from a commodity market to stock and exchange market. Wang and Wang (2019) examine the volatility spillover among crude oil and Chinese sectoral equity markets and find the spillover between these two markets. Vradar (2018) explores the volatility spillover in the stock market and commodity market by using the VAR-BEKK GARCH model. The findings conclude that there is volatility transmission from the stock market to the commodity market. This study also fills the gap of the previous study done by (Katsiampa et al., 2019). In this study, it uses the top 10 currencies. The study measures the mean and volatility y spillover from bitcoin to major types of crypto-currency as well as time-varying correlation and asymmetric behavior of correlation by applying ARMA-GARCH and DCC and ADCC models.

2.1 Asymmetric Volatility Transmission In the Markets

Different studies have been done in asymmetric effects across different markets like the stock market, equity market and commodity market. The literature related to the asymmetric effect in these markets is discussed below. Firstly, Nelson (1991) presents the model which captures the behavior of volatility when prices go upward or downward. Sentana and Wadhwani (1992) examine the volatility response to some news when it arrives in the market. The findings conclude that volatility created by bad news is greater than the volatility created by good news. Engle and Ng (1993) find that the model (GJR) captures the asymmetric effect of the index of the Japanese stock market. Antoniou, Holmes and Priestly (1998) examine the behavior of volatility in the context of asymmetric by using the GJR-GARCH model and find asymmetric effect exists in the stock market. Sadorsky (1999) examines the relation between stock return and oil price volatility through the VAR model. The findings conclude that oil prices affect the stock return and oil price volatility has an asymmetric effect. Kotumus and Booth (1995) examine the effect of asymmetry of good news and bad news on volatility spillover by using the EGARCH model by using the daily data of stock return. The study concludes that bad news creates more volatility as compared to good news.

Chen, Chiang and So (2003) examine the asymmetric effect of USA stock return and volatility by using the TGARCH model for the sample of return series of six indexes. The findings conclude that there is an asymmetric effect in both the return and volatility of the stock market. It further concludes that negative news decreases the return more as compared to the good news. Moreover, negative news creates more volatility as compared to good news. Chen (2007) examines the asymmetric effect of monetary policy on returns of the stock market. The findings conclude that monetary policy has an asymmetric effect on the return of the stock. Alberg, Shalit and Yosef (2008) examine the volatility and conditional variance of stock by using the EGARCH model. The findings conclude that the asymmetric EGARCH model can be used for further risk management and others. Hammed and Kangs (2010) examine the stock market decline. The findings conclude that negative news brings a decline in the volatility of the stock market. Li and Chiou (2011) examine the sensitivity of oil prices and their asymmetric impact on the stock market. The findings conclude that unexpected asymmetric changes in oil prices decrease the stock return. Lee and Zang (2011) examine the asymmetric effect of oil prices on the return of the stock market in G7 countries. The study finds the asymmetric effect of oil prices in stock return. Goudarzi and Ramanarayanan (2011) examine the asymmetric behavior of the volatility Indian stock exchange market by using the TGARCH and EGARCH model by using the time frame of the global financial crisis of 2008-2009. The findings conclude that there is an asymmetric effect exists. Negative news creates more volatility as compared to bad news.

Bashir et al., (2013) investigates the asymmetric volatility in the Asian stock market by using the daily return of stock indices for the time frame from 2007 to 2012. It uses the model of Glosten (1993) GJR-GARCH model. The findings conclude that there is an asymmetric effect in all Asian stock markets. Hofilea and Tomaliwan (2014) investigate the relationship between the stock market return and conditional volatility with the effect of asymmetric. The study applies EGARCAH and TGARCH model for the time frame of 1994 to 2012. The findings conclude that there is no relation between return and volatility. Volatility created by bad news is high as compared to good news. Owidi and Mugo-Waweru (2016) examine the asymmetric effect in the volatility of the Kenyan stock exchange market by using the FIEGARCH model. The findings conclude that there is an asymmetric effect that exists in the Kenya stock exchange market. Sahoo, Behera and Trivedi (2018) find that volatility that is transmitted in the foreign exchange market from the stock market is asymmetric in the case of India. Higher volatility in the foreign exchange market is resulted from negative shocks of the stock market.

Bal, Manglani and Deo (2018) examine the stock market of India and the foreign exchange market in the context of volatility spillover by using the EGARCH model. It finds that there is the asymmetric effect exists. Hung (2019) examines volatility spillover between foreign exchange markets of eastern and European countries for the time frame from 2000 to 2007. It uses the EGARCH model to capture the asymmetric effect. The findings conclude that there is asymmetric exist in these markets. Good news creates more volatility as compared to bad news. Fatima, Rashid and khan (2019) investigate the effect of shocks on Islamic stock exchange by applying the EGARCH model for the time frame of 2009 to 2016. The findings conclude that negative shocks create more volatility as compared to a positive one. Newaz and Park (2019) examine the intensity of trade and asymmetric volatility spillover between the USA and 74 international stock markets. The findings conclude that as intensity of trade increase market volatility more respond to negative news. Xu, Ma, Chen and Zhang (2019) examine the asymmetric volatility spillover between oil and stock markets for the time frame of 2007 to 2016. The findings conclude that there is asymmetric volatility spillovers exist. Bad news creates more volatility as compared to the good one. Nguyen, Nguyen and Pham (2019) examine the asymmetric impact of monetary policy on crypt currency markets. The findings conclude that there is an asymmetric effect between monetary policy and crypto-currency. Chen, Li and Qu (2019) examine the asymmetries in volatility spillover for the time frame of 2007 to 2016 and conclude that spillover that is generated from good news is less strong as compared to spillover that generate from negative news.

Nandy and Chattorpadhay (2019) examine the asymmetric volatility spillover between the Indian stock market and other financial markets in India. Secondly between India stock market with global stock market and foreign exchange markets. The findings concluded that asymmetric volatility spillover exists between the Indian stock market and the foreign exchange market. Habiba, Peilong, Hamid and Shahzad (2019) examine the volatility spillover in Asian stock markets for the time frame from 2002 to 2017. To measure the asymmetric effect of volatility study, use the EGARCH model. The findings conclude that there is asymmetric volatility spillover in all the stock markets. Hasan and Abu (2019) examine the Islamic stock index and conventional index in the context of co-integration and volatility. By applying the EGARCH model, the study concludes that these markets are very reactive to bad news.

Fakhfekh and Jiribi (2019) examine the dynamics of volatility of crypto-currencies by applying five different GARCH models. The study concludes that TGARCH is model is best. Moreover, the asymmetric effect exists and positive shocks create more volatility as compared to negative. Mensi, Soy, Aslan and Kang (2019) examine the asymmetric volatility between bitcoin and metals. The findings conclude that there is a volatility spillover between bitcoin and metals and asymmetric effect exists. Moreover, bitcoin transmits more positive spillover to high precious metals. Luo and wang (2019) examine the asymmetric volatility spillover in the international stock market. The findings conclude that there is asymmetric volatility spillover exists in the international stock market. Bad news creates more volatility as compared to good news. Aye and Sikhosana (2018) examine the asymmetric volatility spillover among the exchange rate and stock return in South Africa for the time frame of 1996 to 2016. The study uses the EGARCH model GJR-GARCAH model and finds that there is asymmetric volatility spillover exists between real exchange rate and stock return of South Africa.

Babalso and Satavros (2017) examine the crypto-currency market for the time frame of 2015 to 2018 through a quantile test and the study concludes that asymmetric behavior exists in return of crypto-currency. Katsiampa (2019) examines the dynamics of the volatility of five crypto-currencies named: bitcoin, ether, ripple and litecoin by applying the BEEK-GARCH model. The findings conclude that time-varying correlation exists and it is positive. There is inter dependency between crypto-currencies. Moreover, asymmetric behavior exists. This study discusses the asymmetric behavior of volatility across many markets like the stock market, equity market, oil market and foreign exchange market. In most market, asymmetric behavior exists and bad news creates more volatility as compared to good news but find very little literate across the crypto-currency market. This study discusses about asymmetric behavior of volatility across the crypto-currency market.

2.2 Time-Varying Conditional Correlation DCC & ADCC

In past decades there are numerous existing literature about GARCH models related to conditional variance and conditional volatility. Firstly, Bollerslev, Engle and Wooldridge (1988) discuss the multivariate GARCH VECH model. This model explains the conditional covariance between the series. Firstly, Engle (2002) presents the concept of dynamic conditional correlation. Cappiello et al., (2006) extend the existing literature of Engle (2002) and discuss the concept of asymmetric dynamic conditional correlation ADCC GARCH model. This model tells about the impact of positive and negative news. In most cases, the negative shocks have a great impact on market volatility of the same sample size. In the past, many studies related to dynamic conditional correlation are conducted. Wang and Moore (2008) estimate the inter-dependency between 3 markets the Czech Republic, Poland and Hungary to euro markets by using the DCC model. The findings conclude that due to the financial crisis there is a high and increasing correlation between CEE and euro markets. It further finds that if there is high financial depth it will lead to higher correlation.

Savva and Aslanidis (2010) estimate the connection between markets of five Central and Eastern European countries from the period of 1997 to 2008 and conclude that there is a high correlation among the largest central and eastern European countries as compared to others. It also finds increasing correlation in the euro area among CEE countries and between Polish, Slovenian and Czech. Chong and Miffre (2010) employ the dynamic condition correlation to examine the stocks hedging and treasury bills with 25 future contracts by using the daily data for the period of 1981 to 2006. The study concludes that there is a decreasing correlation with time between SP 500 and commodity futures. Choi and Hammoudeh (2010) investigate the behavior of volatility in the oil industry by using the GARCH switching approach and DCC GARCH model for the time frame 1990 to 2006 and conclude that there is increasing correlation since 2003. After the Iraq war, it exhibits a decreasing trend of correlation with the SP500 index.

Syllignakis and Kouretas (2011) examine the correlation among CEEC countries (the Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia and Slovenia) to the U.S. Germany & Russia by using weekly data from1997 to 2009. The study uses the dynamic conditional correlation approach and finds that there is a time-varying correlation in all stock market and this trend increase with time. Gijika and Horvath (2013) investigate the time-varying movement in stock markets of central Europe by using daily data from 2001 to 2011. The study applies the model of asymmetric dynamic conditional correlation and conclude that there is a strong correlation among the stock market of central Europe. This behavior increases with time even during the financial crisis and entry of the European Union. In conditional variance and conditional correlation, the stock market exhibits asymmetric behavior There is a positive relation between conditional correlation and conditional variance.

