CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Seasonality, Asymmetry and Non-linearity in Return and Conditional Volatility of Leading Cryptocurrencies

by

Mubasher Ali

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in the

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This thesis is dedicated to My Beloved Parents & Teachers, who are always a light for me in the dark and their unwavering support guided my Unfocused words into Coherent ideas.

CERTIFICATE OF APPROVAL

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Mubasher Ali

(MMS183014)

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	External Examiner	Dr. Ahmad Fraz	P.I.D.E. Islamabad
(b)	Internal Examiner	Dr. Jaleel Ahmed Malik	C.U.S.T. Islamabad
(c)	Supervisor	Dr. Arshad Hassan	C.U.S.T. Islamabad

Dr. Arshad Hassan
Thesis Supervisor
August, 2020

Dr. Mueen Aizaz Zafar
Head
Dept. of Management Sciences
August, 2020

Dr. Arshad Hassan
Dean
Faculty of Management & Social Sciences
August, 2020

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. . . In the Name of **Allah**, The Most Gracious, The Most Merciful. . .

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. . . May Allah bless them all. . .

(Mubasher Ali)

Registration No: MMS183014

Abstract

The purpose of this study is to examine the seasonality, asymmetry and non-linearity in return and conditional volatility of leading crypto-currencies. The study employs the daily data (closing prices) of ten leading crypto-currencies for the period of 4/2013 to 11/2019 that are selected on the basis of market capitalization and availability of data. The study use GARCH model to analyze the return volatility of the leading crypto-currencies. GJR-GARCH or T-GARCH model is used to measure asymmetric behavior in linear setup. E-GARCH model is used to measure asymmetric behavior in non-linear setup. P-GARCH investigates the asymmetry behavior and long memory of returns in the volatility of all leading crypto-currencies, and Q-GARCH model explore non-linearity in behavior of leading crypto-currencies. The findings of the study provide evidence of the volatility persistence. The results show that there exist asymmetric behavior and long memory of returns in the volatility of all selected crypto-currencies. The results also reveal that there exist non-linearity behavior in Ripple, Litecoin, Stellar, Monero, Dash, Nem and Dogecoin. This study recommends to market players like individual investors, policy makers, speculators, portfolio managers to consider seasonality, asymmetry and non-linearity relatively in decision for assets allocation and risk diversification.

Keywords: Crypto-Currencies, Asymmetry, Non-linearity, Seasonality, Volatility, Day of the week effect, Month of the year effect.

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Abbreviations

APARCH/P-GARCH	Asymmetric Power ARCH
BTC	Bitcoin
DOGE	Dogecoin
DASH	Dash
ETH	Ethereuem
E-GARCH	Exponential GARCH
EMH	Efficient Market Hypothesis
GJR-GARCH	Glosten, Jagannathan & Runkle GARCH
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
LTC	Litecoin
Q-GARCH	Quadratic GARCH
T-GARCH	Threshold GARCH
USDT	Tether
XRP	Ripple
XLM	Stellar
XMR	Monero
XEM	Nem

Chapter 1

Introduction

"Crypto-currency is a virtual currency which utilizes cryptography for security purposes and it's one among the new technological advancements in the innovatory world"(Monterio, 2014). A crypto-currency may be a computerized resource intended to function as a mode of trade utilizing cryptography to verify the exchanges and to regulate the flow of units of money (Greenburg, 2011). A crypto-currency is often well-defined as "cash for the web".

The seasonality in the return and volatility of crypto-currencies, also referred to as calendar effects like Monday effect, turn of the month effect, weekend effect, January effect, and the Halloween effect (Kaiser, 2019). Thereby, this study provide an alternative perspective to the on-going debate on the degree of market efficiency for crypto-currencies. Particularly, this study test for the (1) Day of the week effect and (2) Month of the year effect.

The day of the week effect means that returns are different on certain weekdays, whereas the month of the year effect means that returns are different on certain months, which is also known as one of the calendar anomalies in the financial markets, particularly in stock, crypto-currency and foreign exchange markets. The existence of the day of the week effect or month of the year effect is not consistent with the Efficient Market Hypothesis (EMH) that investors could not obtain abnormal returns based on publicly released information. There are many potential explanations proposed for this calendar anomaly, e.g. measurement error, spillover from other markets, information releases after close, investors psychology, etc. As Bitcoin exchanges operate 24/7 without weekends and holidays, return distributions of Bitcoin on weekdays should be the same in calendar time (Ma and Tanizaki, 2019).

Asymmetric behavior means the news ("good news" or "bad news"), events, incidents, that has a great and powerful influence on the decision making of the financial investor. The study of Baur and Dimpfl (2018) investigates asymmetric volatility in the twenty largest crypto-currencies. Alvarez-Ramirez et al. (2018) examines long-range correlations and asymmetry in the Bitcoin market. So, to capture the asymmetries in the return and volatility of the leading crypto-currencies, in term of negative and positive shocks, GJR-GARCH or T-GARCH model of Rabemananjara and Zakoian (1993) and Glosten et al. (1993) and E-GARCH model of Nelson (1991) is used in this study.

Non-linearity is a term used in statistics to describe a situation where there is not a straight-line or direct relationship between an independent variable and a dependent variable. Non-linearity is characterized by an asymmetric mean-reverting property, which has been found to be inherent in the short-term return dynamics of stocks (Corbet and Katsiampa, 2018). This study explore non-linearity in return and volatility of the leading crypto-currencies.

Within the news as lately, Crypto-currencies have established an excellent deal of attention. In 2017, the entire market capitalisation of cryptocurrency has grown up impressively. The market capitalisation of all cryptocurrencies in January 2017, was nearly \$18 billions. As of January 2018, the entire market capitalisation was about \$599 billions. As of October 2019, the entire market capitalisation is nearly \$230 billions. These ups and downs express the volatility in the cryptocurrency market. Even with the exponential growth of Bitcoin and other leading cryptocurrencies, the cryptocurrency market is quite young as Bitcoin was developed in 2009, but actively trading on track in 2013 and thus remains mostly (Caporale et al., 2018). So, it's very important to know how the crypto-currency prices behave.

A growing number of studies has investigated in considerable detail the statistical properties of bitcoin returns. Pichl and Kaizoji (2017) report that crypto-currency markets are even more volatile than foreign exchange markets. Volatility clusterings have been observed by Chu et al. (2017); Catania and Grassi (2017); Katsiampa (2017); Bariviera (2017); Baur et al. (2018); Bouri et al. (2016); Stavroyiannis (2018) among others. Osterrieder and Lorenz (2017) and Begušić et al. (2018) have studied the unconditional distribution of bitcoin returns and found that it has more probability mass in the tails than that of foreign exchange and stock market returns. Regime-switching behaviors are detected by Bariviera et al. (2017); Balcombe and Fraser (2017); and Thies and Molnár (2018) have identified structural breaks via a Bayesian framework in the volatility procedure of bitcoin. Lately, the studies of Lahmiri and Bekiros (2018) and Lahmiri et al. (2018) have nominated that crypto-currency markets (bitcoin) are characterized by long memory and multifractality.

1.1 Theoretical Background

In this section, the most important theory is Market Efficient Theory also called Efficient Market Hypothesis (EMH) proposed by an economist Malkiel and Fama (1970). This theory expresses us that market value reflects all available information. It means that market would be an efficient market, if all available information reflects in the values of the securities (i.e. neither undervalued nor overvalued a security).

In his work, Malkiel and Fama (1970) states three phases of market efficiency theory. 1) Strong form of Market Efficiency; All available information (both public & private) reflects in the prices of a security. 2) Semi-Strong form of Market Efficiency; Public information absorbed by market so quickly that investor cannot take any benefit from the ups and downs in the market through trading 3) Weak form Market Efficiency; Past price behavior does not influences future prices. Investors cannot earn more return by following the past price behavior this information is available to everyone, so no person can earn abnormal profit.

The studies by Urquhart and Hudson (2013); Ito et al. (2014); Noda (2016); Ito et al. (2016); and Urquhart and McGroarty (2016) also examines the market efficiency with procedures derived with the Adaptive Market Hypothesis (AMH).

Crypto-currency is a form of currencies that are likely the most unpredictable or uncertain resource in presence today. Yaya et al. (2019b) explore the crash period of Bitcoin and find a higher persistency of shocks in the attentions of crypto-currency brokers. Many researchers reveal the price of Bitcoin relationship with other economic variables, as the study of Su et al. (2017), reveals that there are four bursting bubbles happened in the U.S.A. and China market during stages of enormous increases in the prices of bitcoin.

The researchers Urquhart (2016); Jiang et al. (2018); Vidal-Tomás and Ibañez (2018); Wei (2018); Caporale et al. (2018); Al-Yahyaee et al. (2018); Zargar and Kumar (2019); Nan and Kaizoji (2019); and Hu et al. (2019) investigates that the crypto-currency market, especially the market for Bitcoin is basically in-efficient. While the research papers by Nadarajah and Chu (2017), and Kristoufek and Vosvrda (2019) expresses that the crypto-currency market is found to be efficient in certain periods.

There are many researchers that explore calendar/seasonal effects like day of the week effect (Caporale and Plastun, 2019a), Month of the year effect (Plastun et al., 2019), January & December effect, Mid of the year effect, Eid Day effect, weekend effect, turn of the month effect, Halloween Effect, etc (Kaiser, 2019). All of these evidences are against the Efficient Market Hypothesis (EMH) market effect since in an efficient market, all the prices are likely to be uncertain all over the market period (Malkiel and Fama, 1970). As we all know that the discussion remains on the efficiency of the cryptocurrency market, and therefore the possibility of such a calendar/seasonal effect contradicts our trust on the efficiency of the cryptocurrency market an extra vigorous time-based analysis is required to systematically examine such distinguishing or encouragement of market efficiency.

1.2 Gap Analysis

Balaban et al. (2001) study the return of stocks, seasonality and asymmetric conditional volatility in world equity markets. Liu and Serletis (2019), explore the spillover effects from the cryptocurrency market to other financial markets in the United States, as well as in other leading economies of the world i.e. United Kingdom (UK), Germany, and Japan. The study of Liu and Tsyvinski (2018), is about the risk and return trade-off of cryptocurrencies (i.e. Bitcoin, Ripple, and Ethereum) to observe how it is different from those of stocks, currencies, and other valuable metals.

Most of the studies have been conducted on cryptocurrencies as an growing assets class. Katsiampa (2017) reveales the in-stability of Bitcoin by using a correlation of GARCH-Models and explore the AR-CGARCH model as the most ideal model. Katsiampa (2019a) use a diagonal BEKK model to investigate the co-movement in volatility between Bitcoin and Ether. Katsiampa (2019a) also provides the indication of crypto-currency market inter-dependencies. While, the work of Katsiampa (2019b) is limited to just two leading crypto currencies i.e. Bitcoin (BTC) & Ethereum (ETH). All the previous literature reviews in the area of crypto-currencies focuses largely on return and volatility in Bitcoin as it is one of the top crypto-currency, which means that there is in-edequate research on other significant and leading crypto-currencies. Former research explores the in-efficiency (Cheah et al. (2018); Urquhart (2016); Nadarajah and Chu (2017)) and un-certainty in Bitcoin (Dyhrberg (2016); Dwyer (2015)).

Most of the researchers just discuss the returns and volatility of the crypto-currencies. Some of the researchers worked on asymmetric volatility of crypto-currencies, but simultaneous exploration of return, seasonality, asymmetric volatility and non-linearity of crypto-currencies is still disregard. This study investigates return, seasonality and asymmetric conditional volatility in crypto-currency market rather than on equity markets. Baur and Dimpfl (2018) analyzes asymmetric volatility effects for the twenty largest crypto-currencies. This study investigates asymmetric conditional volatility effect as well as non-linearity and seasonality effect in ten leading crypto-currencies by using GARCH Models.

1.3 Research Questions

This study addressed following research questions:

Research Question 1

Do crypto-currencies exhibit time varying volatility?

Research Question 2

Is asymmetric behavior exist in the volatility of crypto-currencies?

Research Question 3

How do non-linearity influences volatility of crypto-currencies?

Research Question 4

Is long-memory of returns exist in the volatility of crypto-currencies?

Research Question 5

Do returns and the volatility of crypto-currencies exhibit seasonal behavior?

1.4 Research Objectives

The objectives of the study are may as follows:

Research Objective 1

To study return and volatility dynamics of crypto-currencies.

Research Objective 2

To investigate asymmetric behavior in the volatility of crypto-currencies.

Research Objective 3

To find the effect of non-linearity in the volatility of crypto-currencies.

Research Objective 4

To examine long-memory of returns in the volatility of crypto-currencies.

Research Objective 5

To explore seasonal behavior in the returns and the volatility of crypto-currencies.

1.5 Significance of the Study

Cryptocurrency is one of the risky asset class that is attracting investors. Cryptocurrencies provide them an important opportunity of investment. In the global market, Cryptocurrency has become another source of investment (Weber, 2016). Crypto-currency market become popular with the launch of very first digital currency, a Bitcoin (BTC) in 2009 priced $5 per Bitcoin, and since then now as on June 2020 the price of a Bitcoin (BTC) is $9,801. With the passage of time, it becomes more popular as well as the number of crypto-currencies increases, now over 2600s cryptocurrencies are being traded 24/7 in the crypto-currency market (coimarketcap.com).

The discussion about the seasonality, asymmetry and non-linearity in the return and volatility of the leading crypto-currencies is important with regard to the viability of their function as money. It should not only serve as a medium of exchange, but also as a unit of account and store of value. Moreover, this study is very beneficial for those stakeholders who are interested or directly engaged in buying and selling in the crypto-currency market. It offers them a vision about the ups and downs in the leading crypto-currencies and they may able to regulate this operation in the crypto-currency market, so its very helpful for them to make a decision on investment in different crypto-currencies. Investors can earn abnormal profit by taking a rational decision on time. This study may also helpful for the portfolio managers in pricing, portfolio structuring, hedging startegies, and trading in crypto-currencies.

During the previous couple of years, more efforts are made to research the risk-return, volatility, and benefits for investors. For instance, Corbet et al. (2018b) explore the dynamic relationships between cryptocurrencies and other financial assets, showing that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Phillip et al. (2018) explore the properties of 224 cryptocurrencies and located that, generally, they need several unique properties including leverage effects and Student- error distribution. Liu and Tsyvinski (2018) find that the risk-return tradeoff of cryptocurrencies (Bitcoin, Ripple, and Ethereum) is distinct from those of stocks, currencies, and precious metals. Additionally, this study create an index of exposures to cryptocurrencies of 354 industries within the US and 137 industries in China.

More recently, Kapar and Olmo (2019) suggest that the Bitcoin futures exchange dominates the worth discovery process and find that both prices are driven by a standard factor that's given by a weighted combination of the futures and commodity exchange. On the opposite hand, the consequences of the geopolitical risks on Bitcoin returns and volatility are analyzed by Aysan et al. (2019), showing that Bitcoin are often considered as a hedging tool against global geopolitical risks. There are number of studies that explain the return, seasonality and asymmetric conditional volatility across different financial markets, but very few studies found in the background of crypto-currency market. This study contributes in the body of knowledge (Theoretical Contribution) by investigating seasonal effects (day of the week effect and month of the year effect), asymmetric behavior as well as non-linearity in the return and volatility of ten leading crypto-currencies by using GARCH Models.

In late 2017, the prices of crypto-currencies (especially Bitcoin) were at boom to around $19000 per Bitcoin for very first time in the history. Then Bitcoin price crashed at the start of 2018 and caused prices of other crypto-currencies to fall (Cointelegraph, 2018). Ciaian et al. (2018) said that all other cryptocurrencies (Ethereum, Ripple, Monero, Litecoin, stellar etc.) also effected due to an increase in the popularity of Bitcoin (BTC). Even a single digital currency from all over crypto-currency market can‘t overtake the Bitcoins price yet. However, the procedure to acknowledge (accept) or dismiss (reject) any digital currency by market analysts, investors, managers and controllers is a going concern process.

1.6 Plan of the Study

Chapter 1 includes the Introduction, Theoretical Background, Gap Analysis, Research Questions, Research Objectives and Significance of the study. Chapter 2 includes the Literature Reviews of the past studies as well as the Hypotheses for the study. Chapter 3 covers the Data Description and Research Methodology of the study. Chapter 4 includes the Data Analysis and Results. Finally, Chapter 5 includes the Conclusion, Recommendations and Future Directions of the study.

Chapter 2

Literature Review

During the last decade, the digital currency has been one among the most debated topics in finance. Cryptocurrencies are intended to act as exchange channels, but some analysts claim that cryptocurrencies should be viewed as speculative or risky instruments thanks to high uncertainty (Bação et al., 2018).

Within the financial service sector, a Fintech (financial technology) is one among the most key drivers behind developments. A block-chain technology is one among the technologies (most debated in crypto currencies) that permits direct electronic transfer among two individuals. This transfer is administered within the absence of a third-party like a bank or other financial intermediaries that may cause cost savings (Labbé et al., 2018).

Cryptocurrencies evolution had an impact on the financial sector. The world is moving towards a cashless direction, that is, some Swedish stores are not any longer accepting cash. Cryptocurrencies offer worldwide quick transfers with lower transaction costs, making them attractive to people living under oppressive regimes (Göttfert, 2019).

Digital currency is virtual money in online portfolios of null intrinsic value provided by a code that has no financial institution or government support (Murray, 2018). Cryptocurrency's value isn't measured by either a convertible tangible asset (like gold) or an at currency (like a dollar), it's assessed by its demand and supply interplay (Low and Teo, 2017). This emerging cryptocurrency may perform various functions of the business.

The study of Phillips and Gorse (2018) examine that a crypto-currency can promote transactions of business from individual to individual globally without intermediaries. It can also reduce barriers to trade as costs and boost up productivity. Nonetheless, the utility of cryptocurrency remains uncertain thanks to its significant price fluctuations, the inelastic essence of the computational formula-coded funds, and therefore the lack of state protections (Kiviat, 2015).

The study of Ram (2015) reveal that cryptocurrencies could seem an equivalent as traditional currencies but have significant differences relative to the "fiat" currencies. Central banks don't control the cryptocurrencies i.e., it's not published or released by a state or regulator or any central authority, it's mined through the utilization of technology. It's begun to become popular as how to settle e-commerce purchases and wishes the advantage of goods and services and is additionally said that there's no intrinsic value.

The evolution of Bitcoin and other flowering cryptocurrencies within the market has been analyzed intimately during this decade. Especially, from 2013 when the worth of Bitcoin increased rapidly from around \$150 in mid-2013 to over \$1000 in late 2013, which is understood because the 2013 bubble. Brown (2014) provided evidence of the short-term price predictability of the Bitcoin.

Corbet et al. (2018a) perform an excellent and systematic review of cryptocurrencies research as a financial asset. Cryptocurrency, which may be a modern sort of technological development within the finance area, is vital to review its effect on different professions and practitioners (Boomer, 2016). There are many discussions within the existing literature on the existence of cryptocurrency and on whether cryptocurrencies are considered a trading tool or a speculative investment.

The cryptocurrency market, and in particular the market for Bitcoin, is found to be largely inefficient, see, for example, Urquhart (2016); Jiang et al. (2018); Vidal-Tomás and Ibañez (2018); Wei (2018); Caporale et al. (2018); Al-Yahyaee et al. (2018); Zargar and Kumar (2019); Nan and Kaizoji (2019); and Hu et al.

(2019). However, the cryptocurrency market can be efficient in certain periods as well, see, for example, Kristoufek (2018); Kristoufek and Vosvrda (2019), or a power transformation of Bitcoin return can be weakly efficient (Nadarajah and Chu, 2017). Other studies such as Omane-Adjepong and Alagidede (2019);Omane-Adjepong et al. (2019); Sifat et al. (2019); Antonakakis et al. (2019) and Katsiampa et al. (2019) also show that cryptocurrencies are strongly interlinked reflecting by volatility spill-over, volatility co-movement, lead-lag effect, market co-movement.

Frisby (2014) believes that Bitcoin appears to possess the qualities of cash and even better performance: Its mining process and restricted supply process enable it to work as a worth store. Its divisibility, resilience, accessibility, greater volatility, and fewer transaction fees make it possible for the stock to trade. Dyhrberg (2016) has an equivalent finding in Bitcoin and Gold's GARCH model. The results show that Bitcoin has capabilities of allied hedging, so it is often characterized as a hybrid among a commodity and a currency. By using quantile-on-quantile regressions, Demir et al. (2018) explores the connection among Bitcoin and therefore the index of policy volatility and argues that Bitcoin could also be used as a medium of hedging toward uncertainty. Although several sorts of research notice that speculative bubbles in cryptocurrencies and low intrinsic value leads to several unpredictable factors and reduce stability in prices.

Although several sorts of research notice that speculative bubbles in cryptocurrencies and low intrinsic value leads to several unpredictable factors and reduce stability in prices, thus weakening their function. Urquhart (2016) concludes that Bitcoin is an unstable cryptocurrency throughout the time studied and notes that after mid-2013, Bitcoin provides evidence of being simpler. Fry and Cheah (2016) find the straightforward price of Bitcoin is predicted to be zero. Considerably, high instability and weak Bitcoin correlation, at currencies and gold show that Bitcoin is hard to use as a standard currency or maybe as a hedging tool. Glaser et al. (2014) also, consider that it's more likely to be employed by new Bitcoin users for the aim of speculative investment.

There are many studies that seek to specifically check the price efficiency of Bitcoin. Urquhart (2016) employs six various sorts of tests for efficiency and claims that Bitcoin is ineffective. Moreover, Urquhart further suggests that Bitcoin is growing toward efficiency after such an early transitory period because the market matures. Nadarajah and Chu (2017) implement eight various tests for easy power transmission of returns of Bitcoin and summarize for Bitcoin returns efficiency. Bariviera (2017) further re-examines Bitcoin's efficient market theory employing Range over variance and De-trended Fluctuation Analysis approaches, respectively, to spot long storage and knowledge quality variations. The study concludes that regular returns indicate consistent behavior during the primary half the study period, although their performance has been simpler since 2014.

Ciaian et al. (2016) use an Autoregressive Distributed Lag (ARDL) approach to study interdependencies between Bitcoin and other cryptocurrencies and discover that Bitcoin and other cryptocurrencies, such as Ether, are mutually dependent. Recently, a study is conducted in the background of Fractional integration and cointegration by Yaya et al. (2019a). This study explores Bitcoin's persistence and reliance on alternative coins. In their persistence assessment, it uses a fractional integration strategy and the fractional cointegration method suggested by Johansen (1991) in the VAR set-up to explore the dependency of the combined factors.

Caporale and Plastun (2019a) examine the day of the week effect in the cryptocurrency market by using a variety of statistical techniques i.e., average analysis, Kruskal-Wallis test, ANOVA, Student's t-test, and the regression analysis with dummy variables as well as a trading simulation approach. This study uses daily data of Bitcoin, Ripple, Litecoin, and Dash for the period of 2013 to 2017. Ripple, Litecoin, and Dash are not to exhibit this anomaly. The only exception is the Bitcoin (BTC), for which returns on Monday are significant and higher than those on the other days of the week. In this study, the trading simulation analysis reveals that there exist exploitable profit opportunities. So, most of the results are not significantly different from the random ones and cannot be seen as conclusive evidence against market efficiency.

Baur et al. (2019) explain the time of day, day of the week, and month of the year effects for Bitcoin returns and trading volume. This study uses more than fifteen million observations from seven global and continuously traded Bitcoin exchanges. The results of this study show time-specific anomalies in returns but no persistent effects across time. In contrast, this study find persistent differences in trading activity across all exchanges with lower activity during local evening hours and on weekends. The findings recommend that both retail and institutional investors are actively trading Bitcoin.

Plastun et al. (2019) investigate the month of the year effect in the Bitcoin by using monthly data obtained from CoinMarketCap for the period of June 2010 to May 2019. This study use average analysis, Kruskal-Wallis test, ANOVA, Student's t-test, and the regression analysis with dummy variables. The results of this study shows that July and August returns are much lower than returns on other months. These two months are considered as the worst months to buy Bitcoins. The findings of this study claim to find some holes in the efficiency of the cryptocurrency market, which can be exploited. This provides opportunities for effective portfolio management in the cryptocurrency market.

Ma and Tanizaki (2019) explore the day of the week effect in return and volatility of Bitcoin (BTC) through Stochastic Volatility (SV) model. This study use daily data obtained from Coin-Desk Bitcoin Price Index for the period of January 2013 to December 2018. The findings of this study reveal that the day of the week effect in return equation varies with sample periods, whereas significant and higher volatilities are observed on Monday and Thursday. Thus, the significant and high mean return of Bitcoin on Monday is found as a response to the higher volatility. Besides, the day of the week effect in return and volatility remains robust after accounting for stock market returns and the foreign exchange market returns. The findings of this study also reveal that there is no asymmetry effect in the volatility of Bitcoin (BTC).

Robiyanto et al. (2019) examine the day of the week and month of the year effects in the Bitcoin and Litecoin using GARCH (1,1) analysis. This study uses monthly cryptocurrency returns data for the period of 2014 to 2018. The findings reveal that there exist day of the week and month of the year effect in the cryptocurrency market. The results indicate that the Bitcoin have a potential to generate daily profits on Monday, Wednesday and Thursday. The findings of this study suggest that investors should buy Bitcoin at the end of January and sell them at the end of February.

Long et al. (2020) exhibit the cross-sectional seasonality anomaly in crypto-currency market through portfolio sorts and cross-sectional regressions. This study uses daily data of 151 crypto-currencies for the period of 2016 to 2019. The results of this study shows a significant seasonal behavior: average past same-weekday returns positively predict future performance in the crosssection. Crypto-currencies with high same day return in the past outperform cryptocurrencies with a low same day return. This effect is not subsumed by other established return predictors such as momentum, size, beta, idiosyncratic risk, or liquidity.

2.1 Volatility in Crypto-Currencies

As investors are susceptible to extremely un-differentiated intimidations of the cryptocurrency market. Katsiampa (2019b) analyze the changes within the prices of crypto-currency and consider its co-movements is of primary importance to participants and other institutional investors to understand interconnections of the digital currency market and make informed decisions. Volatility has become a crucial facet of this emerging class. Past studies show that there are many studies on volatility. For instance, inconsistency within the prices of cryptocurrency has been observed by Katsiampa (2019b) and Phillips and Gorse (2018). The interdependency within the cryptocurrency market is additionally studied by Katsiampa (2019b). Cryptocurrency is closely linked to many threats resulting from its excessive uncertainty and speculative nature.

Katsiampa (2019b) explores the volatility co-movement between the two main crypto currencies (Ether and Bitcoin) by applying the Diagonal BEKK model, the main target of his study is only volatility dynamics of Bitcoin and Ether. The research finds indications that the market of digital currency is interdependent. Then he extended his work to leading cryptocurrencies. Gandal and Halaburda (2016) analyze competition within the cryptocurrency market, but most of the researchers focus on the worth volatility, showing that this market is more volatile than others (Cheung et al., 2015; Dwyer, 2015; Bouoiyour and Selmi, 2015).

Katsiampa (2019a) studies spillover impact of fluctuations in major digital currencies using the BEKK-MGARCH technique by taking into consideration three leading digital currencies, including Bitcoin, Litecoin, and Ether, and by using three pair-wise BEKK models for the Bitcoin-Litecoin, Litecoin-ether and Bitcoin-Ether pairs. The discussion of volatility is not stopped here; Yi et al. (2018) study the volatility connectedness within the cryptocurrency market. The study investigates the connection between eight standard digital currencies for static and dynamic instability. The results show that their connectivity fluctuates cyclically and since the top of 2016 has shown a clear upward trend.

Chu et al. (2017) uses the GARCH model to seven digital currencies that were commonest. The findings suggest that digital currencies like Bitcoin, Ethereum, Litecoin, and a number of other others exhibit fairly high volatility, particularly at the inter-daily prices. This study suggest that such sort of investment is right for investors seeking how to take a position or access technology markets in pursuit of risk.

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

Some authors, like Glaser et al. (2014) and Baek and Elbeck (2015) state that Bitcoin is usually used for speculative purposes, thanks to the acute volatility and bubbles. After the fall of Bitcoin price in 2016, many researchers focus about analyzing the efficiency of the Bitcoin market (Jakub, 2015; Urquhart, 2016) and others study the negative bubbles and shocks in cryptocurrencies markets by using econo-physics models (Fry and Cheah, 2016). In 2017, things changed abruptly.

Feder et al. (2018) analyze the increase and fall of cryptocurrencies, especially the dynamics of coin creation, competition, and destruction within the cryptocurrency industry. This study conclude that, unlike the top of the 2013 bubble, some alternative crypto currencies continue to flourish after the autumn of Bitcoin. In fact, the amount of latest digital coins increase impressively, from 22 crypto currencies in August 2017, to 2520 in January 2019.

Other authors also analyze the anomalies within the cryptocurrency market (Kurihara and Fukushima, 2017; Caporale and Plastun, 2019b; Caporale et al., 2018) and therefore the extreme volatility (Dyhrberg, 2016; Corbet et al., 2018b; Hafner, 2020). Catania and Grassi (2017) evaluate Bitcoin volatility by using GAS models, and Phillip et al. (2018) used a stochastic volatility model. Bouri et al. (2017) show, among other things, a negative relation between the US implied volatility index (VIX) and Bitcoin volatility, and Bariviera (2017) test the presence of long memory in Bitcoin series from 2011 to 2017.

Crypto-currencies are among the most important unregulated markets within the world. Foley et al. (2019) document that roughly one-fourth of Bitcoin users may be involved in criminality. This study estimates that about $76bn of criminality annually may involve Bitcoin. It also document that the illegal share of Bitcoin activity has declined with mainstream interest in Bitcoin and with the emergence of more opaque cryptocurrencies. Practical problems associated with investing in cryptocurrencies include illiquidity, theft, fraud, ransom attacks/hacking, and potential constrictive government regulation. Since cryptocurrencies are unregulated, decentralized, untraceable, and anonymous, there are not any protections, liability clauses, or insurers.

Although the absence of comprehension regulation is a crucial problem for the protection from theft and ransom attacks, increased levels of regulation could pose a good bigger problem for these digital coins. Government regulation could disrupt truth nature of cryptocurrencies that creates them attractive to users, could lead on to drastic declines in their value, and will cause significant illiquidity, making them unattractive to investors. Overall, the potential for regulation may be a major threat to cryptocurrencies within the near future.

2.2 Crypto-Currencies and GARCH Models

Urquhart (2017) examines the volatility of bitcoin currency and shed light on the forecasted ability of GARCH models and ARCH models in the bitcoin market. The result indicates that the HAR models are superior in modelling bitcoin currency volatility compared to the traditional GARCH models and that there is no evidence of the leverage effect in bitcoin market. Chu et al. (2017) uses the GARCH model to seven digital currencies.

Earlier, a study investigates the ability to diversify seven cryptocurrencies with the highest market size against economic risk variables such as price of gold, crude prices, rate of interest, Dollar strength and S & P 500. This study reports that each cryptocurrency has structural splits and ARCH fluctuations, indicating a systematic risk on the digital currency market and cryptocurrencies have negligible financial correlations by using weekly data of Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash and Bytecoin from August 2014 to June 2018 (Canh et al., 2019).

Stavroyiannis and Babalos (2017) explore the dynamic properties of bitcoin and the Standard and Poors SP500 index, using different types of econometric methods, including univariate and multivariate GARCH models, and vector autoregressive specifications. In addition, the study also examines whether bitcoin currency can be used as a hedging or safe haven instrument in the USA market and explore if the bitcoin currency owns any attributes of gold asset. The findings of the study indicate that bitcoin currency does not hold any of the hedges, diversifiers or safe-haven instruments; rather, it exhibits intrinsic attributes not related to the US market developments.

Conversely, Dyhrberg (2016) applies asymmetric GARCH methodology to investigate whether the bitcoin currency has hedging capabilities of gold. The findings indicate that bitcoin currency can be used as a hedging instrument against stocks in the Financial Times Stock Exchange Index and the American dollar in a short term. The study therefore suggests that bitcoin currency can be included as financial instruments to hedge market specific risk.

Bouri et al. (2016) use daily returns on bitcoin currency denominated in US dollar over the period of 18 August 2011 - 29 April 2016 to examine the relationship between price returns and volatility changes in the bitcoin market. The study provides no evidence of an asymmetric return-volatility relation in the bitcoin market for the entire period of the study. However, test is carried out to see if there is a difference in the returnvolatility relation before and after the price crash of 2013. The analysis result of the pre-crash period (596 daily observations) and the post-crash period (630 daily observations) indicate a significant inverse relationship between past shocks and volatility before the crash and no significant relationship after crash. Additionally, prior to the price crash of December 2013, positive shocks have increased the conditional volatility more than negative shocks.

Chen et al. (2016) uses a variety of GARCH models to examine the volatility of crypto-currency Index (CRIX) family using daily data covering the period of 01 August 2014 - 06 April 2016. The results of the study indicate that based on the statistical values of the three criteria, namely, log likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC), T-GARCH (1, 1) model is found to be the best model for all the CRIX index families. In addition, the results indicate that the dynamic conditional correlation DCC-GARCH (1,1) provide evidence a persistence of volatility clustering and time varying covariance between the three CRIC indices.

2.3 Hypotheses of the Study

The hypotheses of this study are as follows:

Hypothesis 1:

There exists time varying volatility in the crypto-currencies.

Hypothesis 2:

There exists asymmetric behavior in the volatility of crypto-currencies.

Hypothesis 3:

There exists long-memory returns in the volatility of crypto-currencies.

Hypothesis 4:

There exists non-linearity in the volatility of crypto-currencies.

Hypothesis 5:

There exists seasonal behavior in the returns and the volatility of crypto-currencies.

Chapter 3

Data Description & Research Methodology

Research methodology is a process in which various tools, techniques and concepts are used in a study to explore the answer of the research question in a systematic manner. This section includes almost all the methods and procedures which are applied in this study to explain the volatility and its dynamics. The discussion contains details about the population of study, sample size, other tools and techniques used to meet the objectives of the study considered under this research.

3.1 Population and Sample of the Study

Population of this study is the crypto-currency market (all crypto-currencies) and sample of this study is top ten cryptocurrencies, these cryptocurrencies are selected on the basis of market capitalization ($300 million or above) and availability of data (four years minimum) as mentioned in Table 3.1 below. This study uses secondary financial data and daily data obtained from coinmarket. Cryptocurrency's value isn't measured by either a convertible tangible asset (e.g. Gold) or an at currency (e.g. Dollar), it's evaluated by its demand and supply interplay (Low and Teo, 2017).

The prices of cryptocurrencies are taken in dollar terms, the return of the cryptocurrencies are calculated from the following formula:

$$R_t = ln(\frac{P_t}{P_{t-1}}) \tag{3.1}$$

Where,

ln = Natural log

P_t = The price of crypto currency at time 't'

P_{t-1} = The price of crypto currency at time "$t-1$"

R_t = Return of crypto-currency compounded continuously

TABLE 3.1: Sample Data Details

No.	**Currency**	**Symbol**	**Market Capitalization**	**Sample Data Period**
1	Bitcoin	BTC	$167,123,690,601	Apr 28,2013 to Nov 02, 2019
2	Ethereum	ETH	$19,910,727,389	Aug 07,2015 to Nov 02, 2019
3	Ripple	XRP	$12,709,526,347	Aug 04,2013 to Nov 02, 2019
4	Tether	USDT	$4,125,920,535	Feb 25,2015 to Nov 02, 2019
5	Litecoin	LTC	$3,695,763,760	Apr 29,2013 to Nov 02, 2019
6	Stellar	XLM	$1,399,171,475	Aug 05,2014 to Nov 02, 2019
7	Monero	XMR	$1,075,877,945	May 21,2014 to Nov 02, 2019
8	Dash	DASH	$654,820,234	Feb 14,2014 to Nov 02, 2019
9	Nem	XEM	$381,982,329	Apr 01,2015 to Nov 02, 2019
10	Dogecoin	DOGE	$321,337,436	Dec 15,2013 to Nov 02, 2019

3.2 Econometric Model

Crypto-currency markets share the important stylized facts of foreign exchange, stock and commodity markets. Some authors use the GARCH type models (Chu et al., 2017; Bouri et al., 2017; Katsiampa, 2017; Bariviera, 2017; Baur et al., 2018; Stavroyiannis, 2018; Catania and Grassi, 2017), some use the Markov switching

GARCH model (Ardia et al., 2018), and some use the stochastic volatility model (Phillip et al., 2018).

Robiyanto et al. (2019) apply GARCH (1,1) model to examine the day of the week and month of the year effects in the Bitcoin and Litecoin. To exhibit the cross-sectional seasonality anomaly in the crypto-currency market, Long et al. (2020) use portfolio sorts and cross-sectional regressions. Whereas Ma and Tanizaki (2019) use Stochastic Volatility (SV) model to investigate the day of the week effect in return and volatility of Bitcoin (BTC).

The techniques used in this study are GARCH to analyze the price evolution of the leading cryptocurrencies, GJR-GARCH or T-GARCH to measure asymmetric behavior in linear setup, E-GARCH to measure asymmetric behavior in non-linear setup, P-GARCH to investigate the asymmetry behavior and long memory of returns in the volatility of all leading cryptocurrencies, and Q-GARCH to explore non-linearity in behavior of leading cryptocurrencies.

3.2.1 GARCH

The GARCH model proposed by Engle (1982) and Bollerslev (1986) analyzes the price evolution of the stocks or exchange rates or currencies. The GARCH (p, q) model with two dummies; day of week and month of year has the following form:

For Day of Week:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{6} \delta_i D_i \tag{3.2}$$

$$R_t = \gamma_0 + \sum_{i=1}^{P} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_i u_{t-j}^2 + \sum_{i=1}^{6} \delta_i D_i \tag{3.3}$$

For Month of the Year:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{11} \delta_i M_i \tag{3.4}$$

$$R_t = \gamma_0 + \sum_{i=1}^{P} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_i u_{t-j}^2 + \sum_{i=1}^{11} \delta_i M_i \tag{3.5}$$

which says that the value of the variance scaling parameter h_t now depends both on past values of the shocks, which are captured by the lagged squared residual terms, and on past values of itself, which are captured by lagged h_t terms.

3.2.2 GJR-GARCH or T-GARCH

The GJR-GARCH or Threshold GARCH model is proposed by the works of Rabemananjara and Zakoian (1993), and Glosten et al. (1993). The main target of this model is to capture asymmetries in terms of negative (or bad news) and positive shocks (or good news). To do this, simply add into the variance equation a multiplicative dummy variable to check whether there is a statistically significant difference when shocks are negative (or bad news). The GJR-GARCH model with two dummies; day of week and month of year has the following form:

For Day of Week:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{6} \delta_i D_i \tag{3.6}$$

$$h_t = \gamma_0 + \gamma_1 \mu_{t-1}^2 + \theta \mu_{t-1}^2 d_{t-1} + \delta h_{t-1} + \sum_{i=1}^{6} \delta_i D_i \tag{3.7}$$

For Month of the Year:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{11} \delta_i M_i \tag{3.8}$$

$$h_t = \gamma_0 + \gamma_1 \mu_{t-1}^2 + \theta \mu_{t-1}^2 d_{t-1} + \delta h_{t-1} + \sum_{i=1}^{11} \delta_i M_i \tag{3.9}$$

3.2.3 E-GARCH

The exponential GARCH (E-GARCH) model developed by Nelson (1991) is used to study the asymmetric behavior in non-linear setup. The E-GARCH model with two dummies; day of week and month of year has the following form:

For Day of Week:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{6} \delta_i D_i \tag{3.10}$$

$$log(h_t) = \gamma + \sum_{j=1}^{q} \zeta_j |\frac{\mu_{t-j}}{\sqrt{h_{t-j}}}| + \sum_{j=1}^{q} \xi_i \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_i log(h_{t-i}) + \sum_{i=1}^{6} \delta_i D_i \tag{3.11}$$

For Month of the Year:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{11} \delta_i M_i \tag{3.12}$$

$$log(h_t) = \gamma + \sum_{j=1}^{q} \zeta_j |\frac{\mu_{t-j}}{\sqrt{h_{t-j}}}| + \sum_{j=1}^{q} \xi_i \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_i log(h_{t-i}) + \sum_{i=1}^{11} \delta_i M_i \tag{3.13}$$

Where γ, ζ, ξ, and δ are parameters to estimate asymmetry behavior in the volatility of cryptocurrencies. The left-hand side is the log of the variance series. This makes the leverage effect exponential rather than quadratic, and therefore the estimates of the conditional variance are guaranteed to be non-negative. The E-GARCH model allows for the testing of asymmetries along with non-linearities.

3.2.4 P-GARCH

P-GARCH model is Asymmetric Power Autoregressive Conditional Heteroskedasticity (APARCH). This model is given by Ding et al. (1993) i.e.

$$A_t = \sigma_t \epsilon_t \tag{3.14}$$

Where $\epsilon_t \sim$ N(0,1), and

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{m} \alpha_i(|A_{t-i}| - \gamma_i A_{t-i})\delta + \sum_{j=1}^{s} B_j \sigma_{t-j}^\delta \tag{3.15}$$

Where 0 $<\delta$ and -1 $<\gamma<$1.

The P-GARCH model with two dummies; day of week and month of year has the following form:

For Day of Week:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{6} \delta_i D_i \tag{3.16}$$

$$A_t = \sigma_t \epsilon_t + \sum_{i=1}^{6} \delta_i D_i \tag{3.17}$$

For Month of the Year:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{11} \delta_i M_i \tag{3.18}$$

$$A_t = \sigma_t \epsilon_t + \sum_{i=1}^{11} \delta_i M_i \tag{3.19}$$

As GJR-GARCH or T-GARCH model, the P-GARCH model captures asymmetry in return volatility. Volatility tends to increase more, when the returns are negative as compared to the positive returns of the same magnitude.

3.2.5 Q-GARCH

To examine non-linearity in the volatility of cryptocurrencies, quadratic GARCH or Q-GARCH model will be applied. This model is given by Robert and Victor

(1993) and Sentana (1995). The Q-GARCH model with two dummies; day of week and month of year has the following form:

For Day of Week:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{6} \delta_i D_i \tag{3.20}$$

$$R_t = \gamma_0 + \gamma_1 \mu_{t-1} + \gamma_2 \mu_{t-1}^2 + \gamma_3 h_{t-1} + \sum_{i=1}^{6} \delta_i D_i \tag{3.21}$$

For Month of the Year:

$$R_t = \beta_0 + \beta_1 X_t + \mu_t \sum_{i=1}^{11} \delta_i M_i \tag{3.22}$$

$$R_t = \gamma_0 + \gamma_1 \mu_{t-1} + \gamma_2 \mu_{t-1}^2 + \gamma_3 h_{t-1} + \sum_{i=1}^{11} \delta_i M_i \tag{3.23}$$

Chapter 4

Data Analysis and Discussion

4.1 Data Analysis

This chapter reflect the results of different tests that are applied to explore and analyze the phenomena under debate and interprets these results.

4.1.1 Stationarity of Series

In research, the first and basic step of every analysis is to see the behavior of the data through visualization. Visualization of the data means to check the stationarity and hetroskedasticity of the series and volatility of return. It means that the mean of the series must be constant. All graphs of selected crypto-currencies are attached in **Appendix-A**.

4.2 Descriptive Statistics

The second step is to examine the behavior of data though descriptive statistics of each currency. Average mean returns measure the performance of the leading cryptocurrencies (Table 4.1). The study reports that mean returns of all leading cryptocurrencies are positive except Tether (USDT) that is -0.01%.

Table 4.1: Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
BTC	0.0017	0.0018	0.3574	-0.2662	0.0430	-0.1637	10.6314
ETH	0.0027	-0.0008	0.4123	-1.3021	0.0725	-3.4080	72.9079
XRP	0.0017	-0.0027	1.0273	-0.6163	0.0734	2.0555	32.3188
USDT	-0.0001	0.0000	0.5005	-0.6907	0.0214	-12.1240	805.8920
LTC	0.0010	-0.0003	0.8289	-0.5139	0.0650	1.7081	28.2378
XLM	0.0017	-0.0033	0.7231	-0.3664	0.0763	1.9886	19.2387
XMR	0.0018	-0.001	0.5846	-0.3782	0.0710	0.6394	9.4247
DASH	0.0025	-0.0018	1.2705	-0.4676	0.0769	3.0416	47.9499
XEM	0.0030	-7.78E-05	0.9955	-0.3615	0.08216	1.93496	21.1822
DOGE	0.0010	-0.0022	1.1662	-0.5804	0.0764	2.2399	37.9027

This table shows the descriptive statistics for the series of all leading Crypto-Currencies. Where BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

The highest mean return value is of Nem (XEM) that is 0.30% per day and lowest is of Tether (USDT) that is -0.01% per day. In addition, all cryptocurrencies have a positive standard deviation however, Nem (XEM) exhibits the higher volatility (8.21%) that confirm the logical relationship of risk and return as well that; higher the risk the higher will be the return. It also tells that; this cryptocurrency is more volatile than others. While, Tether (USDT) exhibits the lowest volatility (2.14%). Maximum and Minimum statistics show the max. and min. return earned/day for each cryptocurrency. For example, the average return/ day for Bitcoin (BTC) is 0.17%, maximum return earned/day is 35.7% and min return earned or max loss earned/day is 26.6% and so on.

Skewness tells about the asymmetric behavior of data. Skewness values of Bitcoin (BTC), Ethereum (ETH) & Tether (USDT) shows that distribution of returns is negatively skewed. While on the other hand, Ripple (XRP), Litecoin (LTC), Monero (XMR), Stellar (XLM), Dash (DASH), Nem (XEM) and Dogecoin (DOGE) shows that distribution of returns is positively skewed. The negative trend of skewness shows the continuous decrease in the cryptocurrency returns while the positive trend of skewness shows the continuous increase in the cryptocurrency returns. Kurtosis tells about the tailed-ness of the return distribution. All the values of Kurtosis are positive and >3 that indicates, all series are leptokurtic i.e. fat tails with high peak and get highly effected with the bubbles of cryptocurrency market.