Chang, Macleer and Tansuchatf (2013) examine the volatility spillover and conditional correlation between crude oil and financial markets. They use the return of oil and stock index by using daily data from 1998 to 2009. The VARMA-GARCH and CCC, VARMA-AGARCH and DCC model provide that results of DCC are significant that shows the assumption of constant conditional correlation is not true but in the case of CCC results are not significant. The result of VARMA-GARCH and VARMA-AGARCH shows that there is minor volatility spillover among crude oil and financial markets. VARMA-AGARCH is far better than VARMA-GARCH and CCC because there is an asymmetric effect of good and bad news on conditional variance. Manera, Nicolini and Vignati (2013) estimate the spillover effect of variable, energy and agriculture commodities by applying the dynamic conditional correlation model using the time frame of 1986 to 2010. The study finds a significant relationship between macroeconomic variables and commodity futures.

Further, it concludes that that oil has a significantly positive effect on other energy commodities. Lyocsa and Baumoehl (2014) estimate the conversion procedure of CEE stock markets from segmented to integrate by using asymmetric dynamic conditional correlation (DCC) and find significant and positive results. Katzke (2013) studies the co-movement of the return of South Africa economies. To differentiate the time-varying conditional correlation from conditional variance the study used DCC and asymmetric Multivariate Generalized Auto-regressive Conditional Hetroskedasticity (MV-GARCH) model. The findings conclude that for portfolio management static measures should not be used. It also finds leverage effect among the co-movement.

Creti, Joets and Mignon (2013) examine the concept of conditional correlation by using dynamic conditional correlation (DCC). This study aims to explore the link among the SP 500 index and commodities the time frame from 2001 to 2011. The study finds high conditional volatility in the financial crisis of 2008. It further finds some speculative movement for crude oil, coffee, and cocoa. Demiralay and Ulusoy (2014) examine conditional correlation between SP 500 index and commodity markets by using asymmetric dynamic conditional correlation for the time frame of 1992 to 2013 and conclude that time-varying exists correlation between equities and commodity indices. Singhal and Gosh (2016) estimate the time-varying co-movement between crude oil and return of Indian stock exchange for the period of 2006 to 2015. This phase includes boom, recession and recovery phase of the Indian economy. The study uses the VAR-DCC-GARCH model to examine asymmetric as well as symmetric conditional correlation. It concludes that there is no volatility spillover from the oil market to the Indian stock market. It further finds that dynamic correlation and volatility are significant to provide evidence time-varying dependency of Indian stock exchange on prices of oil.

Tiwari, Raheem and Kang (2019) examine the time-varying correlation between crypto-currency and the U.S stock market by applying the ADCC-EGARCH model. The study concludes that overall time-varying correlation is low and negative news creates more volatility as compared to positive news. Aslanidis, Bariviera and Lbanez (2019) examine the conditional correlation between crypto-currency and other assets class by using the DCC model. The study concludes that the correlation between crypto-currency is positive and the correlation between crypto-currency and assets class like stock, bond and gold is insignificant. Katsiampa (2019) examines the time-varying correlation of five major crypto-currencies named as bitcoin, ether, ripple, litecoin, stellar by using BEKK model. The findings conclude that time-varying correlation exists and positive for all currencies In the past few studies about DCC and ADCC modeling in the crypto-currency market are found. Urquhart and Zhang (2019) explore whether bitcoin can be considered a hedge against other currencies by using the ADCC model. There are a number of studies that examine time-varying conditional correlation by using DCC and ADCC in the context of the stock market, equity market and many others market but very little work in the context of the crypto-currency market are found. The main aim of this paper is to check the time-varying correlation and asymmetric correlation by using DCC and ADCC in the context of the crypto-currency market.

2.3 Hypotheses of the Study

Hypothesis 1

There exists a mean Spill-Over between Bitcoin and other crypto currencies.

Hypothesis 2

There exists a volatility Spill-Over between Bitcoin and other crypto currencies.

Hypothesis 3

There exists a time-varying correlation between Bitcoin and other crypto currencies.

Hypothesis 4

There exists an asymmetric behavior of correlation between Bitcoin and other crypto currencies.

Chapter 3

Data Description & Methodology

The methodology is divided into three parts. The first part is to measure mean and volatility spillover from bitcoin to major crypto-currencies by using ARMA-GARCH in the Mean model. This model is proposed by (Liu & Pan, 1997). In the second part, ARMA-TGARCH and ARAMA-EGARCH model are applied by considering the asymmetric effect of information. In the third part, the dynamic correlation is measured between bitcoin and major type of crypto-currency by using dynamic conditional correlation (DCC) and asymmetric dynamic conditional correlation (ADCC) approach.

3.1 Data Description

This study explains the mean and volatility transmission from bitcoin to following crypto currencies. These currencies are selected on the basis of capitalization of market and longevity. The population of this study is all crypto currencies. Presently crypto currencies are being treated as unit market capitalization. The sample of this study compromise of 10 major crypto currencies as mentioned in Table 3.1 below. The closing prices of each crypto currency are taken from coinmarketcap.com. Prices are quoted in terms of dollar. Data is taken from 2013 to 2019. Return of each currency is calculated by using the formula of return as ...

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where,

ln = Natural Log

r_t is return of crypto currency compounded continuously

P_t is the price of crypto currency at time "t"

P_{t-1} is price of crypto currency at time "t-1"

Table 3.1: Sample Details

SR	Name	Symbol	Time Period
1	Bitcoin	BTC	28-Apr-2013 to 13-Apr-2019
2	Ethereum	ETH	28-Apr-2013 to 13-Apr-2019
3	Ripple	XRP	7-Aug-2015 to 13-Apr-2019
4	Litecoin	LTC	28-Apr-2013 to 13-Apr-2019
5	Monero	XMR	18-May-2014 to 13-Apr-2019
6	Stellar	XLM	3-Aug-2014 to 13-Apr-2019
7	Bitshare	BTS	28-Apr-2013 to 13-Apr-2019
8	Tether	USDT	25-Feb-2015 to 13-Apr-2019
9	NEM	XEM	1-Apr-2015 to 13-Apr-2019
10	Dash	DASH	14-Feb-2014 to 13-Apr-2019

3.2 Econometric Models

The Mean and volatility spillover between bitcoin and other crypto currencies is investigated by using ARMA-GARCH model.

3.2.1 Mean & Volatility Spillover

3.2.1.1 ARMA GARCH Model

The study applies Two-stage ARMA-GARCH in Mean model presented by (Liu & Pan, 1997). It used to measure the transmission of mean and volatility from bitcoin to major crypto currency. In the first step, the return series of bitcoin is modeled through ARMA(1,1) GARCH(1,1) model.

$$r_{k,t} = \tau_o + \tau_1.r_{k,t-1} + \tau_2.v_{k,t} + \tau_3.\epsilon_{k,t-1} + \epsilon_{k,t}, \epsilon_{k,t} \sim N(0, v_{k,t}) \tag{3.1}$$

$$v_{k,t} = \rho_o + \rho_1.v_{k,t-1} + \rho_2.\epsilon^2_{k,t-1} \tag{3.2}$$

Where $r_{k,t}$ is the daily returns of bitcoin at time t and $\epsilon_{k,t}$ is the residual or unexpected return in other words, the error term. Basically, the major objective to include the ARMA (1,1) GARCH structure in the model is the adjustment of serial correlation in the data.

In the second stage, mean return and volatility spillover effects across market are estimated by obtaining the standardized residual and its square in the first stage and replacing them into mean and volatility equation of other currencies as follows ...

$$r_{j,t} = \tau_{j,o} + \tau_{j,1}.r_{j,t-1} + \tau_{j,2}.v_{j,t} + \tau_{j,3}.\epsilon_{j,t-1} + \lambda_j.\epsilon_{k,t} + \epsilon_{j,t}, \epsilon_{j,t}, \sim N(0, v_{j,t}) \tag{3.3}$$

$$v_{j,t} = \rho_{j,o} + \rho_{j,1}.v_{j,t-1} + \rho_{j,2}.\epsilon^2_{j,t-1} + \gamma_j.e^2_{k,t} \tag{3.4}$$

Where $\epsilon_{k,t}$ is the standardized error term for bitcoin and is capturing the mean return spillover effect from these sources. In order to examine the volatility spillover, the exogenous variable $e^2_{k,t}$ - the square of the standardized error term is included in the conditional volatility equation and is defined as $e_{k,t} = \frac{\epsilon_{k,t}}{\sqrt{v_{k,t}}}$.

3.2.1.2 ARMA TGARCH Model

Another volatility model to handle the leverage effect is TGARCH or GJR-GARCH model. firstly This model is introduced by (Glosten, Jaganathan & Runkle, 1993). It captures the asymmetric effect of negative and positive shocks. To do this, multiplicative dummy variable add into variance equation to check when shocks are negative whether there is a statistically significant difference exist or not . The

ARMA-TGARCH in mean model is give as follows ...

$$r_{k,t} = \tau_o + \tau_1.r_{k,t-1} + \tau_2.v_{k,t} + \tau_3.\epsilon_{k,t-1} + \epsilon_{k,t}, \epsilon_{k,t} \sim N(0, v_{k,t}) \tag{3.5}$$

$$v_{k,t} = \rho_o + \rho_1.v_{k,t-1} + \rho_2.\epsilon^2_{k,t-1} + \rho_2.\epsilon^2_{k,t-1} * D_t \tag{3.6}$$

Where $r_{k,t}$ is the daily returns of bitcoin at time t and $\epsilon_{k,t}$ is the residual or unexpected return in other words, the error term. Basically, the major objective to include the ARMA (1,1) GARCH structure in the model is the adjustment of serial correlation in the data.

In the second stage, mean return and volatility spillover effects across market are estimated by obtaining the standardized residual and its square in the first stage and replacing them into mean and volatility equation of other currencies as follows ...

$$r_{j,t} = \tau_o + \tau_{j,1}.r_{j,t-1} + \tau_{j,2}.v_{j,t} + \tau_{j,3}.\epsilon_{j,t-1} + \lambda_j.\epsilon_{k,t} + \epsilon_{j,t}, \epsilon_{j,t} \sim N(0, v_{j,t}) \tag{3.7}$$

$$v_{j,t} = \rho_{j,o} + \rho_{j,1}.v_{j,t-1} + \rho_{j,2}.\epsilon^2_{j,t-1} + \rho_{j,3}.\epsilon^2_{j,t-1} * D_t + \gamma_j.e^2_{k,t} \tag{3.8}$$

In above equation $\epsilon^2_{j,t-1} * D_t$ tells about asymmetric of data. Where $\epsilon_{k,t}$ is the standardized error term for bitcoin and is capturing the mean return spillover effect from these sources. In order to examine the volatility spillover, the exogenous variable $e^2_{k,t}$ - the square of the standardized error term is included in the conditional volatility equation and is defined as $e_{k,t} = \frac{\epsilon_{k,t}}{\sqrt{v_{k,t}}}$.

3.2.1.3 ARMA EGARCH Model

The model of GARCH family that capture the conditional variance and correlation is usually named as asymmetric model the oldest asymmetric model is EGARCH Firstly EGARCH model was discussed by (Harvey & Shephard, 1996). It is the logarithm of conditional volatility to capture the asymmetric effect of good and bad news. The literature about this model is very extensive. It basically studies the asymmetric behavior of data. It separates the size and sign effect. This model tells about how smaller and larger shocks create more volatility and it tells about how good news and bad news are different from each other in creating volatility in market. It sees the growth in exponential context. As equation is on log variance so this model doesnt require any restrictions on parameters and The positivity of variance is already done so this is the main benefit of using this model. ARMA-EGARCH in mean model as explained below ...

$$r_{k,t} = \tau_o + \tau_1.r_{k,t-1} + \tau_2.v_{k,t} + \tau_3.\epsilon_{k,t-1} + \epsilon_{k,t}, \epsilon_{k,t} \sim N(0, v_{k,t}) \tag{3.9}$$

$$\ln \sigma^2_{k,t} = \gamma_o + \gamma_1 \frac{|\mu_{k,t-1}|}{\sigma_{k,t-1}} + \gamma_2 \frac{\mu_{k,t-1}}{\sigma_{k,t-1}} + \gamma_3 \ln \sigma^2_{k,t-1} \tag{3.10}$$

Where $r_{k,t}$ is the daily returns of bitcoin at time t and $\epsilon_{k,t}$ is the residual or unexpected return in other words, the error term. Basically, the major objective to include the ARMA (1,1) GARCH structure in the model is the adjustment of serial correlation in the data.

In the second stage, mean return and volatility spillover effects across market are estimated by obtaining the standardized residual and its square in the first stage and replacing them into mean and volatility equation of other currencies as follows ...

$$r_{j,t} = \tau_{j,o} + \tau_{j,1}.r_{j,t-1} + \tau_{j,2}.v_{j,t} + \tau_{j,3}.\epsilon_{j,t-1} + \lambda_j.\epsilon_{k,t} + \epsilon_{j,t}, \epsilon_{j,t} \sim N(0, v_{j,t}) \tag{3.11}$$

$$\ln \sigma^2_{j,t} = \gamma_o + \gamma_1 \frac{|\mu_{j,t-1}|}{\sigma_{j,t-1}} + \gamma_2 \frac{\mu_{j,t-1}}{\sigma_{j,t-1}} + \gamma_3 \ln \sigma_{j,t-1} + \gamma_k.e^2_{j,t} \tag{3.12}$$

Where $\epsilon_{k,t}$ is the standardized error term for bitcoin and is capturing the mean return spillover effect from these sources. In order to examine the volatility spillover, the exogenous variable $e^2_{k,t}$ - the square of the standardized error term is included in the conditional volatility equation and is defined as $e_{k,t} = \frac{\epsilon_{k,t}}{\sqrt{v_{k,t}}}$.

In above equation $\ln \sigma_{j,t-1}$ is error term if it's signs is negative, it actually indicating bad news and tell that actual return are low. $\frac{|\mu_{j,t-1}|}{\sigma_{j,t-1}}$ tells about size effect. That means its significance or insignificance provides whether larger shocks create more volatility or vice-versa. $\frac{\mu_{j,t-1}}{\sigma_{j,t-1}}$ tells about the sign effect. Its sign and significance explain whether bad news creates more volatility or good news create more volatility. $\gamma_j.e_{j,t}^2$ tells about a volatility spillover.

3.2.2 DCC & ADCC GARCH Models

The model discussed above assumes that correlation is constant. But there is possibility that correlation may be time varying. So to capture this effect the study apply dynamic conditional correlation (DCC-GARCH) model and to capture the asymmetric effect the study apply asymmetric dynamic conditional correlation (ADCC). This model is firstly discussed by Engle (2001) in context of theoretical and empirical properties of dynamic conditional correlation. When two stocks move in same direction the expansion of correlation is marginally. Whereas when two stocks move in opposite direction the correlation reduced, when similar two stocks move inverse way, this correlation is diminished. This effect can be strong in down markets. As usually it is assumed that this deviation is temporarily. Asymmetric DCC give tail dependency only in lower tail.

The mathematical representation of Dynamic Conditional Correlation - DCC is given below ...

$$Q_t = \overline{R} + \sum_{i=1}^{m} \pi_i(\epsilon_{t-i}\epsilon_{t-i}^{\prime} - \overline{R}) + \sum_{i=1}^{m} \xi_i(Q_{t-1} - \overline{R}) \tag{3.13}$$

The mathematical representation Asymmetric Dynamic Conditional Correlation - ADCC is as follow ...

$$\sigma_t = min(\epsilon_t, 0), \overline{N} = \frac{1}{T}\sum_{t=1}^{T} \sigma_t \acute{\sigma_t} \tag{3.14}$$

ADCC-GARCH measures the asymmetric effect of correlation. It explains if it is time-varying correlation then over the period of time will it behave the same or different in good or bad market condition.

Chapter 4

Data Analysis & Discussion

This chapter consists of the application of different models on return series of top 10 major crypto currencies. In the first step the behavior of data is examined by descriptive statistics. It includes all independent and dependent variable of this study. The independent variable is Bitcoin and dependent variable is Litecoin, Tether, Monero, Stellar, Bitshare, Dash, Ethereum, NEM and Ripple. The graph of the series are attached in Appendix-A & Appendix-B.

4.1 Descriptive Statistics

Table 4.1 reports the descriptive statistics of bitcoin and samples of crypto currencies. It captures the 4 important characteristics of data. Those are Mean, Variance, Kurtosis and Skewness. Number of observation are different from each others. As different currencies are launched at different point of time. Average means measure the performance of each currency in market. The mean returns of all the currencies are positive except Tether. Negtaive sign shows there is loss in return and prices are decreased. The highest value of mean return is for NEM (0.3772%) and lowest one is for tether (-0.012%). Other high return currencies include ethereum and dash. The highest risk is for stellar (9.1378%) and followed by XEM (8.53%) that shows higher risk and higher return.

Table 4.1: Descriptive Statistics

Variables	Mean	Max.	Min.	SD	Skewness	Kurtosis
Bitcoin	0.0018	0.3570	-0.2666	0.0420	-0.1240	11.3700
Ripple	0.0019	1.0270	-0.6160	0.0750	2.0310	31.0600
Litecoin	0.0013	0.8280	-0.5130	0.0660	1.7388	28.0880
Monero	0.0020	0.5840	-0.3780	0.0730	0.6460	9.1440
Dash	0.0030	1.2700	-0.4670	0.0760	3.0100	45.8200
NEM	0.0030	0.9900	-0.3610	0.0800	1.9190	20.4200
Ethereum	0.0030	0.4120	-1.3020	0.0750	-3.4050	69.7490
Stellar	0.0022	2.7360	-0.3280	0.0910	16.1100	472.52
Bitshare	0.0008	0.5190	-0.3910	0.0760	0.9450	10.4200
Tether	-0.0001	0.5070	-0.6900	0.0222	-11.5400	723.9100

Useable Observations for Bitcoin and Ripple are 2080, Litecoin 2176, Monero 1791, Dash 1891, NEM 1480, Ethereum 1345, Stellar 1714, Bitshare 1734 and Tether 5073.

The lowest value of standard deviation is for tether (2.2734%). Maximum return in day is earned by stellar and followed by dash and ripple. The maximum loss faced in a day is reported by ethereum. The skewness shows asymmetric behavior and its value is positive for all crypto currency except bitcoin, ethereum and tether. Kurtosis explains about data shape whether it is peak or flat. Kurtosis is positive and greater than 3 for all currencies that shows that all series of currencies have fat tails with high peak.

4.2 ARCH Effect In Bitcoin and Other Major Cryptocurrencies

First of all, the ARCH effect is examined in all crypto currencies. The results are given below. In below table the significance level shows that the ARCH effect exists in all currencies except tether and stellar. So for all those currencies having

ARCH effect we apply the ARMA-GARCH model and for tether and stellar we apply the ARMA model.

Table 4.2: ARCH Effect In Bitcoin and Other Major Cryptocurrencies

Sr. #	**Currencies**	**LR statistics**	**Significance**	**Model**
1	Bitcoin	204.5223	0.0000	ARMA-GARCH
2	XRP	190.8165	0.0000	ARMA-GARCH
3	Litecoin	81.82634	0.0000	ARMA-GARCH
4	Tether	4.80E-05	0.9945	ARMA
5	Stellar	1.44E-05	0.9970	ARMA
6	Monero	45.03879	0.0000	ARMA-GARCH
7	Bitshare	114.6828	0.0000	ARMA-GARCH
8	Ethereum	46.00719	0.0000	ARMA-GARCH
9	NEM	25.91279	0.0000	ARMA-GARCH
10	DASH	33.44839	0.0000	ARMA-GARCH

This table consists of coefficient of ARCH model from bitcoin to all crypto currencies and their p-values are also reported. Based on existence of ARCH effect best model is chosen.

4.2.1 Mean and Volatility Spillover From Bitcoin to the Other Major Crypto Currencies by Using the ARMA GARCH Model

The study measures the transmission of mean and volatility between bitcoin and major type of crypto currencies by using GARCH processes. Table 4.3 report all the results of ARMA-GARCH model with their p-values from bitcoin to major type of crypto currency.