4.3 Seasonality in Return and Volatility of the Leading Crypto Currencies estimated by using GARCH Model

Table 4.2 represents the results of the Mean Equation of GARCH (1,1) Model with weekly dummies. Note that cryptocurrency‘s market volatility is not constant in all cryptocurrencies. The estimated lag-term is significant and negative (α_1 <0) in USDT (0.0000), LTC (0.0355) and XEM (0.0000), which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return. While lag-term is insignificant in BTC, ETH, XRP, XLM, XMR, DASH and DOGE, which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The month of the year effect on mean returns: Monday (D_1) returns of all leading cryptocurrencies except BTC (0.0446), USDT (0.0085) and XLM (0.0191) are insignificant with respect to Sunday (α_0), which means that there is no change in mean returns of Monday (D_1). While BTC (0.0446), USDT (0.0085) and XLM (0.0191) mean returns on Monday (D_1) are significantly higher than mean returns on Sunday (α_0). Tuesday (D_2) returns of all leading cryptocurrencies except USDT (0.0001) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Tuesday (D_2). While USDT (0.0001) mean returns on Tuesday (D_2) are significantly higher than mean returns on Sunday (α_0). Wednesday (D_3) returns of all leading cryptocurrencies except LTC (0.0032) are insignificant with respect to Sunday (α_0), which means that there is no diff-

Table 4.2: Day of the week effect in Mean Returns - GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	-0.000930	0.000005	-0.004029	-0.000915	0.002528	-0.003159	0.001818	0.001059	-0.002530	-0.002034
	(0.4906)	(0.9985)	(0.0295)	(0.0000)	(0.2257)	(0.2068)	(0.5355)	(0.7364)	(0.4655)	(0.2446)
α_1	0.022966	0.019221	0.040138	-0.386449	-0.045046	-0.022041	-0.026318	-0.045060	-0.105170	-0.028793
	(0.3309)	(0.5069)	(0.0899)	(0.0000)	(0.0355)	(0.4204)	(0.3186)	(0.0954)	(0.0000)	(0.2372)
D_1	0.003790	-0.000766	0.002822	0.000775	-0.004894	0.008870	-0.002732	-0.002120	0.002558	0.004994
	(0.0446)	(0.8508)	(0.3020)	(0.0085)	(0.1306)	(0.0191)	(0.6058)	(0.6249)	(0.5883)	(0.1156)
D_2	0.002710	0.005143	0.002942	0.001092	-0.000856	-0.005926	-0.003290	-0.007060	-0.005340	-0.004394
	(0.2384)	(0.2521)	(0.3688)	(0.0001)	(0.8079)	(0.2376)	(0.4927)	(0.0842)	(0.2582)	(0.1324)
D_3	-0.001723	-0.007192	-0.001052	0.000077	-0.008960	-0.002681	-0.003810	-0.003850	-0.000470	-0.002638
	(0.4288)	(0.1195)	(0.7191)	(0.8041)	(0.0032)	(0.4947)	(0.3945)	(0.3360)	(0.9171)	(0.3160)
D_4	0.000150	-0.005104	-0.003576	0.001306	-0.008905	-0.000652	-0.007843	-0.006260	0.005463	-0.001452
	(0.9493)	(0.2371)	(0.2521)	(0.0000)	(0.0331)	(0.8690)	(0.0844)	(0.1094)	(0.2647)	(0.5857)
D_5	0.044430	0.004873	0.007317	0.000968	-0.000596	0.001953	0.000228	0.005291	0.005130	0.006149
	(0.0285)	(0.2920)	(0.0088)	(0.0000)	(0.8780)	(0.6327)	(0.9570)	(0.1920)	(0.2494)	(0.0245)
D_6	0.002758	0.006550	0.003019	0.001128	-0.000300	0.000768	0.003374	-0.002990	0.001814	-0.000122
	(0.1422)	(0.0877)	(0.2226)	(0.0001)	(0.3327)	(0.8260)	(0.4567)	(0.4179)	(0.6390)	(0.9600)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

erence in mean returns of Wednesday (D_3).

While LTC (0.0032) mean returns on Wednesday (D_3) are Significantly lower than mean returns on Sunday (α_0). Thursday (D_4) returns of all leading cryptocurrencies except USDT (0.0000) and LTC (0.0331) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Thursday (D_4). As coefficient of USDT (0.0000) is positive and of LTC (0.0331) is negative; So, USDT mean returns on Thursday (D_4) are significantly higher than mean returns on Sunday and LTC mean returns on Thursday are significantly lower than mean returns on Sunday (α_0). Friday (D_5) returns of all leading cryptocurrencies except BTC (0.0285), XRP (0.0088), USDT (0.0000) and DOGE (0.0245) are insignificant with respect to Sunday (α_0), which means that there is no change in mean returns of Friday (D_5).

As coefficient of BTC (0.0285), XRP (0.0088), USDT (0.0000) and DOGE (0.0245) is positive; So, mean returns on Friday (D_5) are significantly higher than mean returns on Sunday (α_0). Saturday (D_6) returns of all leading cryptocurrencies except USDT (0.0001) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Saturday (D_6). While USDT (0.0001) mean returns on Saturday (D_6) are significantly higher than mean returns on Sunday (α_0).

Table 4.3 represents the results of the variance equation of GARCH (1,1) Model with weekly dummies. The estimated GARCH terms (β_1 & β_2) are significant and positive in all leading cryptocurrencies, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is long run as coefficients of GARCH terms (β_1 & β_2) are closer to 1. The day of the week effect on volatility: Monday (D_1) volatility of all leading cryptocurrencies except ETH (0.4963), DASH (0.6743) and XEM (0.1102) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Monday (D_1) and volatility on Sunday (β_0). While ETH (0.4963), DASH (0.6743) and XEM (0.1102) volatility on Monday (D_1) in not different from Sunday (β_0) volatility.

TABLE 4.3: Day of the week effect in Return and Volatility - GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	-0.000124	0.000266	0.000140	0.000353	-0.000133	0.000036	-0.000258	0.000609	0.000662	-0.000094
	(0.0000)	(0.0213)	(0.0050)	(0.0000)	(0.0050)	(0.7479)	(0.0834)	(0.0000)	(0.0001)	(0.0482)
β_1	0.140541	0.183262	0.266942	0.591425	0.087433	0.169074	0.107703	0.237251	0.505917	0.214968
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.837149	0.742337	0.696987	0.552628	0.887361	0.808463	0.830867	0.722480	0.468877	0.796146
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D_1	0.000300	0.000155	0.000297	-0.000550	0.000510	0.000522	0.002551	0.000089	0.000445	0.000923
	(0.0000)	(0.4963)	(0.0035)	(0.0000)	(0.0000)	(0.0152)	(0.0000)	(0.6743)	(0.1102)	(0.0000)
D_2	0.000673	0.000999	0.001287	-0.000353	0.000997	0.002576	0.000260	-0.000360	0.001818	0.000295
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3596)	(0.0578)	(0.0000)	(0.0086)
D_3	0.000003	-0.000245	-0.000740	-0.000345	-0.000246	-0.001894	-0.000025	-0.000580	-0.000980	-0.000260
	(0.9557)	(0.3169)	(0.0000)	(0.0000)	(0.0172)	(0.0000)	(0.9352)	(0.0010)	(0.0007)	(0.0164)
D_4	0.000261	0.000371	0.002217	-0.000354	0.001943	0.001060	0.000915	0.000664	0.002188	0.000231
	(0.0000)	(0.1039)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0047)	(0.0033)	(0.0000)	(0.0132)
D_5	-0.000004	0.000059	-0.001714	-0.000353	-0.000522	-0.000268	-0.000241	-0.001230	-0.000510	0.000040
	(0.9409)	(0.7924)	(0.0000)	(0.0000)	(0.0000)	(0.2336)	(0.3736)	(0.0000)	(0.1072)	(0.6323)
D_6	0.000060	-0.000987	-0.000115	-0.000348	-0.000904	-0.000691	0.000349	-0.000780	-0.000570	0.000043
	(0.2875)	(0.0000)	(0.2241)	(0.0000)	(0.0000)	(0.0008)	(0.2026)	(0.0000)	(0.0357)	(0.6400)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

Tuesday (D_2) volatility of all leading cryptocurrencies except XMR (0.3596) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Tuesday (D_2) and volatility on Sunday (β_0). While XMR (0.3596) volatility on Tuesday (D_2) is not different from Sunday (β_0) volatility. Wednesday (D_3) volatility of all leading cryptocurrencies except BTC (0.9557), ETH (0.3169) and XMR (0.9352) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Wednesday (D_3) and volatility on Sunday (β_0). While BTC (0.9557), ETH (0.3169) and XMR (0.9352) volatility on Wednesday (D_3) is not different from Sunday (β_0) volatility.

Thursday (D_4) volatility of all leading cryptocurrencies except ETH (0.1039) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Thursday (D_4) and volatility on Sunday (β_0). While ETH (0.1039) volatility on Thursday (D_4)is not different from Sunday (β_0) volatility. Friday (D_5) volatility of XRP (0.0000), USDT (0.0000), LTC (0.0000) and DASH (0.0000) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Friday (D_5) and volatility on Sunday (β_0). While Friday (D_5) volatility of BTC (0.9409), ETH (0.7924), XLM (0.2336), XMR (0.3736), XEM (0.1072) and DOGE (0.6323) is not different from Sunday (β_0) volatility.

Saturday (D_6) volatility of ETH (0.0000), USDT (0.0000), LTC (0.0000), XLM (0.0008), DASH (0.0000) and XEM (0.0357) is significant, which means that there is a difference in volatility of Saturday (D_6) and volatility on Sunday (β_0). While Saturday (D_6) volatility of BTC (0.2875), XRP (0.2241), XMR (0.2026) and DOGE (0.6400) is insignificant, which means that there is no difference in volatility of Saturday (D_6) and volatility on Sunday (β_0).

Table 4.4 represents the results of the Mean Equation of GARCH (1,1) Model with monthly dummies. The estimated lag term is significant and negative ($\alpha_1 < 0$) in USDT (0.0000) and XEM (0.0005). While lag term is insignificant in BTC, ETH, XRP, LTC, XLM, XMR, DASH and DOGE. The month of the year effect on mean returns: January (M_1), February (M_2), March (M_3) and April (M_4) returns of all leading crypto-currencies are insignificant with respect to Decem-

Table 4.4: Month of the year effect in Mean Returns - GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	0.000641	-0.000047	0.000692	0.000829	-0.000119	0.014313	0.003995	0.002911	0.013425	0.000942
	(0.8300)	(0.9913)	(0.8699)	(0.8691)	(0.9847)	(0.2653)	(0.5448)	(0.5501)	(0.0037)	(0.7967)
α_1	0.032459	0.020048	0.045845	-0.385040	-0.032501	-0.028602	-0.029211	-0.041550	-0.100590	-0.036940
	(0.1895)	(0.5028)	(0.0557)	(0.0000)	(0.1249)	(0.3530)	(0.2558)	(0.1117)	(0.0005)	(0.1412)
M_1	-0.006187	0.007561	-0.005992	-0.001101	-0.005307	-0.020274	-0.007254	-0.007480	-0.017110	-0.007330
	(0.2174)	(0.2856)	(0.2282)	(0.8210)	(0.5324)	(0.1402)	(0.3701)	(0.3694)	(0.0783)	(0.1040)
M_2	0.003772	0.009609	-0.004208	-0.000834	-0.000132	-0.023560	-0.000637	0.005992	-0.009990	-0.001970
	(0.3044)	(0.1512)	(0.3859)	(0.8684)	(0.9844)	(0.0890)	(0.9394)	(0.4019)	(0.1086)	(0.6483)
M_3	-0.003582	-0.001967	-0.005886	-0.001090	0.001380	-0.015376	0.003736	0.003854	-0.012670	-0.005030
	(0.4676)	(0.7691)	(0.2477)	(0.8287)	(0.8689)	(0.2622)	(0.6575)	(0.5656)	(0.1782)	(0.3237)
M_4	0.002189	0.005450	-0.002424	-0.000920	0.002457	-0.015569	-0.007067	-0.002450	-0.006660	-0.000610
	(0.5373)	(0.4374)	(0.6790)	(0.8551)	(0.7335)	(0.2404)	(0.3681)	(0.6948)	(0.3323)	(0.9022)
M_5	0.002875	0.011821	-0.006990	-0.000856	0.004659	-0.016767	-0.004140	0.000250	-0.015550	0.001061
	(0.4345)	(0.1500)	(0.1587)	(0.8649)	(0.5395)	(0.2120)	(0.6213)	(0.9655)	(0.0356)	(0.8376)
M_6	-0.000293	-0.003904	-0.001083	-0.000810	-0.000944	-0.017973	-0.001278	-0.005100	-0.017270	-0.001150
	(0.9422)	(0.5663)	(0.8597)	(0.8721)	(0.9058)	(0.1919)	(0.8728)	(0.3890)	(0.0112)	(0.8315)
M_7	-0.000832	-0.002826	-0.007430	-0.000821	-0.002493	-0.018944	-0.002715	-0.001260	-0.019360	-0.004770
	(0.8170)	(0.6762)	(0.1330)	(0.8704)	(0.7151)	(0.1590)	(0.7299)	(0.8441)	(0.0061)	(0.3987)
M_8	-0.001221	0.001100	-0.001546	-0.001059	-0.006748	-0.017633	-0.001306	-0.007070	-0.020150	-0.008430
	(0.7826)	(0.8553)	(0.7692)	(0.8341)	(0.3193)	(0.1870)	(0.8887)	(0.3213)	(0.0045)	(0.1200)
M_9	-0.000637	-0.002237	0.000632	-0.000663	-0.000098	-0.012910	-0.012388	-0.002350	-0.016670	-0.000250
	(0.8552)	(0.7671)	(0.9304)	(0.8954)	(0.9884)	(0.3534)	(0.1154)	(0.6923)	(0.0153)	(0.9565)
M_{10}	0.002372	-0.002602	-0.000973	-0.000948	-0.000671	-0.018549	-0.008971	-0.007070	-0.014210	-0.003680
	(0.4947)	(0.6268)	(0.8464)	(0.8505)	(0.9216)	(0.1684)	(0.2147)	(0.1957)	(0.0056)	(0.4005)
M_{11}	0.002233	-0.003514	-0.002282	-0.000774	-0.000058	-0.019604	0.000745	-0.007470	-0.013380	-0.002390
	(0.6187)	(0.5928)	(0.6355)	(0.8779)	(0.9942)	(0.1500)	(0.9303)	(0.2950)	(0.0504)	(0.6626)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

ber (α_0), which means that there is no difference in mean returns of January (M_1), February (M_2), March (M_3) and April (M_4) as compared to returns of December (α_0).

While May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) returns of all leading cryptocurrencies except XEM are insignificant with respect to December (α_0), which means that there is no difference in mean returns of May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) and returns of December (α_0). As Coefficient of XEM is negative; So, XEM mean returns in May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) are significantly lower than mean returns in December (α_0).

Table 4.5 represents the results of the variance equation of GARCH (1,1) Model with monthly dummies. The estimated GARCH terms (β_1 & β_2) are significant and positive in all leading cryptocurrencies, which means that the volatility persistence is present, the previous year volatility affect current year return and that persistence is long run as coefficients of GARCH terms (β_1 & β_2) are closer to 1.

The month of the year effect on volatility: January (M_1) volatility of BTC (0.0001), USDT (0.0000), XLM (0.0000), XMR (0.0036) and DOGE (0.0490) are significant with respect to December (β_0), which means that there is a difference in volatility of January (M_1) and volatility of December (β_0). While January (M_1) volatility of ETH (0.8824), XRP (0.5720), LTC (0.8248), XEM (0.4630) and DASH (0.0735) is in-significant with respect to December(β_0), which means that there is no difference in volatility of January (M_1) and volatility of December (β_0). February (M_2) volatility of all leading cryptocurrencies are significant except BTC (0.3395), ETH (0.3197) and DASH (0.3533) with respect to December (β_0), which means that there is a difference in volatility of February (M_2) and volatility of December (β_0).

March (M_3) volatility of all leading cryptocurrencies are significant except ETH (0.3393), XMR (0.2314), DASH (0.2338) and XEM (0.4496) with respect to

Table 4.5: Month of the year effect in Return and Volatility - GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	0.000087	0.000374	0.000249	0.000190	0.000188	0.001520	0.000374	0.000271	0.001667	0.000133
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0000)
β_1	0.159296	0.171042	0.327349	0.481503	0.073651	0.205729	0.088041	0.201105	0.465981	0.187309
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.799596	0.729456	0.681600	0.512719	0.898598	0.761301	0.861970	0.758837	0.444198	0.808328
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
M_1	0.000146	0.000015	-0.000036	-0.000189	0.000007	-0.001281	-0.000256	0.000177	0.000385	-0.000061
	(0.0001)	(0.8824)	(0.5720)	(0.0000)	(0.8248)	(0.0000)	(0.0036)	(0.0735)	(0.4630)	(0.0490)
M_2	-0.000023	0.000110	-0.000174	-0.000189	-0.000207	-0.001224	-0.000164	0.000093	-0.001050	-0.000099
	(0.3395)	(0.3197)	(0.0017)	(0.0000)	(0.0000)	(0.0000)	(0.0489)	(0.3533)	(0.0238)	(0.0000)
M_3	0.000079	-0.000101	0.000176	-0.000189	0.000115	-0.001197	-0.000108	0.000115	0.000359	0.000086
	(0.0007)	(0.3393)	(0.0030)	(0.0000)	(0.0000)	(0.0000)	(0.2314)	(0.2338)	(0.4496)	(0.0002)
M_4	-0.000053	0.000106	0.000074	-0.000189	-0.000156	-0.001425	-0.000251	-0.000120	-0.000460	-0.000110
	(0.0123)	(0.3633)	(0.2355)	(0.0000)	(0.0000)	(0.0000)	(0.0012)	(0.0924)	(0.3240)	(0.0000)
M_5	-0.000011	0.000178	-0.000105	-0.000190	-0.000084	-0.001382	-0.000128	-0.000160	-0.000520	-0.000041
	(0.6140)	(0.0943)	(0.0715)	(0.0000)	(0.0001)	(0.0000)	(0.0953)	(0.0244)	(0.2492)	(0.1167)
M_6	0.000024	0.000102	0.000119	-0.000190	0.000054	-0.001271	-0.000231	-0.000089	-0.000860	0.000004
	(0.3311)	(0.4273)	(0.0405)	(0.0000)	(0.0357)	(0.0000)	(0.0072)	(0.1962)	(0.0566)	(0.9026)
M_7	-0.000045	0.000024	-0.000136	-0.000190	-0.000201	-0.001315	-0.000225	0.000018	-0.000560	0.000006
	(0.0365)	(0.8361)	(0.0160)	(0.0000)	(0.0000)	(0.0000)	(0.0052)	(0.7690)	(0.2238)	(0.8560)
M_8	0.000035	-0.000194	-0.000032	-0.000179	-0.000110	-0.001387	0.000240	0.000093	-0.000580	0.000003
	(0.0778)	(0.0333)	(0.5656)	(0.0000)	(0.0000)	(0.0000)	(0.0034)	(0.2324)	(0.1938)	(0.9121)
M_9	-0.000047	0.000208	0.000581	-0.000189	-0.000141	-0.001098	-0.000299	-0.000160	-0.000300	-0.000100
	(0.0213)	(0.0319)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0144)	(0.4950)	(0.0000)
M_{10}	-0.000027	-0.000133	-0.000125	-0.000190	-0.000107	-0.001225	-0.000286	-0.000120	-0.001020	-0.000077
	(0.1940)	(0.1111)	(0.0279)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0763)	(0.0194)	(0.0000)
M_{11}	0.000069	-0.000073	-0.000083	-0.000189	0.000011	-0.001346	0.000022	0.000158	-0.000690	-0.000058
	(0.0103)	(0.4405)	(0.1526)	(0.0000)	(0.7016)	(0.0000)	(0.8112)	(0.0700)	(0.1230)	(0.0125)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

December (β_0), which means that there is a difference in volatility of March (M_1) and volatility of December (β_0). April (M_4) volatility of all leading cryptocurrencies are significant except ETH (0.3633), XRP (0.2355), DASH (0.0924) and XEM (0.3240) with respect to December (β_0), which means that there is a difference in volatility of April (M_4) and volatility of December (β_0). May (M_5) volatility of all leading cryptocurrencies are in-significant except USDT (0.0000), LTC (0.0001), XLM (0.0000) and DASH (0.0244) with respect to December (β_0), which means that there is no difference in volatility of May (M_5) and volatility of December (β_0).

June (M_6) volatility of all leading cryptocurrencies are significant except BTC (0.3311), ETH (0.4273), DASH (0.1962) and DOGE (0.9026) with respect to December (β_0), which means that there is a difference in volatility of June (M_6) and volatility of December (β_0). July (M_7) volatility of all leading cryptocurrencies are significant except ETH (0.8361), DASH (0.7690), XEM (0.2238) and DOGE (0.8560) with respect to December (β_0), which means that there is a difference in volatility of July (M_7) and volatility of December (β_0). August (M_8) volatility of ETH (0.0333), USDT (0.0000), LTC (0.0000), XLM (0.0000) and XMR (0.0034) are significant with respect to December (β_0), which means that there is a difference in volatility of August (M_8) and volatility of December (β_0).

While August (M_8) volatility of BTC (0.0778), XRP (0.5656), DASH (0.2324), XEM (0.1938) and DOGE (0.9121) are in-significant with respect to December (β_0), which means that there is no difference in volatility of August (M_8) and volatility of December (β_0). September (M_9) volatility of all leading cryptocurrencies are significant except XEM (0.4950) with respect to December (β_0), which means that there is a difference in volatility of September (M_9) and volatility of December (β_0). October (M_{10}) volatility of all leading cryptocurrencies are significant except BTC (0.1940), ETH (0.1111) and DASH (0.0763) with respect to December (β_0), which means that there is a difference in volatility of October (M_{10}) and volatility of December (β_0). November (M_{11}) volatility of all leading cryptocurrencies are in-significant except BTC (0.0103), USDT (0.0000), XLM (0.0000) and DOGE (0.0125) with respect to December (β_0), which means that there is no difference in volatility of November (M_{11}) and volatility of December (β_0).

4.4 Seasonality and Asymmetry in Return and Volatility of Crypto Currencies estimated by using GJR-GARCH or T-GARCH Model

Table 4.6 represents the results of the mean equation of T-GARCH (1,1) model with weekday dummies. The estimated lag term is significant and negative (α_1<0) in USDT (0.0000), LTC (0.0200) and XEM (0.0002), which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return. While lag term is insignificant in BTC, ETH, XRP, XLM, XMR, DASH and DOGE, which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The day of the week effect on mean returns: Monday (D_1) returns of all leading cryptocurrencies except BTC (0.0374) and XLM (0.0089) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Monday (D_1) and Sunday (α_0). While BTC (0.0374) and XLM (0.0089) mean returns on Monday (D_1) are significantly higher than mean returns on Sunday (α_0). Tuesday (D_2), Thursday (D_4) and Saturday (D_6) returns of all leading cryptocurrencies except USDT (0.0274), USDT (0.0005) & USDT (0.0217) respectively are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Tuesday (D_2), Thursday (D_4) and Saturday (D_6). While USDT mean returns on Tuesday (D_2), Thursday (D_4) and Saturday (D_6) are significantly higher than mean returns on Sunday (α_0).

Wednesday (D_3) returns of all leading cryptocurrencies except LTC (0.0094) are insignificant with respect to Sunday (α_0), which means that there is no differ-

Table 4.6: Day of the week effect in Mean Returns - T-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	-0.000929	-0.000050	-0.003868	-0.000576	0.002246	-0.003120	0.002459	0.001184	-0.002420	-0.001777
	(0.4877)	(0.9857)	(0.0367)	(0.0116)	(0.2687)	(0.2164)	(0.3866)	(0.6977)	(0.4833)	(0.3084)
α_1	0.021226	0.017281	0.040036	-0.396378	-0.049465	-0.025120	-0.029526	-0.047750	-0.107680	-0.023631
	(0.3747)	(0.5495)	(0.1052)	(0.0000)	(0.0200)	(0.3421)	(0.2365)	(0.0719)	(0.0002)	(0.3389)
D_1	0.003926	-0.000555	0.003209	0.000430	-0.004250	0.009851	-0.001286	-0.001220	0.003049	0.005641
	(0.0374)	(0.8931)	(0.2322)	(0.2084)	(0.1816)	(0.0089)	(0.7964)	(0.7747)	(0.5221)	(0.0747)
D_2	0.002842	0.005644	0.003966	0.000724	-0.000136	-0.002692	-0.002903	-0.006340	-0.004260	-0.003700
	(0.2150)	(0.2107)	(0.2182)	(0.0272)	(0.9686)	(0.5992)	(0.5413)	(0.1194)	(0.3847)	(0.2023)
D_3	-0.001583	-0.006455	-0.000641	-0.000263	-0.008077	-0.001549	-0.002708	-0.003630	-0.000160	-0.002247
	(0.4692)	(0.1715)	(0.8272)	(0.4561)	(0.0094)	(0.6945)	(0.5420)	(0.3545)	(0.9717)	(0.3855)
D_4	0.000396	-0.004173	-0.002097	0.000888	-0.006520	0.001890	-0.006419	-0.005160	0.006249	-0.001265
	(0.8671)	(0.3450)	(0.5064)	(0.0005)	(0.1232)	(0.6436)	(0.1495)	(0.1802)	(0.2225)	(0.6379)
D_5	0.004636	0.005527	0.007670	0.000638	0.000804	0.003108	0.000294	0.005747	0.005758	0.006419
	(0.0250)	(0.2345)	(0.0062)	(0.0121)	(0.8414)	(0.4577)	(0.9437)	(0.1462)	(0.1987)	(0.0187)
D_6	0.002834	0.006608	0.003140	0.000801	-0.002371	0.001293	0.002915	-0.003050	0.002340	-0.000097
	(0.1337)	(0.0832)	(0.2009)	(0.0217)	(0.4579)	(0.7159)	(0.5080)	(0.3919)	(0.5631)	(0.9678)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

ence in mean returns of Wednesday (D_3) and Sunday (α_0). While LTC (0.0094) mean returns on Wednesday (D_3) are significantly lower than mean returns on Sunday (α_0). Friday (D_5) returns of all leading cryptocurrencies except BTC (0.0250), XRP (0.0062), USDT (0.0121) and DOGE (0.0187) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Friday (D_5) and Sunday (α_0). As coefficients of BTC (0.0250), XRP (0.0062), USDT (0.0121) and DOGE (0.0187) are positive; So, mean returns on Friday (D_5) are significantly higher than mean returns on Sunday (α_0).