For ripple and bitshare the τ_1 is significant that means return of these currencies can be forecast through pattern of past prices. So we can say that market is inefficient. Further the value of τ_1 for other currencies like monero, dash, litecoin,

TABLE 4.3: Mean & Volatility Spillover from bitcoin-to-Other Major crypto currencies - ARMA-GARCH Model

	Bitcoin	**Ripple**	**Litecoin**	**Monero**	**Dash**	**Bitshare**	**Ethereum**	**NEM**
τ_o	0.0004	-0.0098	-0.0022	-0.0021	-0.0016	0.0068	-0.0015	-0.0022
	(0.7580)	(0.0000)	(0.3190)	(0.5004)	(0.3620)	(0.1315)	(0.4547)	(0.3680)
τ_1	-0.1762	-1.4226	0.0217	-0.7353	-0.0209	2.9763	0.3442	-0.0537
	(0.8680)	(0.0113)	(0.9728)	(0.3558)	(0.9620)	(0.0081)	(0.4253)	(0.8258)
τ_2	0.8967	0.3715	0.4714	0.2122	0.4031	-0.7118	0.8171	0.4089
	(0.4025)	(0.2613)	(0.4053)	(0.7563)	(0.2952)	(0.3053)	(0.1716)	(0.3191)
τ_3	0.2003	1.4702	-0.0654	0.7046	-0.0381	-2.9534	-0.3237	-0.0547
	(0.8508)	(0.0085)	(0.9178)	(0.3751)	(0.9299)	(0.0085)	(0.4510)	(0.8259)
η	-	0.0488	0.0328	0.0239	-0.0415	-0.0630	0.9568	0.0746
		(0.0647)	(0.3965)	(0.6188)	(0.1786)	(0.1723)	(0.0000)	(0.0272)
ρ_o	4.67E-05	0.0004	8.35E-05	0.0002	0.0002	9.53E-05	2.14E-06	0.0012
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7355)	(0.0000)
ρ_1	0.8695	0.4825	0.8947	0.8447	0.7782	0.8794	0.7677	0.4530
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ρ_2	0.1114	0.5425	0.0765	0.1087	0.1986	0.0977	0.2116	0.5099
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8794)	(0.0000)	(0.0000)
γ	-	4.32E-05	5.60E-05	2.68E-05	-2.69E-05	5.91E-05	0.000133	-2.64E-05
		(0.0000)	(0.0000)	(0.1173)	(0.0185	(0.0000)	(0.0000)	(0.5738)

This table consists of coefficient of ARCH and GARCH model for bitcoin to all other major crypto currencies. p-values are also reported in ().

Ethereum and NEM is insignificant that means today return cant forecast from past prices. The GARCH term τ_2 is insignificant for all currencies that shows there is no persistence of volatility. The error term τ_3 is significant for ripple and Bitshare which shows that these two currencies move in two different directions for correction in future. While the other currencies including monero, dash, litecoin, ethereum and NEM do not consider the past prices shocks for the procedure of correction. The GARCH term ρ_1 is significant for all currencies that means there is persistence of volatility. The residual term ρ_2 is significant for all currencies except bitshare that means today volatility can be forecast by using behavior of past prices. . The value of $\rho_1 + \rho_2$ is close to one that means there is persistence of volatility in long run.

The mean spillover η for ripple, NEM and ethereum is significant and positive which shows that there is mean spillover from bitcoin to NEM and ethereum. While for other currencies the value of mean spillover is insignificant that means there is no mean spill-over from bitcoin to litecoin, dash, monero, and bitshare. The volatility spillover γ is positive and significant for all currencies ripple, litecoin, ethereum, dash, bitshare except monero and NEM Which show that volatility is transmitted from bitcoin to all currencies except monero and NEM. so we can say currencies that have less spillover from bitcoin gives more opportunity of portfolio diversification and those currencies which have high significant spillover from bitcoin gives less opportunity of diversification.

There are many reason behind this phenomenon that why bitcoin effect all other crypto currencies. Bitcoin capture the 40% of crypto currency market. it is the oldest and first form of crypto currency So it is highest capitalized currency in market. It is also most trade able currency. Most of the crypto investors are involved in trading of bitcoin. Secondly, many business start accepting the bitcoin as form of payment. So the bitcoin is the most tradable currency in crypto currency market. So thats why bitcoin have an impact on all other crypto currencies and fluctuation in prices of bitcoin effect the other crypto currencies.

4.2.2 Mean Spillover From Bitcoin to Other Major Crypto Currencies by Using ARMA Model

Table 4.4: Mean Spillover from Bitcoin to Stellar & Tether - ARMA Model

	τ_o	τ_1	τ_2	τ_3	η
Bitcoin	0.0004	-0.1762	-	0.2003	-
	(0.7580)	(0.8680)		(0.8508)	
Steller	0.0039	-0.7621	-	0.7703	-0.0025
	(0.5831)	(0.8039)		(0.8018)	(0.2765)
Tether	0.0031	22.5519	-	-22.5799	-0.0002
	(0.0000)	(0.0000)		(0.0000)	(0.3558)

This table consists of coefficient of ARCH and model for bitcoin to Stellar & Tether. p-values are also reported in ().

Table 4.4 reports the results of mean spillover from bitcoin to tether and stellar by using ARMA model. The return series data of these two crypto currencies is homoscedastic so there is no GARCH series in table. The coefficient of τ_1 is significant for only tether that shows mean return can be forecast by using past price behavior. And positive sign shows that momentum effect exists but τ_1 is insignificant for stellar that mean return cant be estimated by using past price behavior. τ_3 is the coefficient of error term and it significant for tether that shows on the basis of past shocks return of tether will move in opposite direction for correction. The coefficient of mean spillover η is insignificant for both tether and stellar which shows there is no mean spillover from bitcoin to tether and stellar. So we can say that these two currencies will give more advantage of portfolio diversification.

4.2.3 Asymmetric Effect Bitcoin to Other Major Crypto Currencies by Using ARMA-EGARCH Model

In table 4.5 the result of E-GARCH model are reported. It explains size and sign effect. γ_1 and γ_2 tells about size and sign effect. γ_1 tells us about shocks that create more volatility.

Table 4.5: Asymmetric Effect Between Bitcoin & Other Major Crypto Currencies - ARMA-EGARCH Model

	Bitcoin	**Ripple**	**Litecoin**	**Monero**	**Dash**	**Bitshare**	**Ethereum**	**NEM**
τ_o	0.0015	-0.0106	-0.0005	0.0011	-0.0020	0.0070	-0.0002	-0.0019
	(0.1599)	(0.0000)	(0.8201)	(0.7099)	(0.2299)	(0.1290)	(0.9004)	(0.5247)
τ_1	-0.6779	-1.2307	0.8245	-0.5649	0.2026	2.6446	0.5381	0.2383
	(0.4466)	(0.0125)	(0.1334)	(0.4478)	(0.5747)	(0.0190)	(0.1418)	(0.3986)
τ_2	0.7571	0.8963	0.0864	0.0373	0.6709	-0.7756	0.4925	0.5234
	(0.4559)	(0.0051)	(0.8827)	(0.9545)	(0.0973)	(0.2739)	(0.4652)	(0.3222)
τ_3	0.6766	1.3055	-0.8847	0.5199	-0.2729	-2.6431	-0.5337	-0.3541
	(0.4492)	(0.0080)	(0.1044)	(0.4828)	(0.4440)	(0.0192)	(0.1427)	(0.2141)
δ	-	0.0657	0.0773	0.0385	-0.0761	-0.0527	1.0296	0.0253
		(0.0071)	(0.0508)	(0.3698)	(0.0021)	(0.2676)	(0.0000)	(0.5824)
γ_o	-0.5159	-1.2205	-0.3376	-0.4273	-0.5181	-0.4405	-0.4916	-0.7959
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.2532	0.5226	0.1482	0.1844	0.3446	0.2280	0.3102	0.4123
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_2	-0.0045	0.0900	0.0526	0.0762	0.0196	0.0440	0.0174	0.0187
	(0.5198)	(0.0000)	(0.0000)	(0.0000)	(0.0381)	(0.0000)	(0.1442)	(0.2003)
γ_3	0.9470	0.8465	0.9593	0.9464	0.9471	0.9519	0.9606	0.9014
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-	0.0068	0.0129	0.0031	-0.0216	0.0199	0.0280	-0.0024
		(0.0524)	(0.0000)	(0.3321)	(0.0000)	(0.0000)	(0.0000)	(0.7084)

This table reports the coefficients of E-GARCH model. p-values are also reported in ().

If its value is significant it shows large shocks create more volatility. γ_2 tells about sign effect if its value is negative it shows that bad news creates more volatility. If its value is positive, it shows good news creates more volatility The coefficient of τ_1 is only significant for ripple and bitshare that shows mean return can be estimate by using behavior of past price behaviour. While for other currencies its coefficient value is insignificant. The coefficient of GARCH term τ_2 is significant only for ripple that shows mean return can be estimated by using forecasted volatility. The coefficient of residual term $\tau_3$is significant for ripple and bitshare that shows those will move in opposite direction to make correction.

The coefficient of γ_1 and γ_2 tells about sign and size effect. The coefficient of γ_1 is significant for all currencies that show larger shocks create more volatility as compared to small shocks. The coefficient of γ_2 is significant for all currencies except ethereum and NEM. That shows asymmetric behavior exists and positive sign shows that good news creates more volatility. The coefficient of γ_3 is significant that shows persistence of volatility.

The mean spillover δ coefficient is is positive and significant for ripple, litecoin, ethereum and NEM that shows there is mean spillover from bitcoin to these currencies and it is negative and significant for dash which show that there is mean spillover from bitcoin to dash but mean return in bitcoin reduces the return of dash. The volatility spillover θ coefficient is positive and significant for ripple, bit share, ethereum and litecoin and negative and significant for dash. Positive and significant shows that volatility spillover exists from bitcoin to ripple, bitshare, ethereum and litecoin. On the other side negative and significant shows that there is volatility spillover for bitcoin to dash and negative sign shows that volatility of bitcoin decreases the volatility of dash. In all currencies asymmetric behaviour exists except two. Larger shocks create more volatility as compared to smaller shocks and good news create more volatility as compared to bad news. So investors, policy makers, portfolio diversification managers should keep an eye on all the variation in these currencies to avoid any loss.