Table 4.7 represents the results of the variance equation of T-GARCH (1,1) Model with weekday dummies. The estimated GARCH terms (β_1 & β_2) are significant and positive (α_1>0) in all leading cryptocurrencies, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is long run as coefficients of GARCH terms (β_1 & β_2) are closer to 1. The estimated T-GARCH term (β_3) is significant and negative in all leading cryptocurrencies except BTC (0.1111), ETH (0.0702), USDT (0.9260) and XEM (0.0725), which means that there exist asymmetric behavior in XRP, LTC, XLM, XRM, DASH and DOGE.

The day of the week effect on volatility: Monday (D_1) volatility of all leading cryptocurrencies except ETH (0.2752), DASH (0.2595) and XEM (0.0762) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Monday (D_1) and volatility on Sunday (β_0). While ETH (0.2752), DASH (0.2595) and XEM (0.0762) volatility on Monday (D_1) are insignificant. Tuesday (D_2) volatility of all leading cryptocurrencies except XMR (0.1523) and DASH (0.0944) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Tuesday (D_2) and volatility on Sunday (β_0). While XMR (0.1523) and DASH (0.0944) volatility on Tuesday (D_2) is in-significantly different from Sunday (β_0).

Wednesday (D_3) volatility of all leading cryptocurrencies except BTC (0.8960), ETH (0.2837), LTC (0.3930) and XMR (0.9248) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Wednesday (D_3) and volatility on Sunday (β_0). Whereas BTC (0.8960), ETH (0.2837), LTC

Table 4.7: Asymmetry and Day of the week effect in Return and Volatility - T-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	-0.000125	0.000258	0.000167	0.000331	-0.000209	0.000045	-0.000311	0.000580	0.000607	-0.000103
	(0.0000)	(0.0269)	(0.0009)	(0.0000)	(0.0000)	(0.6900)	(0.0406)	(0.0000)	(0.0001)	(0.0292)
β_1	0.148249	0.195796	0.338389	0.464934	0.103992	0.215058	0.138010	0.270090	0.559922	0.248372
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.840251	0.750814	0.673494	0.598108	0.887783	0.804882	0.852161	0.717884	0.461368	0.795796
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_3	-0.019261	-0.046021	-0.106528	-0.004542	-0.042681	-0.114510	-0.089618	-0.073520	-0.103630	-0.071240
	(0.1111)	(0.0702)	(0.0000)	(0.9260)	(0.0000)	(0.0000)	(0.0000)	(0.0015)	(0.0725)	(0.0000)
D_1	0.000305	0.000254	0.000297	-0.000531	0.000607	0.000555	0.002378	0.000240	0.000498	0.000952
	(0.0000)	(0.2752)	(0.0038)	(0.0000)	(0.0000)	(0.0120)	(0.0000)	(0.2595)	(0.0762)	(0.0000)
D_2	0.000677	0.000969	0.001231	-0.000331	0.001076	0.002577	0.000428	-0.000320	0.001897	0.000293
	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1523)	(0.0944)	(0.0000)	(0.0090)
D_3	-0.000007	-0.000267	-0.000670	-0.000323	-0.000096	-0.001923	-0.000031	-0.000570	-0.000970	-0.000249
	(0.8960)	(0.2837)	(0.0000)	(0.0000)	(0.3930)	(0.0000)	(0.9248)	(0.0012)	(0.0007)	(0.0236)
D_4	0.000256	0.000376	0.002110	-0.000332	0.001924	0.001172	0.000823	0.000765	0.002265	0.000233
	(0.0000)	(0.1014)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0124)	(0.0008)	(0.0000)	(0.0129)
D_5	0.000000	0.000016	-0.001590	-0.000331	-0.000420	-0.000250	-0.000155	-0.001250	-0.000450	0.000058
	(0.9988)	(0.9454)	(0.0000)	(0.0000)	(0.0004)	(0.2803)	(0.5830)	(0.0000)	(0.1585)	(0.4817)
D_6	0.000056	-0.000990	-0.000136	-0.000327	-0.000751	-0.000706	0.000423	-0.000750	-0.000530	0.000053
	(0.3243)	(0.0000)	(0.1489)	(0.0000)	(0.0000)	(0.0007)	(0.1232)	(0.0001)	(0.0450)	(0.5613)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

(0.3930) and XMR (0.9248) volatility on Wednesday (D_3) is in-significantly different from Sunday (β_0). Thursday (D_4) volatility of all leading cryptocurrencies except ETH (0.1014) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Thursday (D_4) and volatility on Sunday (β_0). While ETH (0.1014) volatility on Thursday (D_4) is in-significantly different from Sunday (β_0). Friday (D_5) volatility of XRP (0.0000), USDT (0.0000), LTC (0.0004) and DASH (0.0000) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Friday (D_5) and volatility on Sunday (β_0).

While Friday (D_5) volatility of BTC (0.9988), ETH (0.9454), XLM (0.2803), XMR (0.5830), XEM (0.1585) and DOGE (0.4817) is In-significant with respect to Sunday (β_0), which means that there is no change in volatility of Friday (D_5) as volatility on Sunday (β_0) changes. Saturday (D_6) volatility of ETH (0.0000), USDT (0.0000), LTC (0.0000), XLM (0.0007), DASH (0.0001) and XEM (0.0450) is significant with respect to Sunday (β_0), which means that there is a change in volatility of Saturday (D_6) as volatility on Sunday (β_0) changes. While Saturday (D_6) volatility of BTC (0.3243), XRP (0.1489), XMR (0.1232) and DOGE (0.5613) is In-significant with respect to Sunday (β_0), which means that there is no change in volatility of Saturday (D_6) as volatility on Sunday (β_0) changes.

Table 4.8 represents the estimation results of the mean equation of T-GARCH (1,1) model with monthly dummies. The estimated lag term is significant and negative (α_1<0) in USDT (0.0000), LTC (0.0531) and XEM (0.0010), which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return. While lag term is insignificant in BTC, ETH, XRP, XLM, XMR, DASH and DOGE, which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The month of the year effect on mean returns: January (M_1), February (M_2), March (M_3) and April (M_4) returns of all leading crypto-currencies are insignificant with respect to December (α_0), which means that there is no difference in mean returns of January (M_1), February (M_2), March (M_3) and April (M_4) and

Table 4.8: Month of the year effect in Mean Returns - T-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	0.000574	0.000222	0.000369	0.001464	0.000688	0.017078	0.004921	0.002914	0.014425	0.001372
	(0.8494)	(0.9598)	(0.9196)	(0.8121)	(0.9069)	(0.1785)	(0.4333)	(0.5517)	(0.0076)	(0.7175)
α_1	0.033435	0.018832	0.045723	-0.381276	-0.039691	-0.028566	-0.030644	-0.041610	-0.101120	-0.032961
	(0.1842)	(0.5282)	(0.0817)	(0.0000)	(0.0531)	(0.3339)	(0.2225)	(0.1113)	(0.0010)	(0.1923)
M_1	-0.006307	0.007049	-0.003524	-0.002018	-0.004868	-0.020745	-0.006416	-0.007450	-0.017770	-0.007068
	(0.2097)	(0.3181)	(0.4268)	(0.7406)	(0.5634)	(0.1262)	(0.4235)	(0.3715)	(0.0719)	(0.1238)
M_2	0.003728	0.009571	-0.003428	-0.001497	-0.001087	-0.024257	-0.001440	0.005995	-0.010710	-0.001658
	(0.3139)	(0.1517)	(0.4261)	(0.8082)	(0.8684)	(0.0749)	(0.8562)	(0.4017)	(0.1066)	(0.7076)
M_3	-0.003585	-0.002189	-0.005133	-0.001694	0.000800	-0.016966	0.001550	0.003856	-0.013550	-0.005016
	(0.4705)	(0.7484)	(0.2460)	(0.7836)	(0.9208)	(0.2100)	(0.8467)	(0.5655)	(0.1548)	(0.3313)
M_4	0.002221	0.005529	-0.000059	-0.001570	0.002686	-0.017122	-0.006434	-0.002450	-0.007280	-0.000446
	(0.5344)	(0.4318)	(0.9915)	(0.7990)	(0.6960)	(0.1909)	(0.3924)	(0.6952)	(0.3119)	(0.9301)
M_5	0.002913	0.011933	-0.007261	-0.001504	0.004655	-0.018684	-0.004480	0.000250	-0.016660	0.000735
	(0.4327)	(0.1481)	(0.0792)	(0.8071)	(0.5272)	(0.1607)	(0.5673)	(0.9655)	(0.0338)	(0.8883)
M_6	-0.000325	-0.003758	0.001162	-0.001365	-0.001256	-0.019779	-0.001537	-0.005100	-0.017980	-0.000998
	(0.9363)	(0.5815)	(0.8328)	(0.8246)	(0.8704)	(0.1457)	(0.8412)	(0.3897)	(0.0125)	(0.8545)
M_7	-0.000847	-0.002893	-0.006467	-0.001395	-0.002325	-0.020078	-0.002666	-0.001260	-0.020100	-0.004555
	(0.8149)	(0.6703)	(0.1456)	(0.8209)	(0.7236)	(0.1335)	(0.7259)	(0.8443)	(0.0071)	(0.4279)
M_8	-0.001259	0.000906	-0.002385	-0.001758	-0.007011	-0.019450	-0.001261	-0.007080	-0.021010	-0.008219
	(0.7772)	(0.8826)	(0.6262)	(0.7762)	(0.2818)	(0.1418)	(0.8854)	(0.3204)	(0.0052)	(0.1330)
M_9	-0.000564	-0.002322	0.003483	-0.001263	-0.001029	-0.014951	-0.011389	-0.002350	-0.017390	-0.000103
	(0.8722)	(0.7600)	(0.5900)	(0.8377)	(0.8743)	(0.2771)	(0.1307)	(0.6929)	(0.0148)	(0.9820)
M_{10}	0.002390	-0.002630	0.000901	-0.001552	-0.001117	-0.021017	-0.009172	-0.007070	-0.014980	-0.003748
	(0.4958)	(0.6245)	(0.8410)	(0.8011)	(0.8651)	(0.1125)	(0.1896)	(0.1959)	(0.0080)	(0.4037)
M_{11}	0.002239	-0.003573	-0.001471	-0.001385	-0.002369	-0.021594	0.000797	-0.007470	-0.014130	-0.002572
	(0.6229)	(0.5913)	(0.7084)	(0.8222)	(0.7423)	(0.1092)	(0.9239)	(0.2955)	(0.0515)	(0.6454)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

returns of December (α_0). While May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) returns of all leading cryptocurrencies except XEM are insignificant with respect to December (α_0), which means that there is no difference in mean returns of May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) and returns of December (α_0). As Coefficient of XEM is negative; So, XEM mean returns in May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) is significantly lower than mean returns in December (α_0).

Table 4.9 represents the results of the variance equation of T-GARCH (1,1) model with monthly dummies. The estimated GARCH terms (β_1 & β_2) are significant and positive in all leading cryptocurrencies, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is long run as coefficients of GARCH terms (β_1 & β_2) are closer to 1. The estimated T-GARCH term (β_3) is significant and negative in all leading cryptocurrencies except BTC (0.1111), ETH (0.0702), DASH (0.9260) and XEM (0.0725), which means that there exist asymmetric behavior in volatility of XRP, USDT, LTC, XLM, XRM and DOGE.

The month of the year effect on volatility: January (M_1) volatility of BTC (0.0001), USDT (0.0000), XLM (0.0000), XMR (0.0570) and DOGE (0.0462) are significant with respect to December (β_0), which means that there is a difference in volatility of January (M_1) and volatility of December (β_0). While January (M_1) volatility of ETH (0.9916), XRP (0.7792), LTC (0.9543), DASH (0.0743) and XEM (0.5806) are in-significant with respect to December (β_0), which means that there is no difference in volatility of January (M_1) and volatility of December (β_0). February (M_2) volatility of all leading cryptocurrencies are significant except BTC (0.3136), ETH (0.3471), XMR (0.0720) and DASH (0.3547) with respect to December (β_0), which means that there is a difference in volatility of February (M_2) and volatility of December (β_0).

March (M_3) volatility of all leading cryptocurrencies are significant except ETH (0.4133), XMR (0.1320), DASH (0.2342) and XEM (0.6280) with respect to

Table 4.9: Asymmetry and Month of the year effect in Return and Volatility - T-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	0.000090	0.000365	0.000425	0.000234	0.000189	0.001628	0.000310	0.000271	0.001776	0.000135
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0003)	(0.0000)
β_1	0.154418	0.179549	0.602954	0.404085	0.089632	0.260192	0.117041	0.201363	0.489073	0.212219
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.798379	0.734775	0.552254	0.535767	0.901658	0.756019	0.871329	0.758844	0.438312	0.807663
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_3	0.010898	-0.027208	-0.249475	0.114456	-0.037736	-0.136206	-0.066715	-0.000610	-0.044490	-0.056169
	(0.4852)	(0.3216)	(0.0000)	(0.0275)	(0.0000)	(0.0000)	(0.0000)	(0.9769)	(0.4822)	(0.0002)
M_1	0.000145	0.000001	-0.000025	-0.000233	0.000002	-0.001350	-0.000162	0.000177	0.000302	-0.000062
	(0.0001)	(0.9916)	(0.7792)	(0.0000)	(0.9543)	(0.0000)	(0.0570)	(0.0743)	(0.5806)	(0.0462)
M_2	-0.000024	0.000102	-0.000292	-0.000233	-0.000209	-0.001313	-0.000133	0.000093	-0.001130	-0.000100
	(0.3136)	(0.3471)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0720)	(0.3547)	(0.0229)	(0.0000)
M_3	0.000078	-0.000087	0.000167	-0.000233	0.000107	-0.001275	-0.000120	0.000115	0.000249	0.000084
	(0.0009)	(0.4133)	(0.0343)	(0.0000)	(0.0000)	(0.0000)	(0.1320)	(0.2342)	(0.6280)	(0.0003)
M_4	-0.000055	0.000101	0.000180	-0.000233	-0.000161	-0.001524	-0.000199	-0.000120	-0.000550	-0.000103
	(0.0104)	(0.3774)	(0.0284)	(0.0000)	(0.0000)	(0.0000)	(0.0044)	(0.0939)	(0.2699)	(0.0001)
M_5	-0.000012	0.000173	-0.000232	-0.000234	-0.000092	-0.001450	-0.000123	-0.000160	-0.000610	-0.000037
	(0.5797)	(0.0966)	(0.0040)	(0.0000)	(0.0000)	(0.0000)	(0.0827)	(0.0259)	(0.2077)	(0.1339)
M_6	0.000023	0.000093	0.000093	-0.000234	0.000041	-0.001357	-0.000176	-0.000089	-0.000950	0.000002
	(0.3730)	(0.4625)	(0.2133)	(0.0000)	(0.1021)	(0.0000)	(0.0257)	(0.1977)	(0.0488)	(0.9414)
M_7	-0.000048	0.000037	-0.000157	-0.000234	-0.000201	-0.001355	-0.000165	0.000018	-0.000630	0.000002
	(0.0296)	(0.7492)	(0.0407)	(0.0000)	(0.0000)	(0.0000)	(0.0233)	(0.7957)	(0.1969)	(0.5131)
M_8	0.000033	-0.000187	-0.000084	-0.000223	-0.000110	-0.001441	0.000213	0.000093	-0.000660	-0.000003
	(0.1083)	(0.0398)	(0.2642)	(0.0000)	(0.0000)	(0.0000)	(0.0042)	(0.2330)	(0.1608)	(0.9348)
M_9	-0.000051	0.000217	0.000689	-0.000233	-0.000140	-0.001182	-0.000247	-0.000160	-0.000380	-0.000102
	(0.0161)	(0.0274)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0176)	(0.4192)	(0.0000)
M_{10}	-0.000029	-0.000127	-0.000186	-0.000234	-0.000109	-0.001315	-0.000228	-0.000110	-0.001110	-0.000079
	(0.1688)	(0.1274)	(0.0141)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0798)	(0.0189)	(0.0000)
M_{11}	0.000069	-0.000066	-0.000215	-0.000233	-0.000058	-0.001413	0.000077	0.000157	-0.000790	-0.000058
	(0.0115)	(0.4847)	(0.0045)	(0.0000)	(0.0390)	(0.0000)	(0.3687)	(0.0710)	(0.1047)	(0.0084)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

December (β_0), which means that there is a difference in volatility of March (M_3) and volatility of December (β_0). April (M_4) volatility of all leading cryptocurrencies are significant except ETH (0.3774), DASH (0.0939) and XEM (0.2699) with respect to December (β_0), which means that there is a difference in volatility of April (M_4) and volatility of December (β_0). May (M_5) volatility of all leading cryptocurrencies are in-significant except XRP (0.0040), USDT (0.0000), LTC (0.0000), XLM (0.0000) and DASH (0.0259) with respect to December (β_0), which means that there is no difference in volatility of May (M_5) and volatility of December (β_0).

June (M_6) volatility of all leading cryptocurrencies is in-significant except USDT (0.0000), XLM (0.0000), XMR (0.0257) and XEM (0.0488) with respect to December (β_0), which means that there is no difference in volatility of June (M_6) and volatility of December (β_0). July (M_7) volatility of all leading cryptocurrencies are significant except ETH (0.7492), DASH (0.7957), XEM (0.1969) and DOGE (0.5131) with respect to December (β_0), which means that there is a difference in volatility of July (M_7) and volatility of December (β_0). August (M_8) volatility of ETH (0.0398), USDT (0.0000), LTC (0.0000), XLM (0.0000) and XMR (0.0042) are significant with respect to December (β_0), which means that there is a difference in volatility of August (M_8) and volatility of December (β_0).

While August (M_8) volatility of BTC (0.1083), XRP (0.2642), DASH (0.2330), XEM (0.1608) and DOGE (0.9348) is in-significant with respect to December (β_0), which means that there is no difference in volatility of August (M_8) and volatility of December (β_0). September (M_9) volatility of all leading cryptocurrencies are significant except XEM (0.4192) with respect to December (β_0), which means that there is a difference in volatility of September (M_9) and volatility of December (β_0). October (M_{10}) volatility of all leading cryptocurrencies are significant except BTC (0.1688), ETH (0.1274) and DASH (0.0798) with respect to December (β_0), which means that there is a difference in volatility of October (M_{10}) and volatility of December (β_0). November (M_{11}) volatility of all leading cryptocurrencies are significant except ETH (0.4847), XMR (0.3687), DASH (0.0710) and XEM

(0.1047) with respect to December (β_0), which means that there is a difference in volatility of November (M_{11}) and volatility of December (β_0).

4.5 Seasonality and Asymmetric Behavior in the Return and Volatility of Crypto Currencies estimated by using E-GARCH Model

Table 4.10 represents the results of the mean equation of E-GARCH (1,1) Model with weekday dummies. The estimated lag term is in-significant and negative (α_1<0) in BTC (0.7748), ETH (0.9073) and XLM (0.3514), which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return. Whereas lag term is significant in XRP, USDT, LTC, XMR, DASH, XEM and DOGE, which means that past economic shock in currencies has a great effect on today return of currencies and it is possible to forecast present return through past return.

The day of the week effect on mean returns: Monday (D_1) returns of all leading cryptocurrencies except LTC (0.0002), XLM (0.0022) and DOGE (0.0000) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Monday (D_1). While LTC (0.0002), XLM (0.0022) and DOGE (0.0000) mean returns on Monday (D_1) are significantly higher than mean returns on Sunday (α_0). Tuesday (D_2) returns of all leading cryptocurrencies except XRP (0.0000) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns on Tuesday (D_2) and mean returns on Sunday (α_0). While XRP (0.0000) mean returns on Tuesday (D_2) are significantly higher than mean returns on Sunday (α_0).

Wednesday (D_3) returns of all leading cryptocurrencies except LTC (0.0000) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns on Wednesday (D_3) and mean returns on Sunday (α_0). While LTC (0.0000) mean returns on Wednesday (D_3) are significantly lower than

Table 4.10: Day of the week effect in Mean Returns - E-GARCH Model

	BTC	ETH	XRP	USDT	LTC	XLM	XMR	DASH	XEM	DOGE
α_0	0.000455	0.000691	-0.005977	0.000001	0.005366	-0.002977	0.000511	0.004025	-0.001607	-0.005092
	(0.7104)	(0.7855)	(0.0004)	(0.9963)	(0.0016)	(0.2491)	(0.8537)	(0.1705)	(0.6462)	(0.0117)
α_1	0.006544	-0.003022	0.055208	-0.520457	-0.039631	-0.024981	-0.045594	-0.059044	-0.108140	-0.056383
	(0.7748)	(0.9073)	(0.0081)	(0.0000)	(0.0571)	(0.3514)	(0.0533)	(0.0122)	(0.0000)	(0.0097)
D_1	0.001886	-0.001408	0.002835	-0.000271	-0.011433	0.013254	0.001351	-0.005897	0.002313	0.011905
	(0.2861)	(0.7340)	(0.1536)	(0.3309)	(0.0002)	(0.0022)	(0.7818)	(0.1151)	(0.6345)	(0.0000)
D_2	0.002830	0.007285	0.011711	0.000023	-0.003745	0.000089	0.000446	-0.007110	-0.004303	-0.001938
	(0.2231)	(0.1158)	(0.0000)	(0.9540)	(0.2402)	(0.9860)	(0.9242)	(0.0604)	(0.4225)	(0.5717)
D_3	-0.002048	-0.005860	0.000006	0.000000	-0.011924	-0.000200	0.001353	-0.005693	0.001540	0.002047
	(0.2727)	(0.1440)	(0.9982)	(0.9989)	(0.0000)	(0.9580)	(0.7572)	(0.1366)	(0.7551)	(0.4809)
D_4	0.000993	-0.006832	0.001412	-0.000003	-0.007685	0.003277	-0.002473	-0.008966	0.002598	0.004424
	(0.6563)	(0.1242)	(0.6830)	(0.9897)	(0.0243)	(0.4237)	(0.5506)	(0.0113)	(0.6329)	(0.1354)
D_5	0.002009	0.004026	0.010166	0.000001	-0.001372	0.004837	0.003455	0.001580	0.006493	0.008205
	(0.2952)	(0.3384)	(0.0001)	(0.9969)	(0.6936)	(0.2161)	(0.3920)	(0.6697)	(0.2414)	(0.0077)
D_6	0.000901	0.005782	0.002229	-0.000001	-0.003949	0.000653	0.006180	-0.004925	0.000845	0.004766
	(0.5610)	(0.1108)	(0.3487)	(0.9988)	(0.1183)	(0.8422)	(0.1430)	(0.1810)	(0.8323)	(0.0543)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

mean returns on Sunday (α_0). Thursday (D_4) returns of all leading cryptocurrencies except LTC (0.0243) and DASH (0.0113) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns on Thursday (D_4) and mean returns on Sunday (α_0). While LTC (0.0243) and DASH (0.0113) mean returns on Thursday (D_4) are significantly lower than mean returns on Sunday (α_0).