Table 4.6: Asymmetric Effect Between Bitcoin & Other Major Crypto Currencies - ARMA-TGARCH Model

	Bitcoin	**Ripple**	**Litecoin**	**Monero**	**Dash**	**Bitshare**	**Ethereum**	**NEM**
τ_o	0.0004	-0.0096	0.0188	-0.0002	0.0215	0.0064	0.0004	-0.0039
	(0.7496)	(0.0000)	(0.0001)	(0.9931)	(0.0221)	(0.1716)	(0.8255)	(0.1058)
τ_1	-0.2169	-1.6046	3.8262	-0.2830	1.1582	2.8676	0.5465	-0.1536
	(0.8399)	(0.0028)	(0.0000)	(0.8215)	(0.0345)	(0.0146)	(0.2352)	(0.5356)
τ_2	1.0591	0.5510	0.7649	0.1699	-1.7162	-0.4969	0.2882	0.6598
	(0.3225)	(0.0650)	(0.3048)	(0.9307)	(0.0107)	(0.4759)	(0.7177)	(0.0769)
τ_3	0.2385	1.6383	-3.8847	0.2797	-1.1747	-2.8455	-0.5276	0.0314
	(0.8249)	(0.0022)	(0.0000)	(0.8233)	(0.0291)	(0.0154)	(0.2489)	(0.9007)
δ	-	0.0400	0.2287	-0.0161	-0.0147	-0.0654	0.9566	0.1194
		(0.1260)	(0.0000)	(0.8505)	(0.8828)	(0.1594)	(0.0000)	(0.0001)
ρ_o	0.0000	0.0005	0.0024	0.0045	0.0051	0.0001	0.0000	0.0016
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7417)	(0.0000)
ρ_1	0.8715	0.4910	0.4760	0.5479	0.5424	0.8811	0.7692	0.3790
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ρ_2	0.1200	0.7081	0.2039	0.1165	0.1262	0.1164	0.2210	0.4729
	(0.0000)	(0.0000)	(0.0000)	(0.0022)	(0.0005)	(0.0000)	(0.0000)	(0.0000)
ρ_3	-0.0186	-0.3375	0.0423	-0.0657	0.0398	-0.0493	-0.0237	0.1301
	(0.0628)	(0.0000)	(0.0813)	(0.2189)	(0.4499)	(0.0002)	(0.3624)	(0.0395)
ζ	-	3.57E-05	-0.0001	-0.0002	-0.0002	6.43E-05	0.0001	-6.10E-05
		(0.0009)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

This table represents the coefficients of ARMA-TGARCH Model. p-values are also reported in ().

4.2.4 Asymmetric Effect Bitcoin to Other Major Crypto Currencies by Using ARMA-TGARCH Model

In Table 4.6 the results of the ARMA-TGARCH model is reported. It provides information about asymmetric behavior of data. The value of ρ_3 tells about asymmetric of data. Its significance shows that market respond to different to good news and bad news. If its sign is positive, it shows bad news create more volatility and it negative sign shows that good news creates more volatility.

The τ_1 is significant for ripple, litecoin dash and bitshare that shows mean return can be estimated by using behavior of past prices that means market is inefficient. While for other currencies like monero, ethereum and NEM it is insignificant that shows mean return can not be predicted by using behavior of past prices. The coefficient of GARCH term τ_2 is only significant for xrp and dash. That shows mean return can be predicted by using forecasted volatility. The coefficient of residual term τ_3 is significant for ripple, litecoin, dash and bitshare and its value is positively significant for ripple while for others like litecoin , dash and bitshare and its value is negative and significant. That shows the market will move in opposite direction to make a correction.

The coefficient of ρ_1 is significant for all currencies that shows the persistence of volatility. The ρ_2 is positive and significant for all currencies that shows current volatility can be estimated by using behavior of past prices. . Moreover the sum of coefficient of $\rho_1 + \rho_2$ is equal to 1 so persistence of volatility is in the long run. The coefficient of ρ_3 tells about asymmetric behavior of the market and its value is only significant for xrp, bitshare and xem. That shows there is asymmetric behavior in these currencies. Its value is negative and significant for ripple and bitshare that shows bad news creates less volatility as compared to good news and its value is positively significant only for NEM that shows bad news creates more volatility as compared to good news. While for other currencies the coefficient of ρ_3 is insignificant that shows there is symmetric behavior in market.

The coefficient of volatility spillover ζ is positively significant for ripple, bitshare and ethereum that shows there is volatility spillover from bitcoin to ripple, bitshare, and ethereum a while for other currencies like litecoin, monero, dash and NEM is negative and significant that shows there is volatility spillover from bitcoin to litecoin, monero, dash and NEM. Where as negative sign shows that volatility of bitcoin decreases the volatility of these currencies. The coefficient of mean spillover δ is positively significant for litecoin, ethereum and NEM that shows there is mean spillover from bitcoin to litecoin, ethereum and NEM. While for other currencies the coefficient of mean spillover is insignificant that shows there is no mean spillover.

4.3 Time Varying Conditional Correlation - DCC & ADCC

The study measures the transmission of mean and volatility by ARMA-GARCH and ARMA model. Then we applied ARMA-TGARCH and ARMA-EGARCH to measure the asymmetric behavior of data. Now to measures that whether correlation is time-varying or constant over period of time it employs dynamic conditional correlation (DCC) and further to measure the asymmetric of correlation by using asymmetric dynamic conditional correlation (ADCC).

4.3.1 DCC MV-GARCH Models and Estimates Between Bitcoin and Other Major Crypto Currencies

Table 4.7 consists of DCC-GARCH models that are suitable for each currency. These models are selected on the basic of low AIC value.

Table 4.8 report all the results of dynamic conditional correlation from bitcoin to major type of crypto currencies. In this table, study report the p-values of θ_1

shows that highly positive impact of past residual shocks on conditional correlation. Negative and significant shows the partial impact of past residual shocks on conditional correlation . While for tether and NEM the value of θ_1 is insignificant that shows no effect of residual shocks on conditional correlation. The θ_2 is highly

TABLE 4.7: DCC-GARCH Model Selection

Sr.#	Currencies	Selected Model
1	Ripple	GJR/TARCH
2	Litecoin	EGARCH
3	Monero	EGARCH
4	Dash	EGARCH
5	Bitshare	EGARCH
6	NEM	EGARCH
7	Ethereum	EGARCH
8	Tether	GJR/TARCH

This table shows the optimal uni-variate DCC GARCH model with respect to each currencies and then the appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

TABLE 4.8: Dynamic Conditional Correlation Between Bitcoin & Other Crypto Currencies

Sr. #	Currencies	Bitcoin	
		θ_1	θ_2
1	**Ripple**	-0.0120	0.7863
		(0.0000)	(0.0000)
2	**Litecoin**	-0.0063	0.9382
		(0.0000)	(0.0000)
3	**Monero**	-0.0159	0.7951
		(0.0000)	(0.0000)
4	**Dash**	-0.0101	0.9767
		(0.0805)	(0.0000)
5	**Bitshare**	0.0710	0.3265
		(0.0152)	(0.3551)
6	**NEM**	0.0193	0.5553
		(0.3915)	(0.1229)
7	**Ethereum**	0.0692	0.9257
		(0.0000)	(0.0000)
8	**Tether**	0.0741	0.7125
		(0.2013)	(0.0007)

This table consists of coefficients of DCC-GARCH model from bitcoin to major type of crypto currencies. Their p values are also reported. To select the best model AIC criteria is used.

significant for ripple, litecoin, monero, dash, ethereum and tether which exhibit the effect of lagged dynamic conditional correlation. While for other currencies it is insignificant that shows no effect of lagged dynamic conditional correlation in these currencies.

4.3.2 ADCC MV-GARCH Models and Estimates Between Bitcoin and Other Major Crypto Currencies

Table 4.9 consists of ADCC-GARCH models that are suitable for each currency. These models are selected on the basic of low AIC value.

Table 4.9: ADCC-GARCH Model Selection

Sr. No.	**Currencies**	**Selected Model**
1	Ripple	GJR/TARCH
2	Litecoin	EGARCH
3	Dash	EGARCH
4	Bitshare	EGARCH
5	NEM	EGARCH
6	Tether	GJR/TARCH

This table shows the optimal uni-variate ADCC GARCH model with respect to each currencies and then the appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

Table 4.10 reports all the results of asymmetric dynamic conditional correlation from bitcoin to major crypto currencies. Firstly the condition for stability of this model is met that is the value of θ_1 + θ_2 <1. Where as in case of monero, ethereum and stellar, these curreices are not statistically significant so ADCC model can not be applied. The interpretation of θ_1 and θ_2 are same as in DCC model. θ_1 tells about past residual shocks and θ_2 tells about lagged dynamic conditional correlation. The ADCC model has same coefficient θ_1 and θ_2 while having one extra coefficient θ_3 that provide information about shocks of negative and positive news on dynamic condition correlation. The coefficient of θ_1 is positive and significant for litecoin and bitshare while, it is negative significant only for ripple. The significant and positive sign shows that high impact of

TABLE 4.10: Asymmetric Dynamic Conditional Correlation Between Bitcoin & Other Crypto Currencies

Sr. #	**Currencies**	**Bitcoin**		
		θ_1	θ_2	θ_3
1	**Ripple**	-0.0120	0.7771	-0.0534
		(0.0000)	(0.0000)	(0.0715)
2	**Litecoin**	0.0461	-0.0134	-0.0853
		(0.0441)	(0.9468)	(0.0465)
3	**Dash**	-0.0102	0.9771	0.0002
		(0.0906)	(0.0000)	(0.9564)
4	**Bitshare**	0.0842	0.3919	-0.1084
		(0.0087)	(0.2147)	(0.1342)
5	**NEM**	0.0361	0.4379	-0.1093
		(0.1685)	(0.2408)	(0.1195)
6	**Tether**	0.0988	0.7306	-0.0405
		(0.1141)	(0.0001)	(0.4279)

This table contain coefficients from the Asymmetric DCC-MV-GARCH model in for all currencies pair in the study. The parameter values and p-values in parenthesis are reported. Theta (1), Theta (2) and Theta (3) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable uni-variate GARCH model.

past residual shocks on conditional correlation. Negative and significant shows the partial impact of past residual shocks on conditional correlation.. The coefficient of θ_2 is positive and significant for ripple, dash and tether that shows high degree of lagged conditional correlation exists. While for other currencies its value insignificant that shows there is no lagged conditional correlation exists. The coefficient of

θ_3 is negative for lite coin which shows that correlation will decrease while arrival on negative news. The remaining currencies exhibits no variation with respect to correlation.

Chapter 5

Conclusion, Recommendations & Future Directions

5.1 Conclusion

The main focus of this study is to measure mean and volatility spillover from Bitcoin to major crypto currencies; ripple, dash, bitshare, Tether, ethereum, stellar, Monero, NEM and Litecoin by using ARMA-GARCH model and ARMA model. The results of mean spillover is positive only for ripple, NEM and ethereum. It shows that there is mean spillover from bitcoin to ripple, NEM and ethereum. Positive sign shows that increase in return of bitcoin will increase the return in ripple, NEM and ethereum. While for other currencies like litecoin, monero, dash, tether, stellar and bitshare the result is insignificant that shows there is no mean spillover from bitcoin to litecoin, monero, dash, tether, stellar and bitshare so we can say that these currencies will give high opportunity of portfolio diversification. So Hypothesis 1 is supported only for 3 currencies ripple, NEM and ethereum.

Similarly, the volatility spillover result is positive and significant for all currencies except monero and NEM. A significant result shows that there is volatility spillover from bitcoin to ripple, litecoin, dash, bitshare and ethereum. sothese currencies will have less opportunity of portfolio diversification. Positive sign shows that volatility shocks in bitcoin will increase the volatility in these currencies. However, there is a negative and significant result for dash shows that volatility shocks are industry related to volatility in dash. So the hypothesis 2 is supported that there is volatility spillover from bitcoin to major crypto-currencies. So the currencies which have less spillover from bitcoin will give more opportunity of portfolio diversification because there will be less uncertainty in case of those currencies as they are not effected by any spillover from bitcoin.

To consider the asymmetric effect between bitcoin and major crypto-currencies the study applies ARMA-TGARCH and ARMA-EGARCH model. From the results of T-GARCH model, it is observed that there an asymmetric effect in ripple, bitshare and NEM, and its value is negative and significant for ripple and bitshare that shows volatility create by bad news is less than good news. The value is positive and significant only for NEM that shows bad news creates more volatility as compared to good news. While for other currencies litecoin, monero, dash and ethereum there is no asymmetric effect that exists. The coefficient of volatility spillover is positive and significant for ripple, bitshare and ethereum that shows there is volatility spillover from bitcoin to ripple, bitshare, and ethereum. A while for other currencies like litecoin, monero, dash and NEM is negative and significant that shows there is volatility spillover from bitcoin to litecoin, monero, dash and NEM, and negative sign shows that volatility of bitcoin decreases the volatility of these currencies.

The coefficient of mean spillover is positive and significant for litecoin, ethereum and NEM that show there is mean spillover from bitcoin to litecoin, ethereum and NEM. While for other currencies the coefficient of mean spillover is insignificant that shows there is no mean spillover. From the result of the ARMA-EGARCH model, it is concluded that size coefficient is significant for all currencies that shows larger shocks creates more volatility as compared to smaller shocks. Where as coefficient of sign effect is positive and significant for all currencies except ethereum and NEM. Positive and significance shows that good news create more volatility as comapred to bad news. The coefficient of GARCH term is significant for all currencies that show the persistence of volatility exsists. The mean spillover coefficient is positive and significant for ripple, litecoin, ethereum and NEM that shows there is mean spillover from bitcoin to these currencies and it is negative and significant for dash which show that there is mean spillover from bitcoin to dash but return of bitcoin reduces the return of dash. The volatility spillover coefficient is positive and significant for ripple, bitshare, ethereum and litecoin and negative and significant for dash. Positive and significant coefficient shows that volatility spillover exists from bitcoin to ripple, bitshare, ethereum and litecoin. On the other side, negative and significant coefficient shows that there is volatility spillover from bitcoin to dash and negative sign shows that volatility of bitcoin decreases the volatility of dash.

To measure the time-varying correlation between bitcoin and major crypto currencies, DCC-GRACH model is applied. From the results of DCC-GARCH, the study observed time varying correlation exsists in all currencies except stellar. So hypothesis 4 is supported that there is a time-varying correlation that exists between bitcoin and these type of crypto currencies. While from the result of the ADCC-GARCH model, the study concludes that there is asymmetric correlation exists only in case of of litecoin. While for other currencies there is no asymmetric correlation exist. So hypothesis 5 supports only for 1 currencies that is litecoin which shows that correlationis assymetric in nature will decrease on arrival of negative news.

5.2 Recommendations

The discussion regarding the findings provide that all the investors, market player, police makers/regulator of crypto currency and speculator should keep an eye on changes of information that arises on daily basis before investing or any kind of dealing in crypto currency. This may help in making a wise decision about investing in crypto-currency market. This study helps to forecast the return of currency from the past returns. Investors also get to know how changes in bitcoin affect the other currency. So they will avoid taking any risk in making investment decisions. This study is especially helpful for investors and managers whose major concerns to invest in crypto-currency and policymakers and regulators who are conscious about the exposure of bitcoin that global financial system stability is represented by bitcoin. This will help the portfolio managers in resource allocation and portfolio diversification

All the pairs of crypto-currencies show mean and volatility spillover except few. The mean and volatility spillover of bitcoin is affecting the mean and volatility of other crypto-currencies. It shows that these currencies are interdependent with each other. the currencies which have less spillover will be perfect for portfolio diversification. Some currencies show there is a time-varying conditional correlation which shows that correlation is not constant over time. Further asymmetric behavior also exists between crypto-currencies. So investors should keep eye on all the information that bitcoin transmit into other crypto-currencies Based on the results of the study it is suggested that investors and risk management teams fit in these market dynamics in applying any trading strategy for these currencies. It is helpful for portfolio diversification and risk management decision. By understanding this phenomenon of mean and volatility spillover and dependency of crypto-currencies on each other may helpful for managing the investment. Finally, this study helps people, who want to invest in crypto-currency, in making a better decision.

5.3 Limitations & Future Directions

This study focus on mean and volatility spillover transmit from bitcoin to major crypto currency however this study couldnt cover all the aspects The limitation of this study is limited data availability of some new currencies. Some areas of crypto currency are still to discover. This study consider only top 10 currencies. So further by adding the more number of currencies in data set may improve the results. By applying more models of GARCH or through VAR model or through co-integration test or through GRACH-BEKK model and Diebold and Yilmaz methodology may provide more insight about crypto currency market. In this study we considered the mean and volatility spillover within the crypto currency market so further studies could be done by considering the others market like stock market, equity market, commodity, exchange market and energy market with crypto currency market. In pakistan, crypto currency is illlegal but hope so in future it will be legal with proper regulatory system and pakistani investors will get oppotunity to invest in this new form of digital currency.

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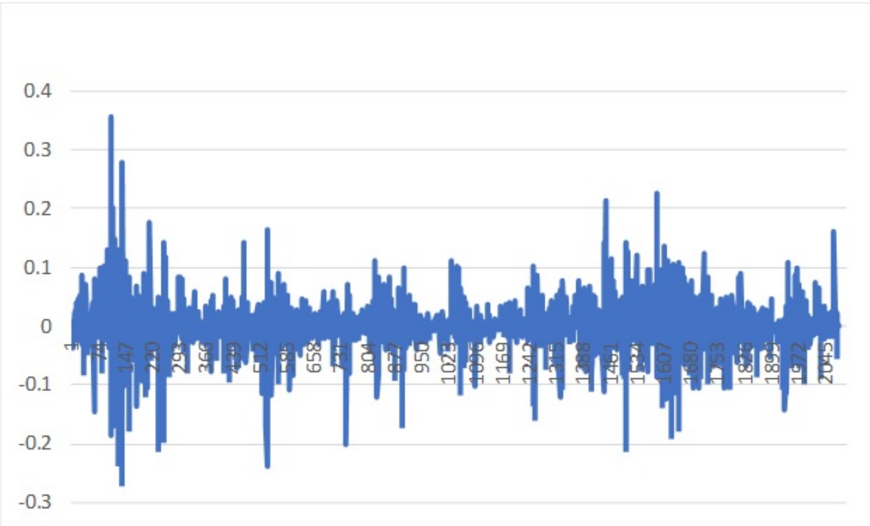
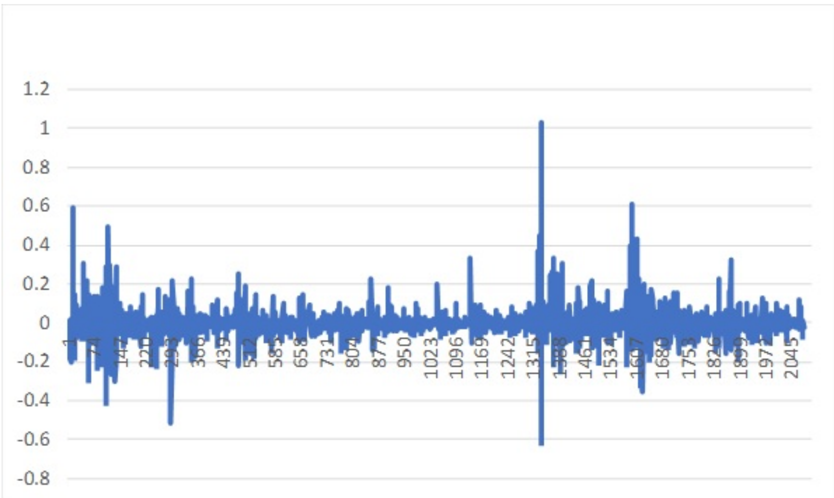
Appendix-A