Friday (D_5) returns of all leading cryptocurrencies except XRP (0.0001) and DOGE (0.0077) are insignificant with respect to Sunday (α_0), which means that there is no difference with mean returns of Friday (D_5). As coefficient of XRP (0.0001) and DOGE (0.0077) is positive; So, mean returns on Friday (D_5) are significantly higher than mean returns on Sunday (α_0). Saturday (D_6) returns of all leading cryptocurrencies except DOGE (0.0543) are insignificant with respect to Sunday (α_0), which means that there is no difference with mean returns of Saturday (D_6). As coefficient of DOGE (0.0543) is positive; So, mean returns on Saturday (D_6) are significantly higher than mean returns on Sunday (α_0).

Table 4.11 represents the results of the variance equation of E-GARCH (1,1) model with weekday dummies. Note that cryptocurrency‘s market volatility is time varying and predictable in all cryptocurrencies. The estimated GARCH terms (β_1 & β_2) are significant and positive in all leading cryptocurrencies except BTC & XEM, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is not long run as coefficients of GARCH terms (β_1 & β_2) are not closer to 1. The estimated E-GARCH term (β_3) is significant and positive in all leading cryptocurrencies, which means that there exist asymmetry behavior in the volatility of all leading cryptocurrencies.

The day of the week effect on volatility; Monday (D_1) volatility of all leading cryptocurrencies except ETH (0.0684), DASH (0.5165) and XEM (0.3725) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Monday (D_1) and volatility on Sunday (β_0). While ETH (0.0684), DASH (0.5165) and XEM (0.3725) volatility on Monday (D_1) are In-Significant. Tuesday (D_2) volatility of all leading cryptocurrencies except XMR (0.3447), DASH (0.1230), XEM (0.7158) and DOGE (0.6839) are significant with

Table 4.11: Asymmetry and Day of the week effect in Return and Volatility - E-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	-0.809498	-0.748106	-1.146517	-8.042639	-0.704750	-0.761414	-0.525460	-0.429760	-0.503953	-0.434001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_1	0.304063	0.318033	0.547910	0.755040	0.192198	0.347381	0.198730	0.352119	0.416056	0.326175
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	-0.006847	0.035807	0.066523	0.086230	0.035775	0.106807	0.076320	0.023496	0.029672	0.062037
	(0.4099)	(0.0178)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0286)	(0.0824)	(0.0000)
β_3	0.933316	0.908474	0.874150	0.379052	0.957603	0.907196	0.949473	0.939563	0.915572	0.959305
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D_1	0.535535	0.281882	0.219077	0.748985	0.911999	0.453805	0.628420	-0.070502	-0.112375	0.351372
	(0.0000)	(0.0684)	(0.0556)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5165)	(0.3725)	(0.0030)
D_2	0.489636	0.337843	0.491926	1.551162	0.533379	0.394713	0.099876	-0.133244	0.042292	0.038360
	(0.0000)	(0.0071)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.3447)	(0.1230)	(0.7158)	(0.6839)
D_3	-0.017261	-0.302599	-0.380516	0.733691	0.248008	-0.447439	0.005691	-0.231119	-0.481854	-0.268729
	(0.8211)	(0.0101)	(0.0000)	(0.0000)	(0.0019)	(0.0000)	(0.9612)	(0.0086)	(0.0000)	(0.0046)
D_4	0.332748	0.173009	0.796355	0.939845	0.725577	0.292650	0.066875	0.080595	0.107397	-0.009720
	(0.0001)	(0.1252)	(0.0000)	(0.0000)	(0.0000)	(0.0051)	(0.5598)	(0.3849)	(0.3120)	(0.9101)
D_5	-0.079380	-0.083837	-0.693269	0.732146	0.150963	-0.201215	-0.114947	-0.432220	-0.321520	-0.078500
	(0.3418)	(0.4372)	(0.0000)	(0.0000)	(0.0000)	(0.0468)	(0.2905)	(0.0000)	(0.0006)	(0.3140)
D_6	-0.120859	-0.455918	-0.127879	1.085028	-0.217621	-0.468220	0.030835	-0.341171	-0.906588	-0.258893
	(0.2206)	(0.0005)	(0.2710)	(0.0000)	(0.0000)	(0.0000)	(0.8128)	(0.0012)	(0.0000)	(0.0198)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

respect to Sunday (β_0), which means that there is a difference in volatility on Tuesday (D_2) and volatility on Sunday (β_0). While XMR (0.3447), DASH (0.1230), XEM (0.7158) and DOGE (0.6839) volatility on Tuesday (D_2) is in-significant.

Wednesday (D_3) volatility of all leading cryptocurrencies except BTC (0.8211) and XMR (0.9612) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Wednesday (D_3) and volatility on Sunday (β_0). While BTC (0.8211) and XMR (0.9612) volatility on Wednesday (D_3) are in-significant. Thursday (D_4) volatility of BTC (0.0001), XRP (0.0000), USDT (0.0000), LTC (0.0000) and XLM (0.0051) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Thursday (D_4) and volatility on Sunday (β_0). While ETH (0.1252), XMR (0.5598), DASH (0.3849), XEM (0.3120) and DOGE (0.9101) volatility on Thursday (D_4) is in-significant.

Friday (D_5) volatility of all leading cryptocurrencies except BTC (0.3418), ETH (0.4372), XMR (0.2905) and DOGE (0.3140) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Friday (D_5) and volatility on Sunday (β_0). While Friday (D_5) volatility of BTC (0.3418), ETH (0.4372), XMR (0.2905) and DOGE (0.3140) is in-significant with respect to Sunday (β_0), which means that there is no difference in volatility of Friday (D_5) and volatility on Sunday (β_0). Saturday (D_6) volatility of all leading cryptocurrencies except BTC (0.2206), XRP (0.2710) and XMR (0.8128) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Saturday (D_6) and volatility on Sunday (β_0). While Saturday (D_6) volatility of BTC (0.2206), XRP (0.2710) and XMR (0.8128) is in-significant with respect to Sunday (β_0), which means that there is no difference in volatility of Saturday (D_6) and volatility on Sunday (β_0).

Table 4.12 represents the results of the mean equation of E-GARCH (1,1) model with monthly dummies. The estimated lag term is significant and negative (α_1<0) in USDT, LTC, XMR, DASH, XEM and DOGE which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return. Whereas lag term is

TABLE 4.12: Month of the year effect in Mean Returns - E-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	0.000926	0.000068	-0.000378	0.000617	0.006339	0.027081	0.004534	0.000626	0.004370	0.002475
	(0.8069)	(0.9886)	(0.9373)	(0.7012)	(0.1586)	(0.0011)	(0.4388)	(0.8947)	(0.6413)	(0.4736)
α_1	0.012593	-0.005955	0.041110	-0.476401	-0.037728	-0.027897	-0.046364	-0.052703	-0.111442	-0.059352
	(0.5869)	(0.8199)	(0.0682)	(0.0000)	(0.0580)	(0.3430)	(0.0488)	(0.0294)	(0.0002)	(0.0151)
M_1	-0.004582	0.005588	-0.003494	-0.000615	-0.007758	-0.028386	-0.004562	-0.003247	-0.007574	-0.004824
	(0.3512)	(0.4651)	(0.5229)	(0.7064)	(0.2755)	(0.0025)	(0.5646)	(0.6769)	(0.5720)	(0.3532)
M_2	0.003873	0.011881	-0.003626	-0.000537	-0.005267	-0.039322	0.001937	0.008503	-0.002081	-0.004130
	(0.3556)	(0.0533)	(0.4992)	(0.7442)	(0.3409)	(0.0000)	(0.7970)	(0.2008)	(0.8402)	(0.2662)
M_3	-0.002549	-0.000952	0.000329	-0.000614	-0.006181	-0.028023	0.003418	0.006912	-0.002133	-0.010761
	(0.5404)	(0.9039)	(0.9496)	(0.8672)	(0.3392)	(0.0027)	(0.6580)	(0.2467)	(0.8570)	(0.0044)
M_4	0.001009	0.008066	0.000634	-0.000667	-0.002374	-0.025828	-0.005412	0.001949	0.000315	-0.000909
	(0.8164)	(0.2354)	(0.9136)	(0.6815)	(0.6404)	(0.0046)	(0.4540)	(0.7612)	(0.9761)	(0.8561)
M_5	0.002007	0.014041	-0.003139	-0.000637	0.004995	-0.028801	-0.003158	0.001736	-0.001423	0.001018
	(0.6278)	(0.0843)	(0.6424)	(0.7056)	(0.3484)	(0.0015)	(0.6858)	(0.7733)	(0.8988)	(0.8287)
M_6	-0.001699	-0.000883	0.016043	-0.000613	-0.008971	-0.029238	0.000660	-0.004346	-0.007404	0.000433
	(0.7192)	(0.9025)	(0.0014)	(0.7095)	(0.1370)	(0.0028)	(0.9293)	(0.4552)	(0.5031)	(0.9269)
M_7	-0.001517	-0.002407	-0.005076	-0.000622	-0.008429	-0.029698	-0.003866	-0.004048	-0.009139	-0.007804
	(0.7257)	(0.7278)	(0.3395)	(0.7021)	(0.1204)	(0.0009)	(0.6027)	(0.4509)	(0.4044)	(0.0641)
M_8	-0.001032	0.000155	-0.000073	-0.000665	-0.011607	-0.030293	-0.001648	-0.006769	-0.009439	-0.008976
	(0.8215)	(0.9804)	(0.9900)	(0.6826)	(0.0313)	(0.0007)	(0.8296)	(0.3286)	(0.3687)	(0.0776)
M_9	-0.001706	0.001861	0.018556	-0.000616	-0.006352	-0.027790	-0.008308	0.000019	-0.006303	-0.000097
	(0.6789)	(0.7921)	(0.0003)	(0.7087)	(0.2164)	(0.0034)	(0.2448)	(0.9974)	(0.5377)	(0.9829)
M_{10}	0.002150	-0.002417	0.000321	-0.000613	-0.006713	-0.029210	-0.009786	-0.004151	-0.003020	-0.004951
	(0.6046)	(0.6804)	(0.9526)	(0.7058)	(0.2249)	(0.0014)	(0.1323)	(0.4462)	(0.7532)	(0.2197)
M_{11}	0.003745	-0.002378	0.000244	-0.000609	-0.005206	-0.028898	0.000040	-0.004014	-0.002287	-0.003835
	(0.4353)	(0.7378)	(0.9651)	(0.7188)	(0.4678)	(0.0040)	(0.9958)	(0.5065)	(0.8275)	(0.4477)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

in-significant in BTC (0.5869), ETH (0.8199), XRP (0.0682) and XLM (0.3430) which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The month of the year effect on mean returns: January (M_1), February (M_2), April (M_4), May (M_5), July (M_7), October (M_{10}) and November (M_{11}) returns of all leading cryptocurrencies except XLM are in-significant with respect to December (α_0), which means that there is no difference in mean returns of January (M_1), February (M_2), April (M_4), May (M_5), July (M_7), October (M_{10}) and November (M_{11}) and returns of December (α_0). June (M_6) and September (M_9) returns of all leading crypto-currencies except XRP & XLM are in-significant with respect to December (α_0), which means that there is no difference in mean returns of June (M_6) and September (M_9) and returns of December (α_0).

As co-efficient of XLM is negative; So, XLM mean returns in June (M_6) and September (M_9) is significantly lower than mean returns in December (α_0). While co-efficient of XRP is positive; So, XRP mean returns in June (M_6) and September (M_9) is significantly higher than mean returns in December (α_0). August (M_8) returns of all leading cryptocurrencies except LTC (0.0313) and XLM (0.0007) are in-significant with respect to December (α_0), which means that there is no difference in mean returns of August (M_8) and returns of December (α_0). As co-efficients of LTC (0.0313) and XLM (0.0007) are negative; So, LTC and XLM mean returns in August (M_8) is significantly lower than mean returns in December (α_0). March (M_3) returns of all leading cryptocurrencies except XLM (0.0027) and DOGE (0.0044) are in-significant with respect to December (α_0), which means that there is no difference in mean returns of March (M_3) and returns of December (α_0). As co-efficients of XLM (0.0027) and DOGE (0.0044) are negative; So, XLM and DOGE mean returns in March (M_3) is significantly lower than mean returns in December (α_0).

Table 4.13 represents the results of the variance equation of E-GARCH (1,1) model with monthly dummies. The estimated GARCH terms (β_1 & β_1) are significant in all leading cryptocurrencies except BTC, DASH & XEM, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is not long run as co-efficients of GARCH terms (β_1 & β_2) are not closer to 1. The estimated E-GARCH term (β_3) is significantly negative in all leading cryptocurrencies, which means that there exist asymmetry behavior in volatility of all leading crypto-currencies.

The month of the year effect on volatility: January (M_1) volatility of XRP (0.0385), USDT (0.0000), LTC (0.0043) and XLM (0.0000) is significant with respect to December (β_0), which means that there is a difference in volatility of January (M_1) and volatility of December (β_0). While January (M_1) volatility of BTC (0.1648), ETH (0.9221), XRM (0.5268), DASH (0.5765), XEM (0.2810) and DOGE (0.8015) are in-significant with respect to December (β_0), which means that there is no difference in volatility of January (M_1) and volatility of December (β_0). February (M_2) volatility of all leading cryptocurrencies is significant except ETH (0.1798), XMR (0.7619) and DASH (0.8644) with respect to December (β_0), which means that there is a difference in volatility of February (M_2) and volatility of December (β_0).

March (M_3) volatility of XRP (0.0521), USDT (0.0000), LTC (0.0000), XLM (0.0000) and DOGE (0.0016) is significant with respect to December (β_0), which means that there is a difference in volatility of March (M_3) and volatility of December (β_0). While March (M_3) volatility of BTC (0.2602), ETH (0.3710), XMR (0.9215), DASH (0.4854) and XEM (0.3262) is in-significant with respect to December (β_0), which means that there is no difference in volatility of March (M_3) and volatility of December (β_0). May (M_5) volatility of all leading cryptocurrencies is significant except ETH (0.2534), XRP (0.6181), XMR (0.4225) and DOGE (0.1128) with respect to December (β_0), which means that there is a difference in volatility of May (M_5) and volatility of December (β_0).

June (M_6) volatility of all leading cryptocurrencies is in-significant except USDT (0.0000), XLM (0.0000), DASH (0.0055) and XEM (0.0002) with respect to December (β_0), which means that there is no difference in volatility of June (M_6) and volatility of December (β). July (M_7) volatility of all leading cryptocurrencies is significant except ETH (0.7558), XMR (0.0877) and DASH (0.1309) with respect

Table 4.13: Asymmetry and Month of the year effect in Return and Volatility - E-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	-0.696086	-0.663029	-0.784071	-9.025126	-0.234950	-0.780260	-0.322844	-0.550425	-0.890836	-0.389547
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_1	0.302694	0.266147	0.460055	0.606439	0.151813	0.400035	0.152220	0.331784	0.450252	0.307957
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	-0.018469	0.030580	0.037694	-0.209970	0.026857	0.091581	0.057745	0.011615	0.009615	0.051226
	(0.0710)	(0.0361)	(0.0008)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2495)	(0.6303)	(0.0000)
β_3	0.919982	0.918832	0.910318	0.015841	0.969741	0.877346	0.959938	0.939546	0.868403	0.965699
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
M_1	0.027601	-0.002527	-0.048082	-2.165686	-0.032749	-0.167299	-0.011384	-0.012446	-0.041831	0.003502
	(0.1648)	(0.9221)	(0.0385)	(0.0000)	(0.0043)	(0.0000)	(0.5268)	(0.5765)	(0.2810)	(0.8015)
M_2	-0.066688	0.036981	-0.159125	-2.373592	-0.113832	-0.231920	-0.004245	0.003908	-0.236956	-0.115209
	(0.0033)	(0.1796)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7819)	(0.8644)	(0.0000)	(0.0000)
M_3	0.019428	0.023784	0.036416	0.939022	0.048069	-0.198746	-0.001672	-0.015509	-0.034568	0.042504
	(0.2602)	(0.3710)	(0.0521)	(0.0000)	(0.0000)	(0.0000)	(0.9215)	(0.4854)	(0.3262)	(0.0016)
M_4	-0.081956	-0.001681	-0.037275	-2.226170	-0.074859	-0.283599	-0.043981	-0.047374	-0.166404	-0.064674
	(0.0000)	(0.9520)	(0.0488)	(0.0000)	(0.0000)	(0.0000)	(0.0052)	(0.0241)	(0.0000)	(0.0000)
M_5	-0.058810	0.028626	-0.009317	-1.552507	-0.048998	-0.212498	-0.011433	-0.042906	-0.105588	-0.023196
	(0.0082)	(0.2534)	(0.6181)	(0.0000)	(0.0001)	(0.0000)	(0.4225)	(0.0526)	(0.0007)	(0.1128)
M_6	-0.030595	0.021265	-0.046903	-1.683858	0.000275	-0.228063	-0.022168	-0.058439	-0.137410	-0.023123
	(0.1804)	(0.4541)	(0.0982)	(0.0000)	(0.9773)	(0.0000)	(0.2268)	(0.0055)	(0.0002)	(0.0896)
M_7	-0.077490	0.008931	-0.118757	-2.469911	-0.103081	-0.192882	-0.028544	-0.029085	-0.131682	-0.030478
	(0.0007)	(0.7558)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0877)	(0.1309)	(0.0001)	(0.0142)
M_8	-0.038613	-0.046604	-0.049218	-1.464542	-0.044501	-0.261386	0.050310	0.018069	-0.159957	-0.024576
	(0.0702)	(0.0787)	(0.0227)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.3371)	(0.0000)	(0.0869)
M_9	-0.093533	0.048494	0.088861	-2.158550	-0.069336	-0.138889	-0.044939	-0.096238	-0.099413	-0.038919
	(0.0000)	(0.0362)	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0009)	(0.0000)	(0.0014)	(0.0009)
M_{10}	-0.059004	-0.028495	-0.142958	-2.697114	-0.039207	-0.152816	-0.041179	-0.042108	-0.218915	-0.057631
	(0.0063)	(0.1978)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0145)	(0.0317)	(0.0000)	(0.0000)
M_{11}	0.024697	0.006434	-0.044740	-1.818278	0.008971	-0.161585	0.043049	0.006362	-0.151599	-0.036589
	(0.2252)	(0.8082)	(0.0602)	(0.0000)	(0.3335)	(0.0001)	(0.0090)	(0.7610)	(0.0004)	(0.0038)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

to December (β_0), which means that there is a difference in volatility of July (M_7) and volatility of December (β_0). August (M_8) volatility of all leading cryptocurrencies except BTC (0.1083), ETH (0.2642), DASH (0.2330) and DOGE (0.9348) is significant with respect to December (β_0), which means that there is a difference in volatility of August (M_8) and volatility of December (β_0).

September (M_9) volatility of all leading cryptocurrencies is significant with respect to December (β_0), which means that there is a difference in volatility of September (M_9) and volatility of December (β_0). October (M_{10}) and April (M_4) volatility of all leading cryptocurrencies is significant except ETH with respect to December (β_0), which means that there is a difference in volatility of October (M_{10}) and April (M_4) and volatility of December (β_0). November (M_{11}) volatility of USDT (0.0000), XLM (0.0001), XMR (0.0090), XEM (0.0004) and DOGE (0.0038) is significant with respect to December (β_0), which means that there is a difference in volatility of November (M_{11}) and volatility of December (β_0). While November (M_{11}) volatility of BTC (0.2252), ETH (0.8082), XRP (0.0602), LTC (0.3335) and DASH (0.7610) is in-significant with respect to December (β_0), which means that there is no difference in volatility of November (M_{11}) and volatility of December (β_0).

4.6 Seasonality, Asymmetry and Long Memory Returns and Volatility of Crypto Currencies estimated by using P-GARCH Model

Table 4.14 represents the results of the mean equation of P-GARCH (1,1) model with weekday dummies. The estimated lag term is significant and negative (α_1<0) in USDT (0.0000), LTC (0.0202), DASH (0.0068) and XEM (0.0000), which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return.Whereas lag term is in-significant in BTC, ETH, XRP, XLM, XMR and DOGE, which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The day of the week effect on mean returns: Monday (D_1) returns of all leading crypto-currencies except XLM (0.0045) and DOGE (0.0395) are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns of Monday (D_1). While XLM (0.0045) and DOGE (0.0395) mean returns on Monday (D_1) are significantly higher than mean returns on Sunday (α_0). Tuesday (D_2) returns of all leading crypto-currencies except XRP (0.0022) are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns of Tuesday (D_2). While XRP (0.0022) mean returns on Tuesday (D_2) are significantly higher than mean returns on Sunday (α_0).

Wednesday (D_3) returns of all leading cryptocurrencies except LTC (0.0050) are insignificant with respect to Sunday (α_0), which means that there is no difference in mean returns of Wednesday (D_3). While LTC (0.0050) mean returns on Wednesday (D_3) are significantly lower than mean returns on Sunday (α_0). Thursday (D_4) returns of all leading crypto-currencies except ETH (0.0500) are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns of Thursday (D_4).

While ETH (0.0500) mean returns on Thursday (D_4) are significantly lower than mean returns on Sunday (α_0). Friday (D_5) returns of all leading crypto-currencies except XRP (0.0057) and DOGE (0.0342) are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns on Friday (D_5) and mean returns on Sunday (α_0). As co-efficients of XRP (0.0057) and DOGE (0.0342) are positive; So, mean returns on Friday (D_5) are significantly higher than mean returns on Sunday (α_0). Saturday (D_6) returns of all leading cryptocurrencies are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns on Saturday (D_6) mean returns on Sunday (α_0).

TABLE 4.14: Day of the week effect in Mean Returns - P-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	-0.001073	0.000941	-0.003532	0.000001	0.002590	-0.003114	0.002055	0.001554	0.000133	-0.001858
	(0.3795)	(0.7165)	(0.0334)	(0.8115)	(0.1889)	(0.2108)	(0.4525)	(0.5836)	(0.9524)	(0.3361)
α_1	-0.003589	-0.009800	0.036858	-0.444319	-0.048966	-0.035794	-0.037106	-0.065778	-0.111622	-0.038106
	(0.8699)	(0.6899)	(0.0907)	(0.0000)	(0.0202)	(0.1709)	(0.1270)	(0.0068)	(0.0000)	(0.0896)
D_1	0.003437	-0.001931	0.001293	-0.000232	-0.004962	0.010729	-0.000029	-0.002347	0.001447	0.006457
	(0.0642)	(0.6296)	(0.5597)	(0.1864)	(0.1244)	(0.0045)	(0.9953)	(0.5429)	(0.6029)	(0.0395)
D_2	0.003628	0.007229	0.088890	-0.000075	-0.000795	0.000919	-0.001965	-0.005871	-0.004416	-0.003601
	(0.0883)	(0.1044)	(0.0022)	(0.4972)	(0.8161)	(0.8586)	(0.6724)	(0.1231)	(0.1371)	(0.2409)
D_3	-0.000342	-0.005980	-0.000437	0.000010	-0.008437	-0.000459	-0.001674	-0.003838	0.002076	-0.001056
	(0.8665)	(0.1531)	(0.8596)	(0.5925)	(0.0050)	(0.9037)	(0.7012)	(0.3086)	(0.4620)	(0.6933)
D_4	0.002718	-0.008562	-0.000671	-0.000112	-0.006157	0.003081	-0.004794	-0.005979	0.001670	0.000249
	(0.1873)	(0.0500)	(0.8144)	(0.2114)	(0.1414)	(0.4483)	(0.2724)	(0.0965)	(0.5095)	(0.9301)
D_5	0.003359	0.002745	0.007002	-0.000031	0.000671	0.003404	0.000863	0.004736	0.002897	0.005803
	(0.0884)	(0.4928)	(0.0057)	(0.4583)	(0.8654)	(0.3860)	(0.8319)	(0.1831)	(0.3394)	(0.0342)
D_6	0.002796	0.004789	0.003283	-0.000010	-0.002826	0.001530	0.003565	-0.002857	-0.000862	0.001038
	(0.0965)	(0.1609)	(0.1583)	(0.7750)	(0.3634)	(0.6501)	(0.4083)	(0.4112)	(0.7231)	(0.6722)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

Table 4.15 represents the results of the variance equation of P-GARCH (1,1) model with weekday dummies. The estimated GARCH terms (β_1 & β_2) are significant in all leading crypto-currencies except BTC, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is not long run as coefficients of GARCH terms (β_1 & β_2) are not closer to 1. The estimated P-GARCH terms (β_3 & β_4) are significant and positive in all leading cryptocurrencies, which means that there exist asymmetric behavior and long memory of returns in the volatility of all leading cryptocurrencies.

The day of the week effect on volatility; Monday (D_1) volatility of all leading cryptocurrencies except ETH (0.3498), DASH (0.3585) and XEM (0.8174) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Monday (D_1) and volatility on Sunday (β_0). While ETH (0.3498), DASH (0.3585) and XEM (0.8174) volatility on Monday (D_1) is in-significant. Tuesday (D_2) volatility of all leading crypto-currencies except XMR (0.1397), DASH (0.2919), XEM (0.1022) and DOGE (0.2032) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Tuesday (D_2) and volatility on Sunday (β_0). While XMR (0.1397), DASH (0.2919), XEM (0.1022) and DOGE (0.2032) volatility on Tuesday (D_2) is in-significant.

Wednesday (D_3) volatility of all leading crypto-currencies except BTC (0.9909), LTC (0.6626) and XMR (0.6102) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Wednesday (D_3) and volatility on Sunday (β_0). While BTC (0.9909), LTC (0.6626) and XMR (0.6102) volatility on Wednesday (D_3) is in-significant. Thursday (D_4) volatility of all leading crypto-currencies except ETH (0.4221) and DOGE (0.1109) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Thursday (D_4) and volatility on Sunday (β_0). While ETH (0.4221) and DOGE (0.1109) volatility on Thursday (D_4) is in-significant.

Friday (D_5) volatility of XRP (0.0000), USDT (0.0000), LTC (0.0157), DASH (0.0008) and XEM (0.0007) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Friday (D_5) and volatility on Sunday (β_0).

Table 4.15: Asymmetry, Long memory and Day of the week effect in Return and Volatility - P-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	-0.001216	0.008781	0.003094	-0.000361	-0.000626	0.001309	-0.001469	0.003112	0.047178	-0.000211
	(0.1079)	(0.0296)	(0.0017)	(0.0000)	(0.0095)	(0.3025)	(0.0816)	(0.0028)	(0.0000)	(0.6250)
β_1	0.160902	0.173250	0.296268	0.469443	0.093826	0.162406	0.100721	0.224829	0.228403	0.207143
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.011709	-0.123890	-0.149359	0.085261	-0.151916	-0.335929	-0.333105	-0.097463	-0.146603	-0.146736
	(0.6847)	(0.0264)	(0.0000)	(0.0027)	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0027)	(0.0000)
β_3	0.833890	0.787457	0.704075	0.730350	0.890217	0.826560	0.862506	0.766895	0.711129	0.821751
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_4	1.000555	0.921524	1.108626	1.116032	1.648209	1.148194	1.440202	1.309100	0.381614	1.350614
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D_1	0.007725	0.003588	0.003180	0.000669	0.001965	0.006135	0.009752	0.001330	0.002026	0.005849
	(0.0044)	(0.3498)	(0.0195)	(0.0000)	(0.0046)	(0.0223)	(0.0011)	(0.3585)	(0.8174)	(0.0030)
D_2	0.010791	0.008347	0.010998	0.000443	0.002687	0.016492	0.001899	-0.001182	0.012096	0.000895
	(0.0005)	(0.0317)	(0.0000)	(0.0000)	(0.0005)	(0.0004)	(0.1397)	(0.2919)	(0.1022)	(0.2032)
D_3	0.000011	-0.009413	-0.006650	0.001298	-0.000127	-0.012578	0.000693	-0.002405	-0.025910	-0.001572
	(0.9909)	(0.0299)	(0.0001)	(0.0000)	(0.6626)	(0.0003)	(0.6102)	(0.0379)	(0.0004)	(0.0524)
D_4	0.006268	0.002545	0.018089	-0.000041	0.004719	0.008223	0.003620	0.003467	0.023252	0.001286
	(0.0029)	(0.4281)	(0.0000)	(0.0526)	(0.0003)	(0.0038)	(0.0386)	(0.0343)	(0.0023)	(0.1109)
D_5	0.000027	-0.003464	-0.014979	0.000752	-0.000703	-0.001700	-0.000291	-0.006364	-0.022668	-0.000009
	(0.9807)	(0.2910)	(0.0000)	(0.0000)	(0.0157)	(0.3702)	(0.7894)	(0.0008)	(0.0007)	(0.9890)
D_6	-0.000913	-0.017954	-0.002188	0.000302	-0.001729	-0.007513	0.002174	-0.003664	-0.038536	-0.000459
	(0.4799)	(0.0036)	(0.1076)	(0.0000)	(0.0014)	(0.0088)	(0.1133)	(0.0112)	(0.0000)	(0.5415)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

While Friday (D_5) volatility of BTC (0.9807), ETH (0.2910), XLM (0.3702), XMR (0.7894) and DOGE (0.9890) is in-significant with respect to Sunday (β_0), which means that there is no difference in volatility of Friday (D_5) and volatility on Sunday (β_0). Saturday (D_6) volatility of all leading crypto-currencies except BTC (0.4799), XRP (0.1076), XMR (0.1133) and DOGE (0.5415) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Saturday (D_6) and volatility on Sunday (β_0). While Saturday (D_6) volatility of BTC (0.4799), XRP (0.1076), XMR (0.1133) and DOGE (0.5415) is in-significant with respect to Sunday (β_0), which means that there is no difference in volatility of Saturday (D_6) and volatility on Sunday (β_0).

Table 4.16 represents the results of the mean equation of P-GARCH (1,1) model with monthly dummies. The estimated lag term is significantly negative (α_1<0) in USDT, LTC, DASH, XEM and DOGE which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return. While lag term is in-significant in BTC (0.7846), ETH (0.9129), XRP (0.0874), XLM (0.2282) and XMR (0.1491) which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The month of the year effect on mean returns: January (M_1) and April (M_4) returns of all leading crypto-currencies except USDT are in-significant with respect to December (α_0), which means that there is no difference in mean returns of January (M_1) and April (M_4) and returns of December (α_0). As Coefficient of USDT is negative; So, USDT mean returns in January (M_1) and April (M_4) is significantly lower than mean returns in December (α_0). May (M_5), June (M_6) and September (M_9) returns of all leading crypto-currencies except USDT and DOGE are in-significant with respect to December (α_0), which means that there is no difference in mean returns of May (M_5), June (M_6) and September (M_9) and returns of December (α_0).

As co-efficient of USDT is negative; So, USDT mean returns in May (M_5),

Table 4.16: Month of the year effect in Mean Returns - P-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	0.000363	-0.000367	0.000468	0.003806	0.008279	0.020991	0.004932	0.000891	0.003135	-0.002791
	(0.9096)	(0.9379)	(0.9055)	(0.0000)	(0.1301)	(0.0601)	(0.4180)	(0.8491)	(0.4186)	(0.2762)
α_1	0.005835	-0.002942	0.046080	-0.472850	-0.038799	-0.033573	-0.035533	-0.057689	-0.136242	-0.057527
	(0.7846)	(0.9129)	(0.0874)	(0.0000)	(0.0344)	(0.2282)	(0.1491)	(0.0168)	(0.0000)	(0.0011)
M_1	-0.003536	0.006246	-0.003879	-0.004076	-0.006532	-0.022375	-0.005655	-0.003018	-0.007455	0.003039
	(0.4249)	(0.4145)	(0.4122)	(0.0000)	(0.3714)	(0.0634)	(0.4784)	(0.7140)	(0.1948)	(0.3129)
M_2	0.005088	0.011038	-0.003566	-0.003837	-0.008276	-0.031363	-0.000877	0.008187	-0.002881	0.000935
	(0.1562)	(0.0911)	(0.4378)	(0.0000)	(0.1742)	(0.0075)	(0.9103)	(0.2242)	(0.4964)	(0.7288)
M_3	-0.001827	-0.000962	-0.004540	-0.004023	-0.013652	-0.020212	0.001895	0.006953	-0.003428	-0.006148
	(0.6150)	(0.8970)	(0.3356)	(0.0000)	(0.0340)	(0.0942)	(0.8093)	(0.2563)	(0.6125)	(0.0265)
M_4	0.001573	0.007795	0.000235	-0.003329	-0.003778	-0.020193	-0.005949	0.001327	0.000041	0.006589
	(0.6746)	(0.2615)	(0.9668)	(0.0000)	(0.5251)	(0.0838)	(0.4165)	(0.8311)	(0.9915)	(0.0723)
M_5	0.002571	0.013772	-0.006270	-0.003808	0.003143	-0.021962	-0.004167	0.001715	0.000259	0.009172
	(0.4749)	(0.1032)	(0.1910)	(0.0000)	(0.6218)	(0.0628)	(0.5915)	(0.7613)	(0.9631)	(0.0249)
M_6	-0.001238	-0.001395	0.001616	-0.003883	-0.009673	-0.022816	-0.000925	-0.004381	-0.004077	0.006912
	(0.7713)	(0.8510)	(0.7828)	(0.0000)	(0.1189)	(0.0626)	(0.9025)	(0.4407)	(0.4102)	(0.0368)
M_7	-0.001152	-0.001903	-0.006043	-0.003798	-0.010481	-0.023232	-0.003214	-0.002105	-0.007493	-0.002739
	(0.7589)	(0.7819)	(0.1888)	(0.0000)	(0.0818)	(0.0480)	(0.6676)	(0.7200)	(0.1447)	(0.3433)
M_8	0.001534	0.000965	-0.001924	-0.003812	-0.014004	-0.023599	-0.001340	-0.006071	-0.006545	-0.005275
	(0.7090)	(0.8769)	(0.7155)	(0.0000)	(0.0236)	(0.0430)	(0.8738)	(0.3890)	(0.1825)	(0.2030)
M_9	-0.001459	0.001705	0.002442	-0.003755	-0.007856	-0.020702	-0.010650	-0.000206	-0.005581	0.006345
	(0.6839)	(0.8146)	(0.7202)	(0.0000)	(0.1842)	(0.0916)	(0.1499)	(0.9711)	(0.2315)	(0.0324)
M_{10}	0.002879	-0.001994	0.000656	-0.003807	-0.008955	-0.023196	-0.009294	-0.004430	-0.002198	0.000425
	(0.4171)	(0.7310)	(0.8901)	(0.0000)	(0.1490)	(0.0464)	(0.1719)	(0.4099)	(0.6000)	(0.8852)
M_{11}	0.003898	-0.002425	-0.001289	-0.003751	-0.005693	-0.023753	0.000934	-0.004269	0.000519	-0.001829
	(0.4089)	(0.7340)	(0.7631)	(0.0000)	(0.4503)	(0.0499)	(0.9082)	(0.5051)	(0.9114)	(0.5442)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

June (M_6) and September (M_9) is significantly lower than mean returns in December (α_0). While co-efficient of DOGE is positive; So, DOGE mean returns in May (M_5), June (M_6) and September (M_9) is significantly higher than mean returns in December (α_0). February (M_2), July (M_7), October (M_{10}) and November (M_{11}) returns of all leading crypto-currencies except USDT & XLM are in-significant with respect to December (α_0), which means that there is no difference in mean returns of February (M_2), July (M_7), October (M_{10}) and November (M_{11}) and returns of December (α_0).

As co-efficient of USDT and XLM is negative; So, USDT and XLM mean returns in February (M_2), July (M_7), October (M_{10}) and November (M_{11}) is significantly lower than mean returns in December (α_0). August (M_8) returns of all leading crypto-currencies except USDT (0.0000), LTC (0.0236) and XLM (0.0430) are in-significant with respect to December (α_0), which means that there is no difference in mean returns of August (M_8) and returns of December (α_0). As co-efficient of USDT (0.0000), LTC (0.0236) and XLM (0.0430) is negative; So, USDT, LTC and XLM mean returns in August (M_8) is significantly lower than mean returns in December (α_0).

March (M_3) returns of all leading crypto-currencies except USDT (0.0000), LTC (0.0340) and DOGE (0.0265) are in-significant with respect to December (α_0), which means that there is no difference in mean returns of March (M_3) and returns of December (α_0). As co-efficient of USDT (0.0000), LTC (0.0340) and DOGE (0.0265) is negative; So, USDT, LTC and DOGE mean returns in March (M_3) is significantly lower than mean returns in December (α_0).

Table 4.17 represents the results of the variance equation of P-GARCH (1,1) model with monthly dummies. The estimated GARCH terms (β_1 & β_2) are significant in all leading crypto-currencies except BTC, ETH, DASH & XEM, which means that the volatility persistence exist, the previous year volatility affect current year return and that persistence is not long run as coefficients of GARCH terms (β_1 & β_2) are not closer to 1. The estimated P-GARCH terms (β_3 & β_4) are significant and positive in all leading crypto-currencies, which means that there exist asymmetric behavior and long memory of returns in the volatility of all leading crypto-currencies.

The month of the year effect on volatility: January (M_1) volatility of all leading crypto-currencies except BTC (0.0117) and XLM (0.0008) are in-significant with respect to December (β_0), which means that there is a difference in volatility of January (M_1) and volatility of December (β_0). As co-efficient of XLM is negative; So, XLM mean returns in January (M_1) is significantly lower than mean returns in December (β_0). While co-efficient of BTC is positive; So, BTC mean returns in January (M_1) is significantly higher than mean returns in December (β_0). February (M_2) volatility of XRP (0.0042), LTC (0.0000), XLM (0.0014), XEM (0.0005) and DOGE (0.0007) is significant with respect to December (α_0), which means that there is a difference in volatility of February (M_2) and volatility of December (β_0).

While February (M_2) volatility of BTC (0.1213), ETH (0.3665), USDT (0.1731), XMR (0.1966) and DASH (0.6158) is in-significant with respect to December (β_0), which means that there is no difference in volatility of February (M_2) and volatility of December (α_0). March (M_3) volatility of all leading crypto-currencies is significant except BTC (0.0346), LTC (0.0008) and XLM (0.0014) with respect to December (β_0), which means that there is a difference in volatility of March (M_3) and volatility of December (β_0). April (M_4) volatility of BTC (0.0294), LTC (0.0003), XLM (0.0011), XMR (0.0498) and XEM (0.0047) is significant with respect to December (β_0), which means that there is a difference in volatility of April (M_4) and volatility of December (β_0).

While April (M_4) volatility of ETH (0.8351), XRP (0.1149), USDT (0.4314), DASH (0.0686) and DOGE (0.1979) is in-significant with respect to December (β_0), which means that there is no difference in volatility of April (M_4) and volatility of December (β_0). May (M_5) volatility of XRP (0.0491), USDT (0.0244), LTC (0.0390), XLM (0.0011) and DASH (0.0306) is significant with respect to December (β_0), which means that there is a difference in volatility of May (M_5) and volatility

Table 4.17: Seasonality, Asymmetry and Long memory in Return and Volatility - P-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	0.002958	0.003569	0.000937	0.000299	0.004663	0.011002	0.000851	0.002315	0.034352	0.006385
	(0.0150)	(0.0968)	(0.0022)	(0.0239)	(0.0005)	(0.0032)	(0.0420)	(0.0060)	(0.0003)	(0.0003)
β_1	0.163243	0.156843	0.400721	0.422926	0.078693	0.201884	0.083966	0.191547	0.270417	0.184733
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.062392	-0.089403	-0.130040	0.089669	-0.277006	-0.308042	-0.271147	-0.032775	-0.031947	-0.251740
	(0.0984)	(0.1264)	(0.0000)	(0.0286)	(0.0000)	(0.0000)	(0.0000)	(0.2893)	(0.5054)	(0.0000)
β_3	0.820709	0.792843	0.619312	0.720278	0.918142	0.768481	0.884285	0.804193	0.665614	0.830732
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_4	0.977446	1.138501	1.690601	1.192049	0.758086	1.132349	1.559827	1.207313	0.578247	0.648266
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
M_1	0.001618	-0.000101	-0.000066	-0.000236	-0.000094	-0.007002	-0.000310	0.000677	0.002103	0.001122
	(0.0117)	(0.8670)	(0.7126)	(0.1239)	(0.8860)	(0.0008)	(0.1791)	(0.2375)	(0.4997)	(0.3302)
M_2	-0.000731	0.000641	-0.000603	-0.000172	-0.004266	-0.007528	-0.000248	0.000262	-0.011195	-0.003723
	(0.1213)	(0.3665)	(0.0042)	(0.1731)	(0.0000)	(0.0014)	(0.1966)	(0.6158)	(0.0005)	(0.0007)
M_3	0.000980	0.000031	0.000354	-0.000181	0.002261	-0.006983	-0.000237	0.000124	0.002102	0.001523
	(0.0346)	(0.9629)	(0.0609)	(0.1682)	(0.0008)	(0.0014)	(0.2673)	(0.8102)	(0.4493)	(0.1639)
M_4	-0.001081	0.000139	-0.000280	-0.000103	-0.002603	-0.008834	-0.000479	-0.000830	-0.008129	-0.001357
	(0.0294)	(0.8351)	(0.1149)	(0.4314)	(0.0003)	(0.0011)	(0.0498)	(0.0686)	(0.0047)	(0.1979)
M_5	-0.000325	0.000863	-0.000371	-0.000298	-0.001392	-0.007875	-0.000259	-0.001036	-0.002618	-0.000662
	(0.4185)	(0.2263)	(0.0491)	(0.0244)	(0.0390)	(0.0011)	(0.1926)	(0.0306)	(0.2867)	(0.5535)
M_6	0.000049	0.000594	0.000196	-0.000290	0.000431	-0.007459	-0.000404	-0.000790	-0.005751	0.000286
	(0.9119)	(0.4446)	(0.2535)	(0.0271)	(0.4296)	(0.0011)	(0.1057)	(0.0717)	(0.0244)	(0.7821)
M_7	-0.000889	0.000187	-0.000363	-0.000299	-0.003786	-0.007227	-0.000395	-0.000104	-0.003748	0.000046
	(0.0666)	(0.7911)	(0.0377)	(0.0239)	(0.0000)	(0.0008)	(0.0882)	(0.7840)	(0.1520)	(0.9606)
M_8	0.000072	-0.001291	-0.000162	0.000108	-0.001170	-0.008178	0.000579	0.000518	-0.006123	-0.000079
	(0.8597)	(0.1083)	(0.2852)	(0.4385)	(0.0659)	(0.0010)	(0.0430)	(0.2502)	(0.0167)	(0.9422)
M_9	-0.000979	0.001275	0.001324	-0.000192	-0.002530	-0.006075	-0.000589	-0.001313	-0.002263	-0.000971
	(0.0521)	(0.0906)	(0.0008)	(0.1417)	(0.0013)	(0.0016)	(0.0267)	(0.0142)	(0.3350)	(0.2987)
M_{10}	-0.000586	-0.000761	-0.000413	-0.000299	-0.001333	-0.007047	-0.000539	-0.000723	-0.010156	-0.001680
	(0.1748)	(0.1925)	(0.0293)	(0.0239)	(0.0206)	(0.0014)	(0.0375)	(0.0613)	(0.0001)	(0.0715)
M_{11}	0.001181	-0.000093	-0.000419	-0.000134	0.001232	-0.007378	0.000309	0.000650	-0.006754	-0.000747
	(0.0294)	(0.8729)	(0.0289)	(0.2989)	(0.0399)	(0.0015)	(0.2745)	(0.1911)	(0.0197)	(0.4949)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

of December (β_0). While May (M_5) volatility of BTC (0.4185), ETH (0.2263), XMR (0.1926), XEM (0.2867) and DOGE (0.5535) is in-significant with respect to December (β_0), which means that there is no difference in volatility of May (M_5) and volatility of December (β_0).

June (M_6) volatility of all leading crypto-currencies are in-significant except USDT (0.0271), XLM (0.0011) and XEM (0.0244) with respect to December (β_0), which means that there is no difference in volatility of June (M_6) and volatility of December (β_0). July (M_7) volatility of all leading crypto-currencies are in-significant except XRP (0.0377), USDT (0.0239), LTC (0.000) and XLM (0.0008) with respect to December (β_0), which means that there is no difference in volatility of July (M_7) and volatility of December (β_0). August (M_8) volatility of all leading crypto-currencies except XLM (0.0010), XMR (0.0430) and XEM (0.0167) is in-significant with respect to December (β_0), which means that there is no difference in volatility of August (M_8) and volatility of December (β_0).

September (M_9) volatility of all leading crypto-currencies except ETH (0.0906), USDT (0.1417), XEM (0.3350) and DOGE (0.2987) is significant with respect to December (β_0), which means that there is a difference in volatility of September (M_9) and volatility of December (β_0). October (M_{10}) volatility of all leading crypto-currencies except BTC (0.1748), ETH (0.1925), DASH (0.0613) and DOGE (0.0715) is significant with respect to December (β_0), which means that there is a difference in volatility of October (M_{10}) and volatility of December (β_0). November (M_{11}) volatility of BTC (0.0294), XRP (0.0289), LTC (0.0399), XLM (0.0015) and XEM (0.0197) is significant with respect to December (β_0), which means that there is a difference in volatility of November (M_{11}) and volatility of December (β_0). While November (M_{11}) volatility of ETH (0.8729), USDT (0.2989), XMR (0.2745), DASH (0.1911) and DOGE (0.4949) is in-significant with respect to December (β_0), which means that there is no difference in volatility of November (M_{11}) and volatility of December (β_0).

4.7 Seasonality and Non-Linearity in Return and Volatility of the Crypto Currencies estimated by using Q-GARCH Model

Table 4.18 represents the results of the mean equation of Q-GARCH (1,1) Model with weekly dummies. The estimated lag term is significant and negative (α_1<0) in USDT (0.0000) and XEM (0.0000), which means that past economic shock in currencies has negative effect on today return of currencies and it is possible to forecast present return through past return. Whereas lag term is in-significant in BTC, ETH, XRP, LTC, XLM, XMR, DASH and DOGE, which means that past economic shock in currencies has no effect on today return of currencies and it is not possible to forecast present return through past return.

The day of the week effect on mean returns: Monday (D_1) returns of all leading cryptocurrencies except BTC (0.0433), XLM (0.0149) and DOGE (0.0321) are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns of Monday (D_1) and mean returns on Sunday (α_0). While BTC (0.0433), XLM (0.0149) and DOGE (0.0321) mean returns on Monday (D_1) are significantly higher than mean returns on Sunday (α_0). Tuesday (D_2), Thursday (D_4) and Saturday (D_6) returns of all leading crypto-currencies are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns of Tuesday (D_2), Thursday (D_4) and Saturday (D_6) and mean returns of Sunday (α_0).