Graphical Representation Of Return Series

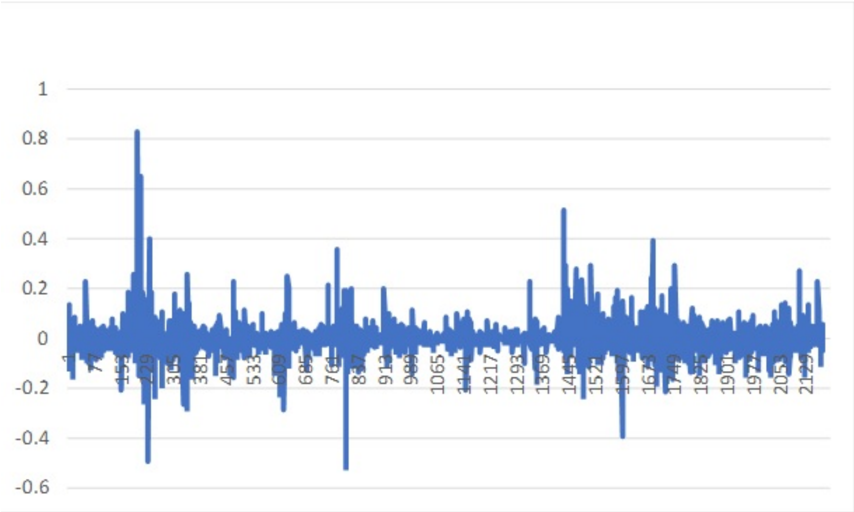
Bitcoin



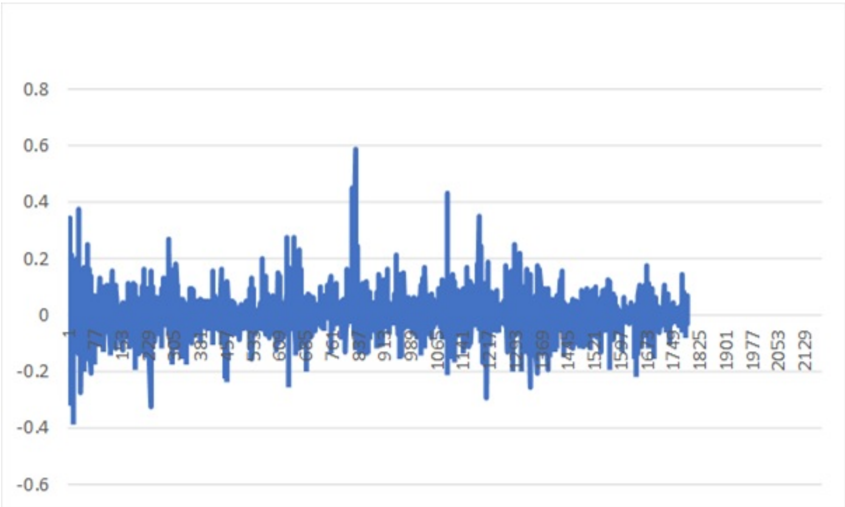
Ripple



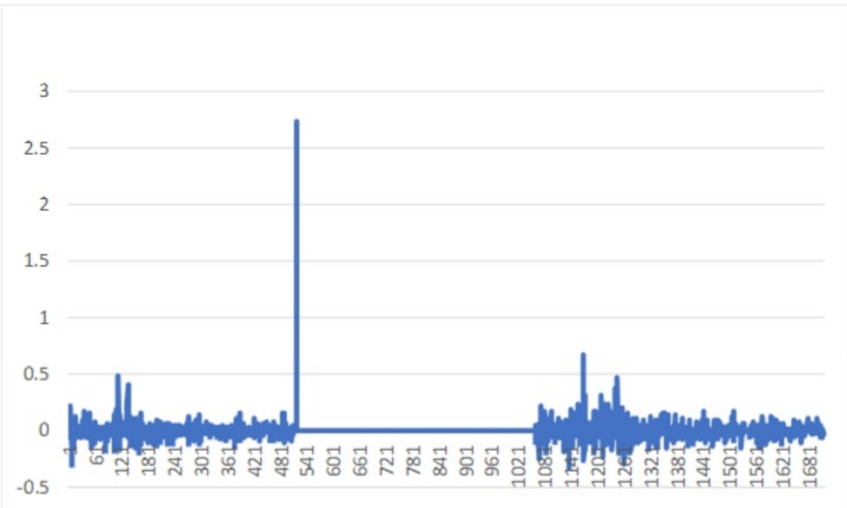
Litecoin



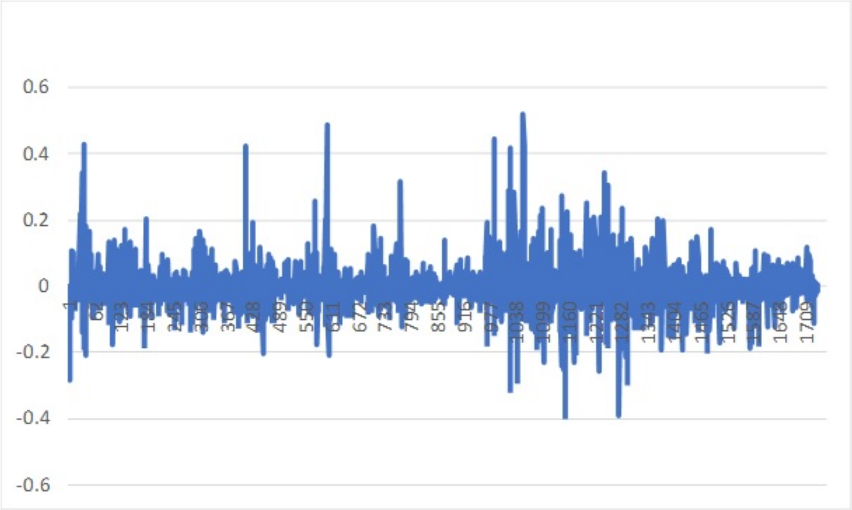
Monero



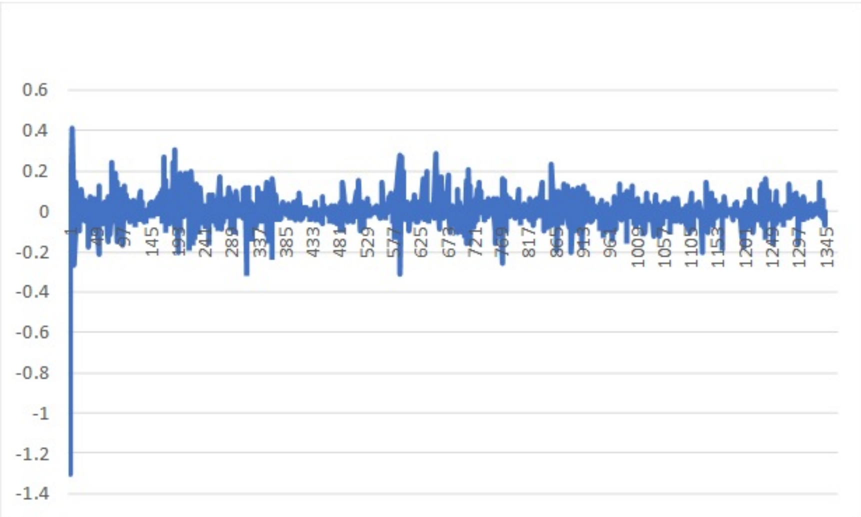
Steller



Bitshare



Ethereum



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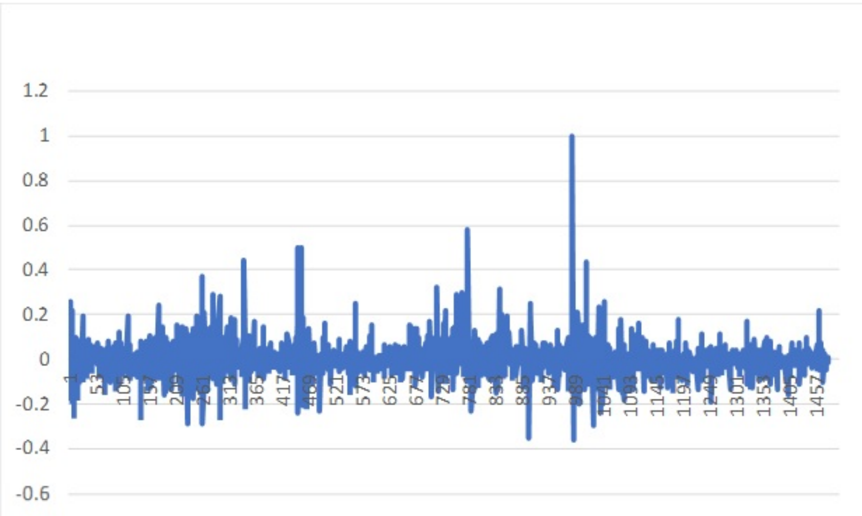
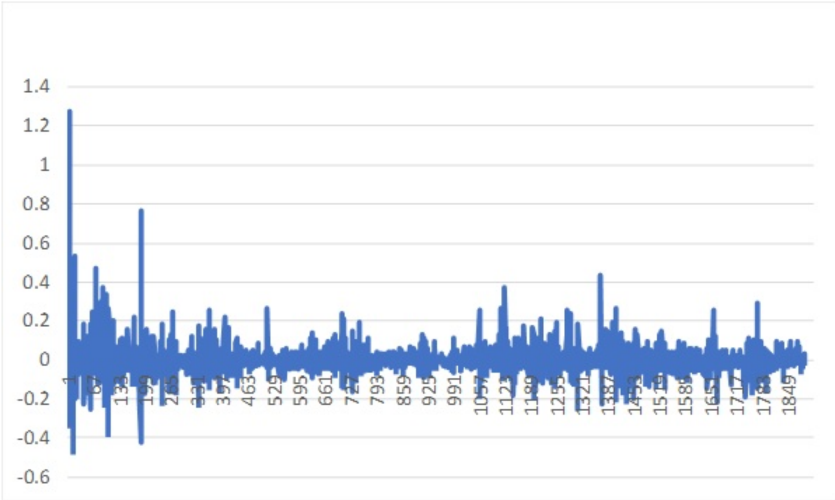


Dash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1.2
1
0.8
0.6
0.4
0.2
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-0.2
-0.4
-0.6
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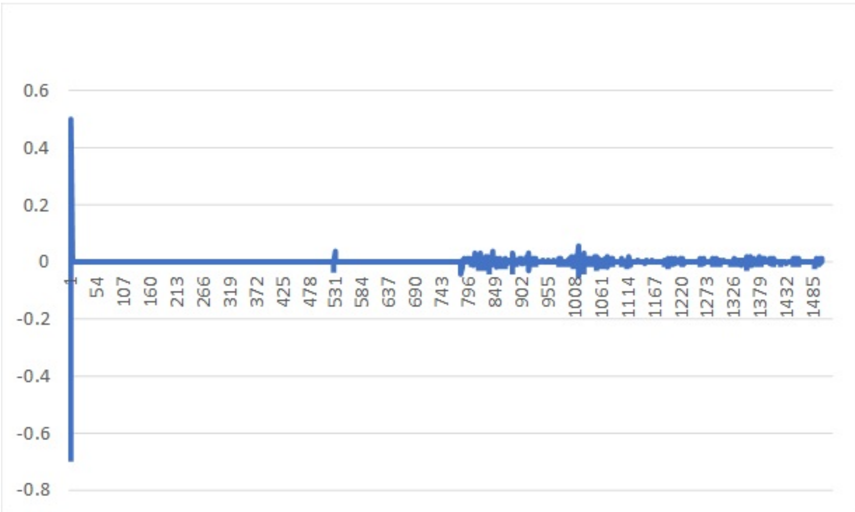
595
661
793
859
925
991
1849