Wednesday (D_3) returns of all leading crypto-currencies except USDT (0.0036), LTC (0.0317) are in-significant with respect to Sunday (α_0), which means that there is no difference in mean returns of Wednesday (D_3) and mean returns on Sunday (α_0). While USDT (0.0036), LTC (0.0317) mean returns on Wednesday (D_3) are significantly lower than mean returns on Sunday (α_0). Friday (D_5) returns of all leading crypto-currencies except BTC (0.0326), XRP (0.0048) and DOGE (0.0151) are in-significant with respect to Sunday (α_0), which means that

Table 4.18: Day of the week effect in Mean Returns - Q-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	-0.000905	0.000107	-0.003629	0.000000	0.000440	-0.002522	0.002276	0.000696	-0.002288	-0.001716
	(0.5090)	(0.9697)	(0.0496)	(0.9992)	(0.8132)	(0.3035)	(0.3958)	(0.7364)	(0.5067)	(0.3303)
α_1	0.024517	0.021263	0.036136	-0.351481	-0.034513	-0.027034	-0.027689	-0.043779	-0.110617	-0.030377
	(0.3084)	(0.4780)	(0.1454)	(0.0000)	(0.1180)	(0.3193)	(0.2771)	(0.0954)	(0.0000)	(0.2300)
D_1	0.003876	-0.000837	0.002813	0.000016	-0.003147	0.008877	-0.000826	-0.000608	0.002952	0.006660
	(0.0433)	(0.8382)	(0.2872)	(0.9676)	(0.3183)	(0.0149)	(0.8616)	(0.6249)	(0.5365)	(0.0321)
D_2	0.002818	0.005076	0.003466	0.000063	-0.000440	-0.004093	-0.003070	-0.005636	-0.003478	-0.002745
	(0.2248)	(0.2592)	(0.2875)	(0.8716)	(0.8892)	(0.4532)	(0.5008)	(0.0842)	(0.4797)	(0.3482)
D_3	-0.001620	-0.007299	-0.000931	-0.001213	-0.006910	-0.002749	-0.003469	-0.002522	-0.000271	-0.001933
	(0.4613)	(0.1151)	(0.7579)	(0.0036)	(0.0317)	(0.4892)	(0.4271)	(0.3360)	(0.9531)	(0.4567)
D_4	0.000284	-0.005167	-0.001840	0.000313	-0.004771	0.000867	-0.005558	-0.003291	0.006723	-0.000948
	(0.9062)	(0.2353)	(0.5628)	(0.4276)	(0.1827)	(0.8290)	(0.2061)	(0.1094)	(0.1797)	(0.7256)
D_5	0.004562	0.004744	0.007798	-0.000046	0.002048	0.003068	0.001288	0.006299	0.006712	0.006696
	(0.0326)	(0.3056)	(0.0048)	(0.9065)	(0.5310)	(0.4495)	(0.7504)	(0.1920)	(0.1493)	(0.0151)
D_6	0.002796	0.006507	0.003263	0.000116	-0.000548	0.001586	0.003852	-0.001874	0.003000	0.000566
	(0.1429)	(0.0911)	(0.1705)	(0.7657)	(0.8759)	(0.6534)	(0.3798)	(0.4179)	(0.4638)	(0.8163)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

there is no difference in mean returns of Friday (D_5). As co-efficient of BTC (0.0326), XRP (0.0048) and DOGE (0.0151) is positive; So, mean returns on Friday (D_5) are significantly higher than mean returns on Sunday (α_0).

Table 4.19 represents the results of the variance equation of Q-GARCH (1,1) model with weekday dummies. The estimated GARCH terms (β_1 & β_2) are significant and positive in all leading crypto-currencies, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is long run as co-efficients of GARCH terms (β_1 & β_2) are closer to 1. The estimated Q-GARCH term (β_3) is significant and positive in all leading crypto-currencies except BTC (0.3555), ETH (0.9061) and USDT (0.1575), which means that there exist non-linearity in the volatility of XRP, LTC, XLM, XMR, DASH, XEM and DOGE.

The day of the week effect on volatility: Monday (D_1) volatility of all leading crypto-currencies except ETH (0.5180) and XEM (0.0717) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Monday (D_1) and volatility on Sunday (β_0). While ETH (0.5180) and XEM (0.0717) volatility on Monday (D_1) are in-significant. Tuesday (D_2) volatility of all leading crypto-currencies except DASH (0.2086) are significant with respect to Sunday (β_0), which means that there is a difference in volatility on Tuesday (D_2) and volatility on Sunday (β_0). While DASH (0.2086) volatility on Tuesday (D_2) is in-significant.

Wednesday (D_3) volatility of all leading crypto-currencies except BTC (0.8605), ETH (0.3227) and XMR (0.4796) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Wednesday (D_3) and volatility on Sunday (β_0). While BTC (0.8605), ETH (0.3227) and XMR (0.4796) volatility on Wednesday (D_3) is in-significant. Thursday (D_4) volatility of all leading crypto-currencies except ETH (0.1003) is significant with respect to Sunday (β_0), which means that there is a difference in volatility on Thursday (D_4) and volatility on Sunday (β_0). While ETH (0.1003) volatility on Thursday (D_4) is in-significant. Friday (D_5) volatility of XRP (0.0000), USDT (0.0000), LTC (0.0423) and DASH

Table 4.19: Non-linearity and Day of the week effect in Return and Volatility - Q-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	-0.000119	0.000282	0.000159	0.000117	-0.000615	-0.000084	-0.000475	0.000506	0.000617	-0.000100
	(0.0000)	(0.0148)	(0.0017)	(0.0000)	(0.0000)	(0.4440)	(0.0010)	(0.0000)	(0.0000)	(0.0433)
β_1	0.141448	0.186557	0.294381	0.345453	0.087879	0.152259	0.092623	0.231035	0.502289	0.218765
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.834803	0.735323	0.664715	0.703565	0.877626	0.817766	0.856844	0.718908	0.460539	0.792018
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_3	0.000304	0.000138	0.003562	-0.000211	0.001695	0.004208	0.005043	0.003570	0.005451	0.003579
	(0.3555)	(0.9061)	(0.0004)	(0.1575)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0200)	(0.0000)
D_1	0.000298	0.000149	0.000301	-0.000201	0.001233	0.000688	0.002490	0.000431	0.000510	0.000902
	(0.0000)	(0.5180)	(0.0023)	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0434)	(0.0717)	(0.0000)
D_2	0.000672	0.000981	0.001245	-0.000116	0.001302	0.003007	0.000624	-0.000246	0.001905	0.000311
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0366)	(0.2086)	(0.0000)	(0.0058)
D_3	-0.000010	-0.000241	-0.000584	-0.000108	0.000553	-0.002046	0.000226	-0.000518	-0.000966	-0.000264
	(0.8605)	(0.3227)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4796)	(0.0045)	(0.0008)	(0.0183)
D_4	0.000273	0.000376	0.002135	-0.000120	0.001571	0.001281	0.000905	0.000916	0.002347	0.000232
	(0.0000)	(0.1003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0051)	(0.0001)	(0.0000)	(0.0134)
D_5	-0.000010	0.000054	-0.001558	-0.000117	0.000255	-0.000248	0.000047	-0.001218	-0.000500	0.000121
	(0.8540)	(0.8079)	(0.0000)	(0.0000)	(0.0423)	(0.2825)	(0.8674)	(0.0000)	(0.1143)	(0.1560)
D_6	0.000047	-0.000993	-0.000148	-0.000114	0.000330	-0.000484	0.000625	-0.000668	-0.000523	0.000024
	(0.4098)	(0.0000)	(0.1149)	(0.0000)	(0.0104)	(0.0227)	(0.0188)	(0.0003)	(0.0493)	(0.7965)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

(0.0000) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Friday (D_5) and volatility on Sunday (β_0).

While Friday (D_5) volatility of BTC (0.8540), ETH (0.8079), XLM (0.2825), XMR (0.8674), XEM (0.1143) and DOGE (0.1560) is in-significant with respect to Sunday (β_0), which means that there is no difference in volatility of Friday (D_5) and volatility on Sunday (β_0). Saturday (D_6) volatility of all leading crypto-currencies except BTC (0.4098), XRP (0.1149) and DOGE (0.7965) is significant with respect to Sunday (β_0), which means that there is a difference in volatility of Saturday (D_6) and volatility on Sunday (β_0). While Saturday (D_6) volatility of BTC (0.4098), XRP (0.1149) and DOGE (0.7965) is in-significant with respect to Sunday (β_0), which means that there is no difference in volatility of Saturday (D_6) as volatility on Sunday (β_0).

Table 4.20 represents the results of the mean equation of GARCH (1,1) model with monthly dummies. The estimated GARCH term is significant and negative (α_1<0) in USDT (0.0000) and XEM (0.0006). While GARCH term is in-significant in BTC, ETH, XRP, LTC, XLM, XMR, DASH and DOGE. The month of the year effect on mean returns: January (M_1), February (M_2), March (M_3) and April (M_4) returns of all leading crypto-currencies are in-significant except USDT with respect to December (α_0), which means that there is no difference in mean returns of January (M_1), February (M_2), March (M_3), April (M_4) and returns of December (α_0).

As co-efficient of USDT is positive; So, USDT mean returns in January (M_1), February (M_2), March (M_3) and April (M_4) is significantly higher than mean returns in December (α_0). While May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) returns of all leading crypto-currencies except USDT and XEM are in-significant with respect to December (α_0), which means that there is no difference in mean returns of May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}), November (M_{11}) and returns of December (α_0). As co-efficient of USDT is positive; So, USDT mean returns in May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}) and November (M_{11}) is significantly higher than mean returns in

Table 4.20: Month of the year effect in Mean Returns - Q-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
α_0	0.000607	-0.000576	0.001104	-0.005658	-0.001323	0.014502	0.004804	0.002782	0.014515	0.025776
	(0.8389)	(0.8958)	(0.7874)	(0.0000)	(0.8204)	(0.2612)	(0.4497)	(0.5679)	(0.0026)	(0.1046)
α_1	0.033286	0.023280	0.040986	-0.243517	-0.025211	-0.034564	-0.029494	-0.042410	-0.103110	-0.043409
	(0.1874)	(0.4575)	(0.1108)	(0.0000)	(0.2521)	(0.2593)	(0.2434)	(0.1074)	(0.0006)	(0.1299)
M_1	-0.006141	0.008447	-0.005110	0.005923	-0.005509	-0.018872	-0.005963	-0.007407	-0.017547	-0.030379
	(0.2203)	(0.2496)	(0.2905)	(0.0000)	(0.4886)	(0.1723)	(0.4527)	(0.3730)	(0.0714)	(0.0585)
M_2	0.003812	0.009745	-0.003753	0.005763	0.000332	-0.022233	-0.000565	0.006132	-0.010558	-0.027873
	(0.2987)	(0.1452)	(0.4290)	(0.0000)	(0.9592)	(0.1049)	(0.9445)	(0.3891)	(0.0928)	(0.0811)
M_3	-0.003575	-0.001629	-0.006016	0.004484	0.001219	-0.014232	0.002709	0.003868	-0.013411	-0.029380
	(0.4688)	(0.8043)	(0.2254)	(0.0000)	(0.8636)	(0.3008)	(0.7355)	(0.5634)	(0.1519)	(0.0713)
M_4	0.002246	0.005608	-0.002199	0.004270	0.002087	-0.013781	-0.006568	-0.002358	-0.007064	-0.025245
	(0.5261)	(0.4288)	(0.7111)	(0.0000)	(0.7546)	(0.3014)	(0.3909)	(0.7057)	(0.3021)	(0.1234)
M_5	0.002867	0.011971	-0.006950	0.006027	0.004074	-0.014938	-0.004279	0.000342	-0.016641	0.023339
	(0.4354)	(0.1482)	(0.1434)	(0.0000)	(0.5469)	(0.2716)	(0.5919)	(0.9525)	(0.0267)	(0.1535)
M_6	-0.000261	-0.003776	-0.001597	0.005766	-0.000518	-0.017466	-0.001104	-0.005014	-0.017834	-0.025147
	(0.9485)	(0.5803)	(0.7903)	(0.0000)	(0.9450)	(0.2088)	(0.8873)	(0.3975)	(0.0096)	(0.1264)
M_7	-0.000806	-0.002623	-0.007643	0.005378	-0.002327	-0.017520	-0.002312	-0.001195	-0.020193	-0.029550
	(0.8223)	(0.6992)	(0.1110)	(0.0000)	(0.7241)	(0.1969)	(0.7629)	(0.8524)	(0.0047)	(0.0745)
M_8	-0.001167	0.001731	-0.002291	0.004339	-0.007000	-0.016805	-0.001857	-0.006958	-0.021097	-0.032127
	(0.7924)	(0.7784)	(0.6618)	(0.0000)	(0.2972)	(0.2120)	(0.8336)	(0.3302)	(0.0032)	(0.0484)
M_9	-0.000585	-0.001519	0.000947	0.005705	0.000475	-0.011539	-0.011913	-0.002230	-0.017275	-0.024042
	(0.8667)	(0.8402)	(0.8931)	(0.0000)	(0.9454)	(0.4126)	(0.1190)	(0.7061)	(0.0133)	(0.1352)
M_{10}	0.002402	-0.002291	-0.000307	0.005286	-0.000542	-0.017543	-0.008579	-0.006961	-0.014807	-0.027732
	(0.4887)	(0.6723)	(0.9492)	(0.0000)	(0.9317)	(0.1921)	(0.2227)	(0.2011)	(0.0042)	(0.0840)
M_{11}	0.002277	-0.003149	-0.001773	0.005486	0.001119	-0.017959	0.000120	-0.007430	-0.014131	-0.027528
	(0.6124)	(0.6341)	(0.6932)	(0.0000)	(0.8745)	(0.1910)	(0.9886)	(0.2968)	(0.0411)	(0.0972)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

December (α_0). As co-efficient of XEM is negative; So, XEM mean returns in May (M_5), June (M_6), July (M_7), August (M_8), September (M_9), October (M_{10}) and November (M_{11}) is significantly lower than mean returns in December (α_0).

Table 4.21 represents the results of the variance equation of GARCH (1,1) Model with monthly dummies. The estimated GARCH terms (β_1 & β_2) are significant and positive in all leading crypto-currencies, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is long run as coefficients of GARCH terms (β_1 & β_2) are closer to 1. The estimated Q-GARCH term (β_3) is significant and positive (β_3>0) in all leading crypto-currencies except BTC (0.9944), ETH (0.3776), DASH (0.9100) and XEM (0.3785), which means that there exist non-linearity in the volatility of XRP, USDT, LTC, XLM, XMR, XEM and DOGE.

The month of the year effect on volatility: January (M_1) volatility of BTC (0.0001), USDT (0.0000), LTC (0.0267), XLM (0.0000) and DOGE (0.0490) are significant with respect to December (β_0), which means that there is a difference in volatility of January (M_1) as volatility of December (β_0) changes. While January (M_1) volatility of ETH (0.7536), XRP (0.8239), XMR (0.0785), XEM (0.4930) and DASH (0.0671) is in-significant with respect to December (β_0), which means that there is no difference in volatility of January (M_1) and volatility of December (β_0). February (M_2) volatility of all leading crypto-currencies is significant except BTC (0.3533), ETH (0.3117), XMR (0.1373) and DASH (0.3554) with respect to December (β_0), which means that there is a difference in volatility of February (M_2) and volatility of December (β_0).

March (M_3) volatility of all leading crypto-currencies is significant except ETH (0.2474), XMR (0.0707), DASH (0.2013) and XEM (0.5566) with respect to December (β_0), which means that there is a difference in volatility of March (M_3) and volatility of December (β_0). April (M_4) volatility of all leading crypto-currencies is significant except ETH (0.3415), DASH (0.0904) and XEM (0.2603) with respect to December (β_0), which means that there is a difference in volatility

Table 4.21: Seasonality and Non-linearity in Return and Volatility - Q-GARCH Model

	BTC	**ETH**	**XRP**	**USDT**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**DOGE**
β_0	0.000089	0.000415	0.000315	0.000085	0.000255	0.001682	0.000275	0.000271	0.001728	0.002874
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0000)
β_1	0.162110	0.182854	0.386389	0.326132	0.086854	0.192030	0.086505	0.201105	0.465416	0.262115
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.796104	0.709524	0.626366	0.552395	0.885933	0.756923	0.872842	0.758837	0.437686	0.734194
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_3	0.000003	-0.001235	0.003483	-0.000912	0.002581	0.006065	0.003607	0.722480	0.002357	0.003995
	(0.9944)	(0.3776)	(0.0014)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9100)	(0.3385)	(0.0000)
M_1	0.000149	0.000034	-0.000018	-0.000085	-0.000081	-0.001409	-0.000153	0.000177	0.000368	-0.002802
	(0.0001)	(0.7536)	(0.8239)	(0.0000)	(0.0267)	(0.0000)	(0.0785)	(0.0671)	(0.4930)	(0.0000)
M_2	-0.000023	0.000119	-0.000211	-0.000083	-0.000269	-0.001421	-0.000116	0.000093	-0.001087	-0.002844
	(0.3533)	(0.3117)	(0.0020)	(0.0000)	(0.0000)	(0.0000)	(0.1373)	(0.3554)	(0.0244)	(0.0000)
M_3	0.000081	-0.000132	0.000199	-0.000083	-0.000057	-0.001342	-0.000147	0.000115	0.000290	-0.002590
	(0.0009)	(0.2474)	(0.0054)	(0.0000)	(0.0199)	(0.0000)	(0.0707)	(0.2013)	(0.5566)	(0.0000)
M_4	-0.000053	0.000118	0.000143	-0.000083	-0.000220	-0.001564	-0.000158	-0.000120	-0.000546	-0.002755
	(0.0123)	(0.3415)	(0.0593)	(0.0000)	(0.0000)	(0.0000)	(0.0340)	(0.0994)	(0.2604)	(0.0000)
M_5	-0.000012	0.000184	-0.000128	-0.000084	-0.000213	-0.001481	-0.000103	-0.000160	-0.000564	-0.271000
	(0.5893)	(0.1006)	(0.0703)	(0.0000)	(0.0000)	(0.0000)	(0.1611)	(0.0246)	(0.2297)	(0.0000)
M_6	0.000025	0.000114	0.000104	-0.000084	-0.000005	-0.001402	-0.000164	-0.000089	-0.000884	-0.002655
	(0.3387)	(0.4018)	(0.1374)	(0.0000)	(0.8677)	(0.0000)	(0.0426)	(0.2059)	(0.0576)	(0.0000)
M_7	-0.000046	0.000009	-0.000120	-0.000083	-0.000247	-0.001408	-0.000148	0.000018	-0.000557	-0.002616
	(0.0391)	(0.9393)	(0.0839)	(0.0000)	(0.0000)	(0.0000)	(0.0584)	(0.8031)	(0.2442)	(0.0000)
M_8	0.000036	-0.000218	-0.000042	-0.000073	-0.000120	-0.001469	0.000232	0.000093	-0.000588	-0.002704
	(0.0932)	(0.0274)	(0.5362)	(0.0000)	(0.0000)	(0.0000)	(0.0034)	(0.2161)	(0.2021)	(0.0000)
M_9	-0.000049	0.000199	0.000624	-0.000081	-0.000136	-0.001247	-0.000181	-0.000160	-0.000326	-0.002816
	(0.0255)	(0.0552)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0142)	(0.0191)	(0.4810)	(0.0000)
M_{10}	-0.000028	-0.000152	-0.000148	-0.000084	-0.000205	-0.001351	-0.000185	-0.000120	-0.001062	-0.002782
	(0.1903)	(0.0906)	(0.0355)	(0.0000)	(0.0000)	(0.0000)	(0.0110)	(0.0771)	(0.0194)	(0.0000)
M_{11}	0.000069	-0.000089	-0.000147	-0.000082	-0.000130	-0.001473	0.000095	0.000158	-0.000741	-0.002712
	(0.0111)	(0.3769)	(0.0321)	(0.0000)	(0.0000)	(0.0000)	(0.2936)	(0.0711)	(0.1137)	(0.0000)

Where values in parenthesis are the p-values. BTC=Bitcoin, ETH=Ethereum, XRP=Ripple, USDT=Tether, LTC=Litecoin, XLM=Stellar, XMR=Monero, DASH=Dash, XEM=Nem, DOGE=Dogecoin.

of April (M_4) and volatility of December (β_0). May (M_5) volatility of all leading crypto-currencies is in-significant except USDT (0.0000), LTC (0.0000), XLM (0.0000), DASH (0.0246) and DOGE (0.0000) with respect to December (β_0), which means that there is no difference in volatility of May (M_5) and volatility of December (β_0).

June (M_6) volatility of all leading crypto-currencies is in-significant except USDT (0.0000), XLM (0.0000), XMR (0.0426) and DOGE (0.0000) with respect to December (β_0), which means that there is no difference in volatility of June (M_6) and volatility of December (β_0). July (M_7) volatility of all leading crypto-currencies is significant except ETH (0.9393), XRP (0.0839), DASH (0.8031) and XEM (0.2442) with respect to December (β_0), which means that there is a difference in volatility of July (M_7) and volatility of December (β_0). August (M_8) volatility of all leading crypto-currencies except BTC (0.0932), XRP (0.5362), DASH (0.2161) and XEM (0.2021) is in-significant with respect to December (β_0), which means that there is no difference in volatility of August (M_8) and volatility of December (β_0).

September (M_9) volatility of all leading crypto-currencies is significant except XEM (0.4810) with respect to December (β_0), which means that there is a difference in volatility of September (M_9) and volatility of December (β_0). October (M_{10}) volatility of all leading crypto-currencies is significant except BTC (0.1903), ETH (0.0906) and DASH (0.0771) with respect to December (β_0), which means that there is a difference in volatility of October (M_{10}) and volatility of December (β_0). November (M_{11}) volatility of all leading crypto-currencies are in-significant except ETH (0.3769), XMR (0.2936), DASH (0.0711) and XEM (0.1137) with respect to December (β_0), which means that there is no difference in volatility of November (M_{11}) and volatility of December (β_0).

Chapter 5

Conclusion, Recommendations & Future Directions

5.1 Conclusion

The main focuses of the study are to; analyze the price behavior of the leading cryptocurrencies, measure asymmetry behavior in linear and non- linear setup, explore seasonality, investigate the long memory of returns volatility of all leading cryptocurrencies, explain non-linearity in behavior of leading cryptocurrencies. To achieve these objectives of the study, different types of GARCH Models have been used. The techniques used in this study are GARCH, GJR-GARCH or T-GARCH, E-GARCH, P-GARCH, and Q-GARCH.

To analyze the price behavior of the leading cryptocurrencies, GARCH (1,1) model has been used. The estimated GARCH terms (β_1 & β_2) are significant positive in all selected leading cryptocurrencies, which means that the volatility persistence exist, the previous year volatility effect current year return and that persistence is long run as coefficients of GARCH terms (β_1 & β_2) are closer to 1.

GJR-GARCH (1,1) or T-GARCH (1,1) model has been used, to measure asymmetric behavior in linear setup. The estimated T-GARCH term (β_3) is significantly negative in all selected leading cryptocurrencies except Bitcoin, Ethereum, Tether and Nem, which means that there exist asymmetric behavior in Ripple, Litecoin, Stellar, Monero, Dash and Dogecoin. The estimated T-GARCH term (β_3) with monthly dummies is significantly negative in all selected leading cryptocurrencies except Bitcoin, Ethereum, Dash and Nem, which means that there exist asymmetric behavior in Ripple, Tether, Litecoin, Stellar, Monero, and Dogecoin.

In this study, seasonality capture in two ways: a) The day of the week effect b) The month of the year effect. On the basis of lowest Akaike Information Criterion (AIC), it is concluded that there exist day of the week effect in the return and volatility of crypto-currencies; Monday effect exist in the mean returns of Stellar and Dogecoin as well as in the volatility of Bitcoin, Ripple, Tether, Stellar, Litecoin, Monero and Dogecoin. There exist Tuesday effect in the mean return of Ripple and in the volatility of Bitcoin, Ethereum, Ripple, Tether, Stellar, Litecoin, Monero and Dogecoin.

Wednesday effect exist in the mean return of Litecoin and in the volatility of Ripple, Tether, Stellar, Dash, Nem, Litecoin, Dogecoin and Ethereum. There exist Thursday effect in the volatility of Bitcoin, Ripple, Tether, Stellar, Dash, Nem, Litecoin, Monero and Dogecoin. Friday effect exist in the mean returns of Ripple and Dogecoin as well as in the volatility of Ripple, Tether, Dash, Nem and Litecoin. There exist Saturday effect in the volatility of Tether, Stellar, Dash, Nem, Litecoin, Monero and Ethereum.

On the basis of lowest Akaike Information Criterion (AIC), it is also concluded that there exist month of the year effect in the return and volatility of crypto-currencies; January effect exist in the mean return of Tether and in the volatility of Bitcoin, Litecoin and Stellar. There exist February effect in mean returns of Tether and Stellar as well as in the volatility of Stellar, Nem, Litecoin, Dogecoin and Ripple. March effect exist in Tether and Dogecoin as well as in the volatility of Bitcoin, Stellar, Litecoin, Dogecoin and Ripple.

There exist April effect in the mean return of Tether and in the volatility of Bitcoin, Ripple, Stellar, Nem, Litecoin, Monero and Dogecoin. May effect exist in the mean return of Tether and in the volatility of Ripple, Tether, Stellar, Dash and Litecoin. There exist June effect in the mean return of Tether and in the volatility of Tether, Stellar, Nem, and Monero. July effect exist in the mean returns of Tether and Stellar as well as in the volatility of Ripple, Tether, Stellar, Litecoin and Dogecoin.