Tether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319
372
425
478
531
584
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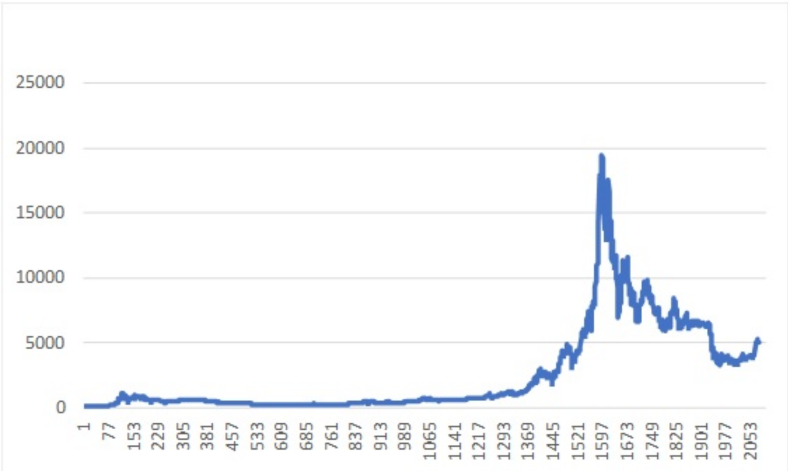
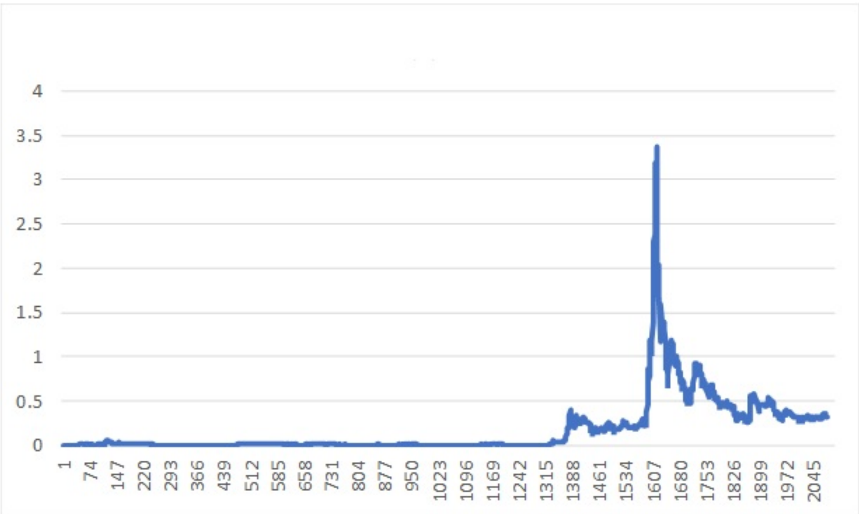
Appendix-B

Graphical Representation Of Prices

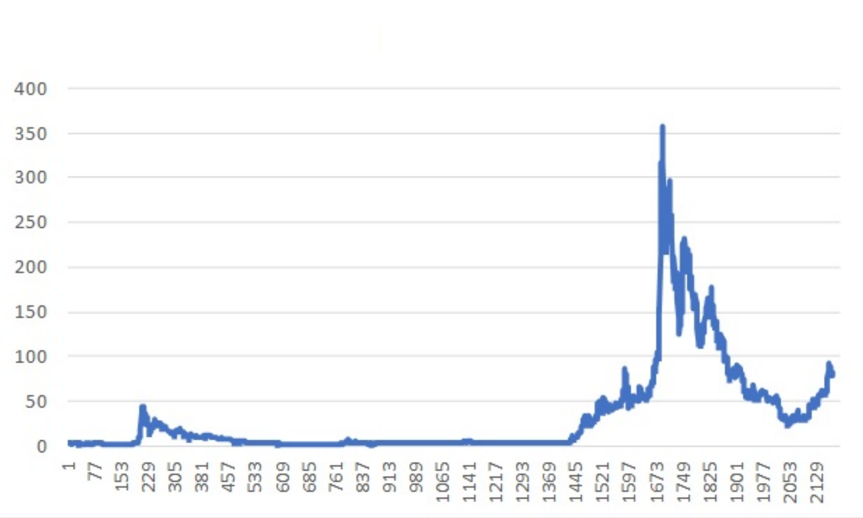
Bitcoin



Ripple

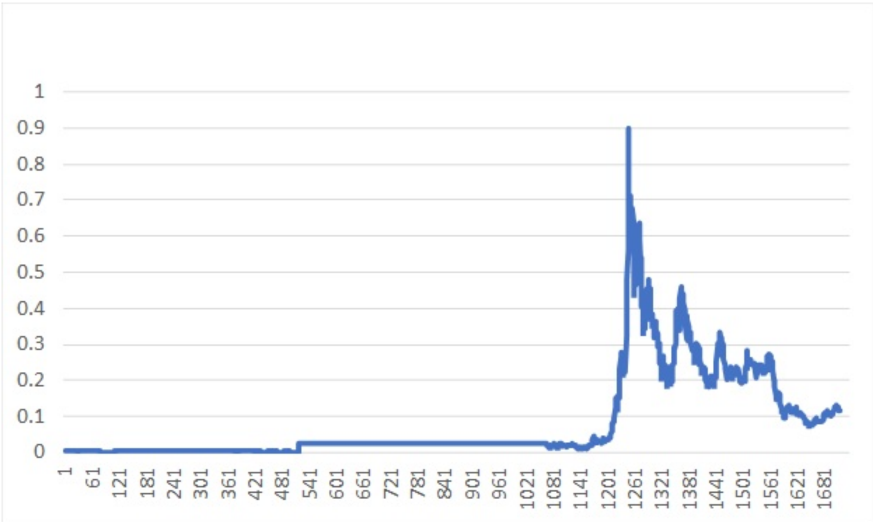


Litecoin

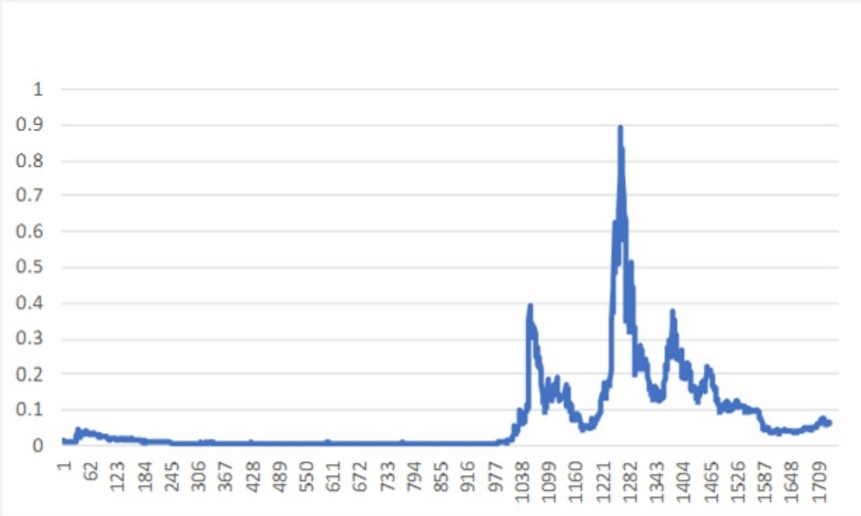


Monero

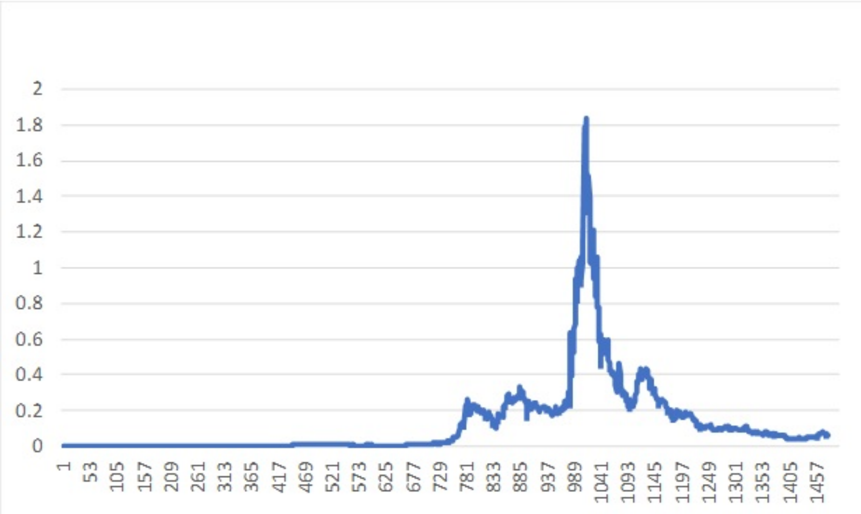
Steller



Bitshare



NEM



Ethereum

Dash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1400
1200
1000
800
600
400
200
0
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208
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346
415
484
553
622
691
760
829
898
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1243
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1450
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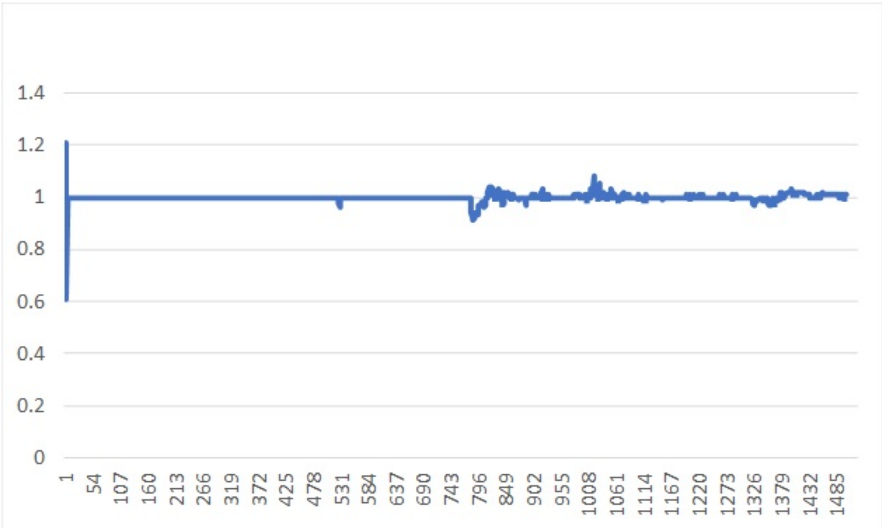
1657
1726
1795
1864

Tether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0
1
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478
531
584
637
690
743
796
849
902
955
1008
1061
1114
1167
1220
1273
1326
1379
1432
1485