There exist August effect in the mean returns of Tether and Stellar as well as in the volatility of Stellar, Litecoin, Nem and Monero. September effect exist in the mean return of Tether and in the volatility of Bitcoin, Ripple, Stellar, Dash, Litecoin, Monero and Dogecoin. There exist October effect in the mean returns of Tether and Stellar as well as in the volatility of Tether, Ripple, Stellar, Nem, Litecoin, Monero and Dogecoin. November effect exist in the mean returns of Tether and Stellar as well as in the volatility of Bitcoin, Ripple, Stellar, Nem, Litecoin and Dogecoin. All of these evidences are not consistent with the Efficient Market Hypothesis (EMH) since in an efficient market, all the prices are likely to be uncertain all over the market period (Malkiel and Fama, 1970).

To measure asymmetric behavior in non-linear setup, E-GARCH (1,1) model has been used. The estimated E-GARCH term (β_3) is significantly negative in all selected leading cryptocurrencies, which means that there exist asymmetric behavior in volatility of all selected leading crypto-currencies. P-GARCH (1,1) model has been used to investigate the asymmetric behavior and long memory of returns in the volatility of all leading cryptocurrencies. The estimated P-GARCH terms (β_3 & β_4) is significantly positive in all leading cryptocurrencies, which means that there exist asymmetric behavior and long memory of returns in the volatility of all leading cryptocurrencies.

To explore non-linearity in behavior of leading cryptocurrencies, Q-GARCH (1,1) model has been used. The estimated Q-GARCH term (β_3) with weekdays dummies, is significantly positive in all leading cryptocurrencies except Bitcoin, Ethereum, and Tether, which means that there exist Non-Linearity in Ripple, Litecoin, Stellar, Monero, Dash, Nem and Dogecoin. The estimated Q-GARCH term (β_3) with monthly dummies is significantly positive (β_3>0) in all leading cryptocurrencies except Bitcoin, Ethereum, Dash, and Nem, which means that there exist Non-Linearity in Ripple, Tether, Litecoin, Stellar, Monero, and Dogecoin.

5.2 Recommendations

This study strongly recommends to all market players like individual investors, policy makers, speculators, portfolio managers as well as crypto-fund managers should have an eye on the behavior of cryptocurrency market specially on the seasonal behavior of return and volatility. This may be very helpful to make a rational investment decision while investing in a crypto-currency market.

This study is very beneficial or helpful for those stakeholders who are interested or directly engaged in buying and selling in the crypto-currency market. It provide information about the ups and downs in the leading crypto-currencies and help them to operate in the crypto-currency market, so its very helpful for them to make a decision on investment in different crypto-currencies. Finally, this study may also be helpful for the portfolio managers in portfolio structuring and risk management.

5.3 Limitations & Future Direction

This study is limited to only top ten crypto-currencies. So, a comprehensive study can also be conducted by including more crypto-currencies in the sample size as cryptocurrency market keeps growing with new exchanges and new coins. Moreover, the historical time-series data has been used in this study is the daily closing prices of crypto-currencies, but further research may explore through high frequency data of a digital currency.

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Appendix A

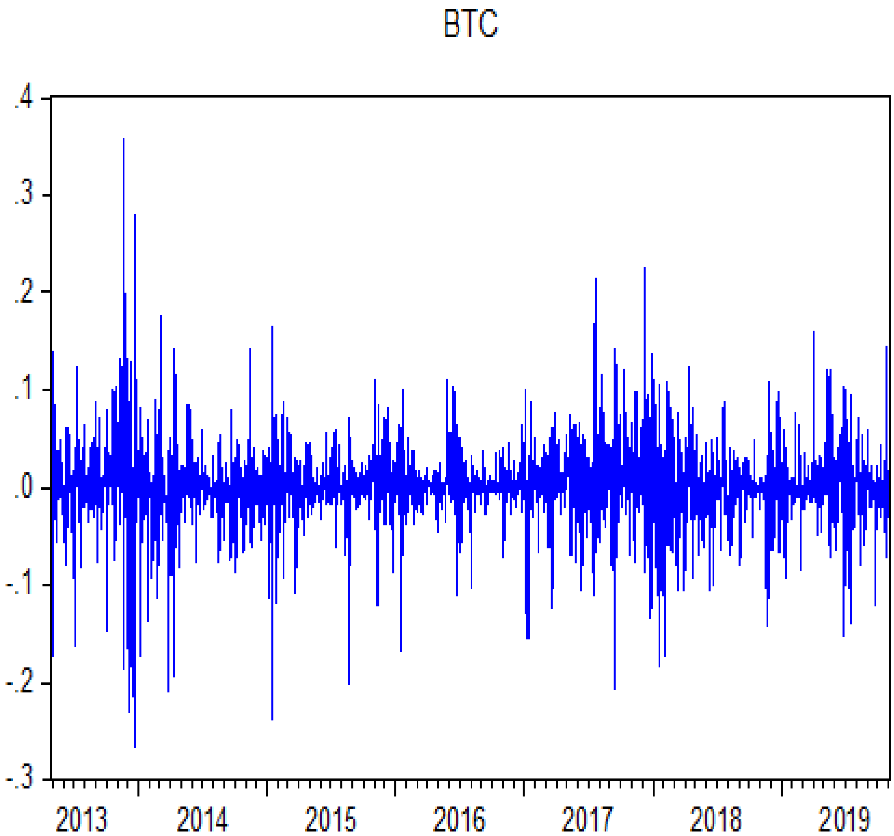

FIGURE 5.1: Return of the Bitcoin

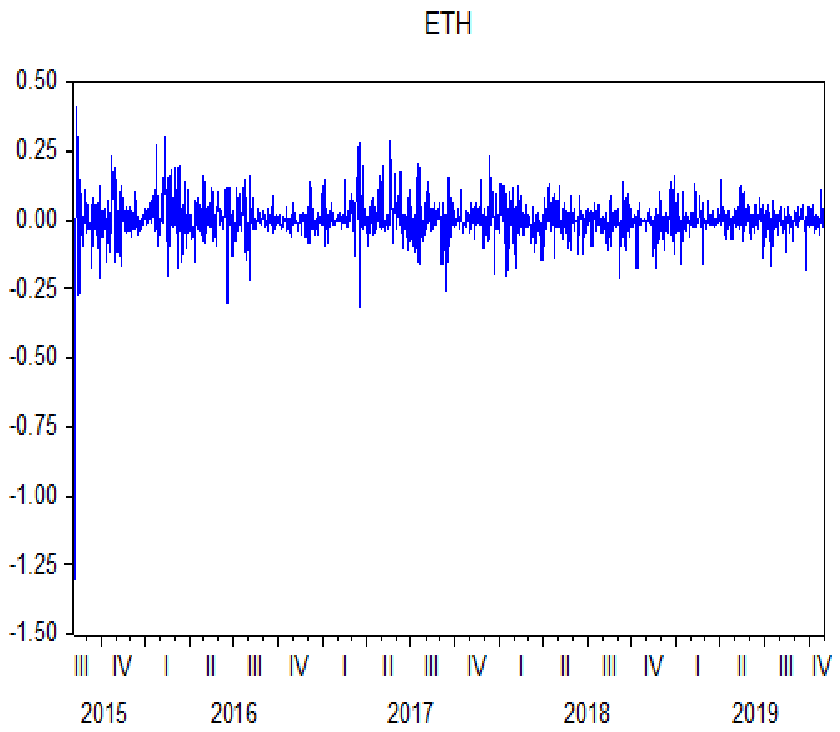

FIGURE 5.2: Return of the Ethereum

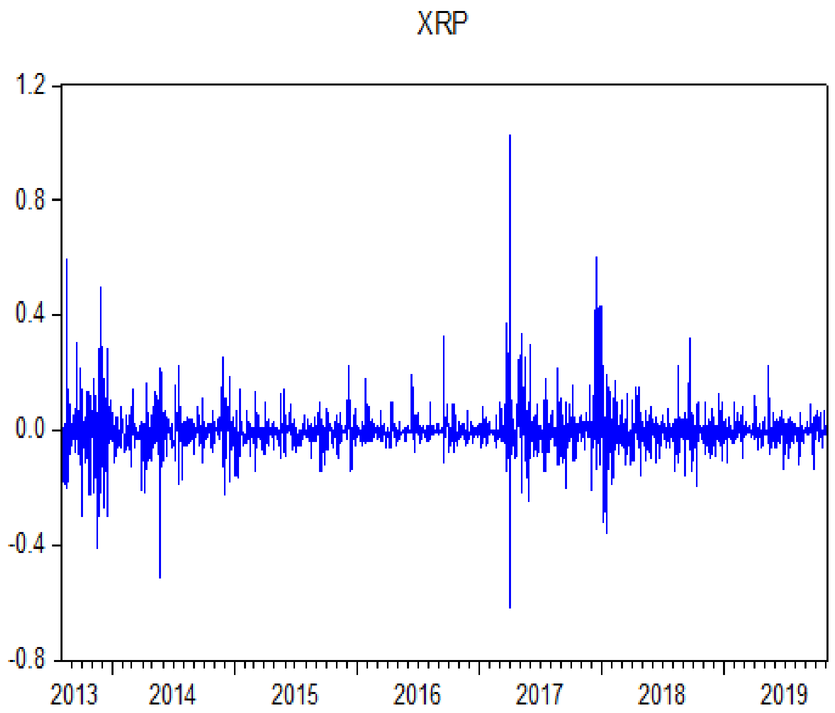

FIGURE 5.3: Return of the Ripple

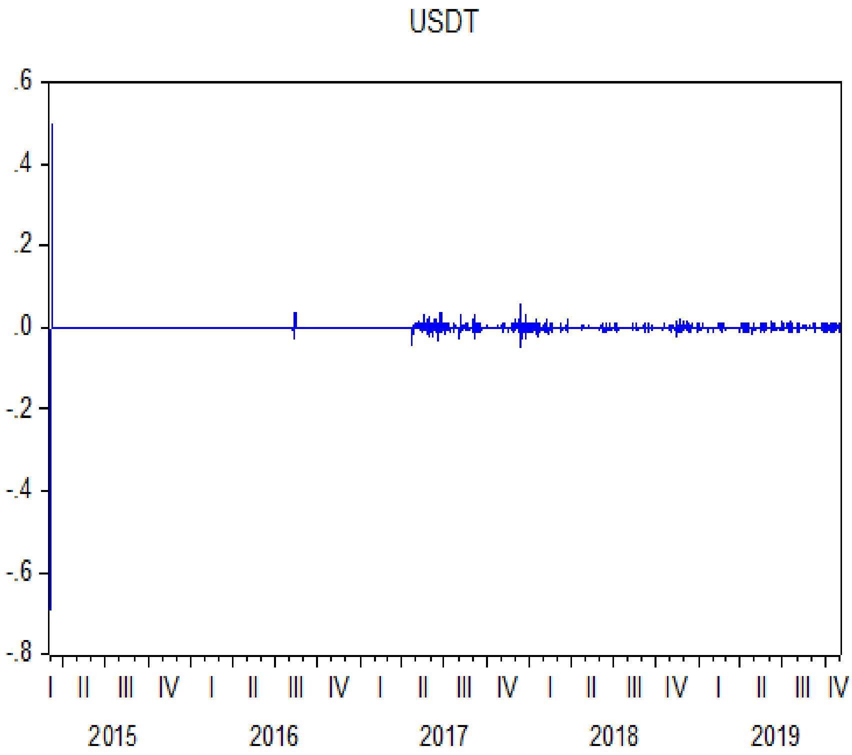

FIGURE 5.4: Return of the Tether

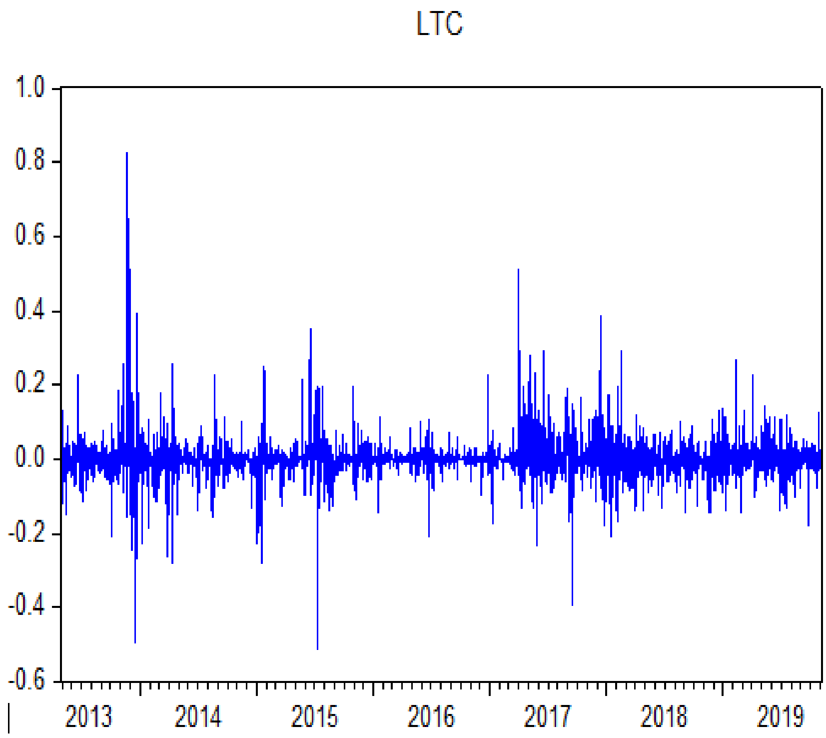

FIGURE 5.5: Return of the Litecoin

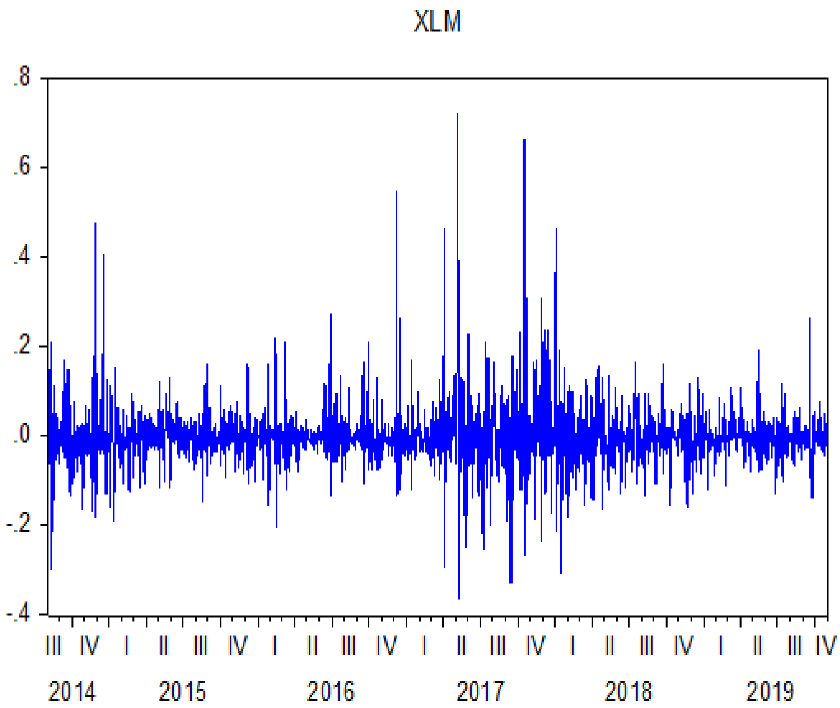

FIGURE 5.6: Return of the Stellar

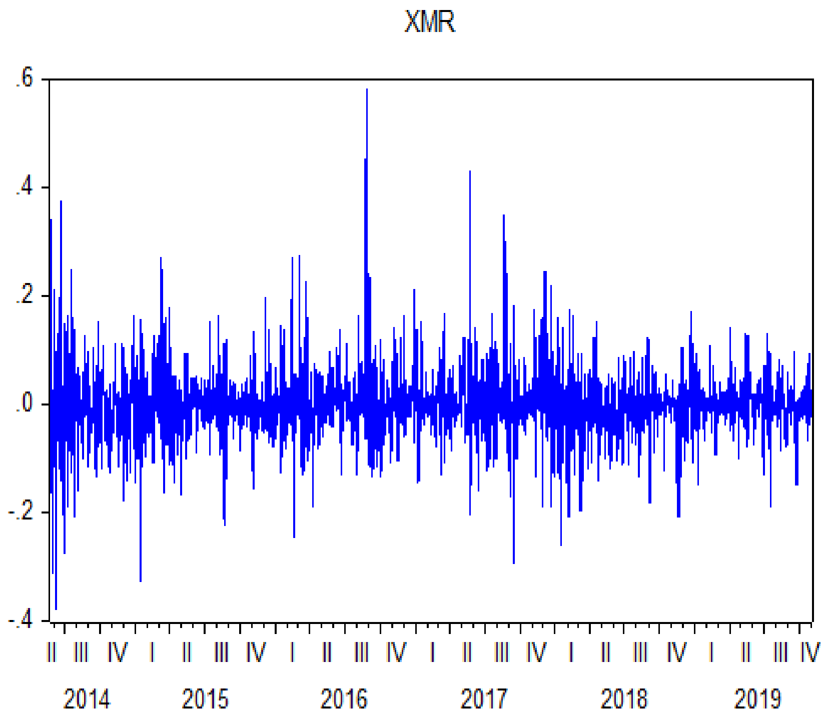

FIGURE 5.7: Return of the Monero

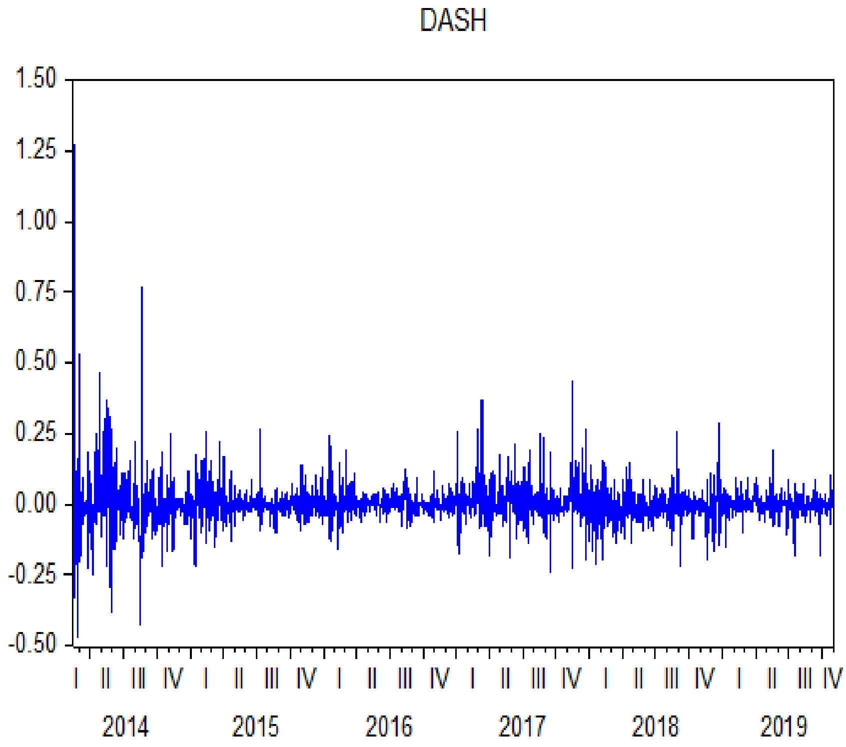

FIGURE 5.8: Return of the Dash

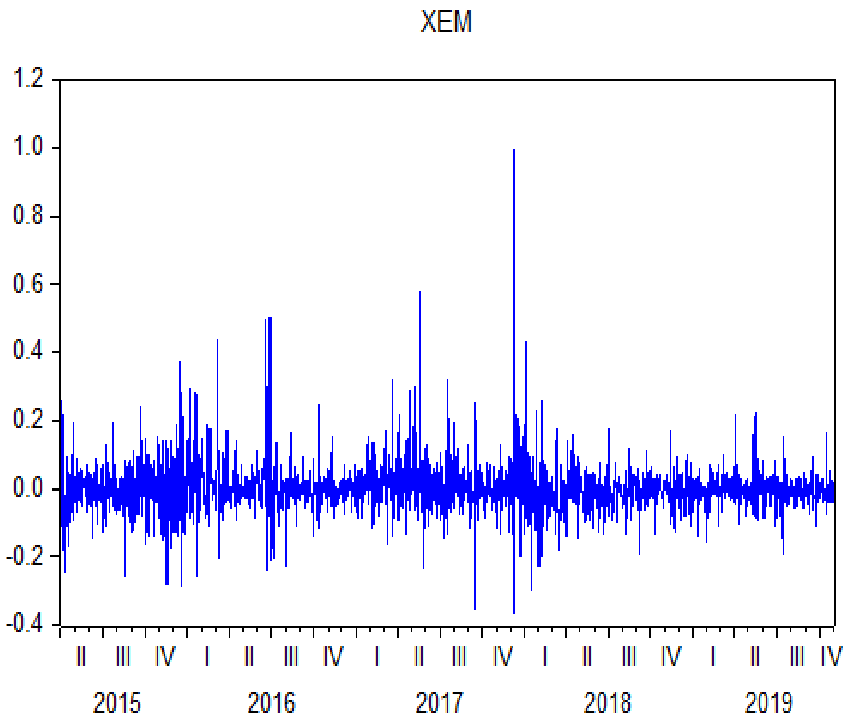

FIGURE 5.9: Return of the Nem

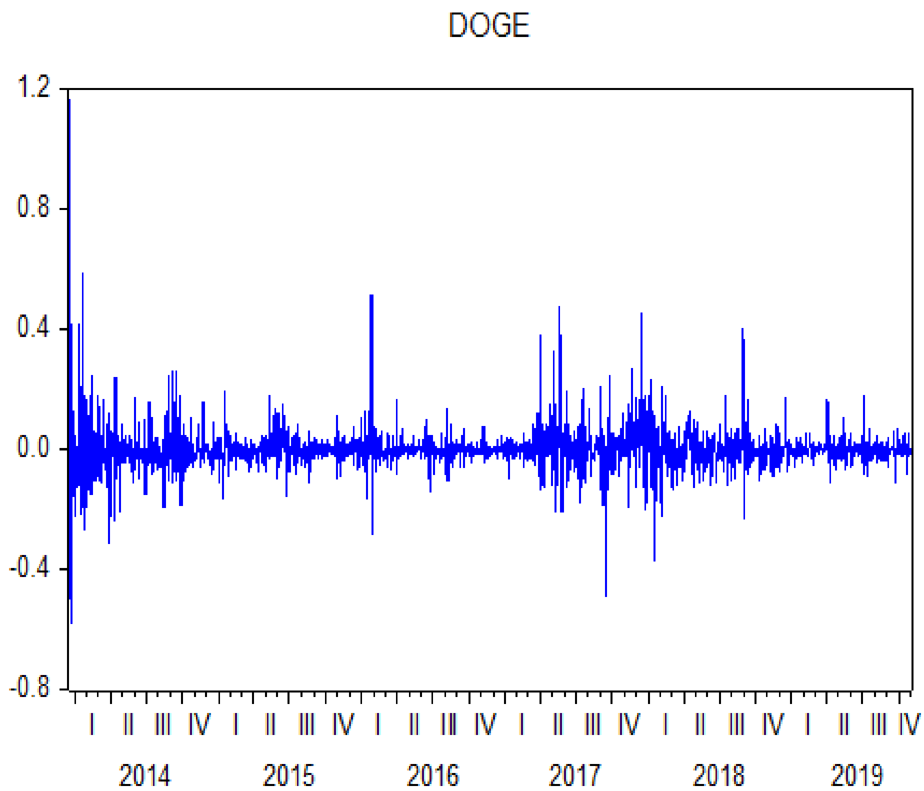

Figure 5.10: Return of the Dogecoin