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Crypto currency: An Emerging Blockchain Technology in Finance and its Day of the Week Effect

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Abstract

Cryptocurrency is a virtual coin or currency, which is secured by the cryptographic algorithms. They are decentralized networks with blockchain technology and are not issued by any central body, thus making them resistant to government manipulation or intervention. The growth of the cryptocurrency is increasing rapidly for the past few years and this study will help the investors to take correct decision while trading. The Efficient Market Hypothesis states that, the share price will reflect all the information about the shares. Thus, the share price of cryptocurrencies is expected to reflect the calendar anomaly, the day of the week effect. This study aims to examine the day of the week effect for the top 15 cryptocurrencies (coinmarketcap.com) and Dummy variable regression is used in thus study. The study is expected to provide evidence for the presence of Monday effect, Holiday effect and Weekday effect in the cryptocurrencies under study.

Keywords: Cryptocurrency, trading, share price, calendar anomaly, regression

1. INTRODUCTION

1. Introduction

1.1 Overview

Cryptocurrencies are the virtual money based on the blockchain technology, protected with cryptographic algorithms, while the identity of the users is veiled. They have evolved erratically over the short period of time. They are designed to be cheaper and more reliable than the coins issued by the central authority. With the recent growth in this industry, cryptocurrencies become the major interest of large number of investors. Overall, cryptocurrency is a digital currency acts as a standard currency, enabling users to employ virtual payment without the intervention of government.

The first cryptocurrency introduced was Bitcoin in the year 2009 and with this an array of many cryptocurrencies was introduced in the market. The other cryptocurrencies are primarily clones of Bitcoin and other major cryptocurrencies, yet having novel features and certain fundamental differences. These cryptocurrencies have forayed into the market share of Bitcoin which has decreased from 86% (March 2015) to 60% (August 2020). Several dimensions of the cryptocurrencies are studied by researchers, the asset class of currencies (Corbet et. al.,2019), volatility of cryptocurrencies (Conrad et.al., 2019), dynamic linkages of cryptocurrencies (Corbet et al., 2018), investment option (Shahzad et.al., 2019) and market anomalies [7].

Table 1.1 Top 15 Cryptocurrencies till the year 2017

Rank	Name	Symbol	Market Cap	Year
1	Bitcoin	BTC	$434,091,386,908	2009
2	Ethereum	ETH	$66,319,514,491	2015
3	Tether	USDT	$20,527,534,782	2015
4	XRP	XRP	$12,147,699,898	2014
5	Litecoin	LTC	$6,874,997,268	2011
6	Bitcoin Cash	BCH	$5,211,912,431	2017
7	Binance Coin	BNB	$4,586,581,287	2017
8	Cardano	ADA	$4,280,127,166	2015
9	Chainlink	LINK	$4,103,348,006	2017
10	Stellar	XLM	$2,992,036,558	2014
11	Monero	XMR	$2,749,243,961	2014
12	EOS	EOS	$2,251,942,218	2017
13	NEM	XEM	$1,936,843,935	2015
14	TRON	TRX	$1,850,420,412	2017
15	Dash	DASH	$2,419,347,657	2014

The past five years has a remarkable development in the cryptocurrency industry as the number of cryptocurrencies active now in the market is 30 times higher than the count in the year 2015. Each cryptocurrency follow a unique blockchain technology, which are allied from the technology used for Bitcoin. The trading volume of cryptocurrency as of October 5, 2020 is $83 billion (coinmarketcap.com/cryptocurrency). This explains the increased interest and participation in trading activity among the share market investors. In India, as of now the government maintains a neutral state regarding cryptocurrency. The Supreme Court has advised the central board to prepare a regulatory framework for the cryptocurrency.

1.2 Efficient Market Hypothesis

The Efficient Market Hypothesis introduced by Fama in 1970 states that the price of the share will reflect all about the share. The deviation from the market efficiency hypothesis is called anomalies. The cryptocurrencies have the calendar effects such as Monday effect, Holiday effect, Weekday effect, Yearend effect, and Halloween effect, Mid-year effect, which are explained and researched by various researchers. The calendar anomalies result provides evidence against the market hypothesis. Though the number researches in the cryptocurrency field is growing rapidly, the analysis involving the Calendar effect is still to be explored deeply. To be precise, the calendar effect analysis for the cryptocurrencies except Bitcoin is numbered. Thus, this analysis would be beneficial to researchers, analysts and investors or traders to understand the behaviour of the cryptocurrencies during different time period throughout the year.

In this study, the Generalized Autoregressive ConditionalHeteroskedastic (GARCH) modelis used as it has many advantages comparing to other models. This model is consistence and capable of capturing the abnormalities in the taken cryptocurrencies. This reason is important to be considered while studying cryptocurrency as they are vulnerable to model specifications.

1.3 Block Chain Technology

The rationality of each cryptocurrency coins is delivered by a blockchain. It is a constantly growing list of records, known as blocks, which are linked and protected using cryptography. Typically, each block has a hash pointer that is used as a link to a previous block, timestamp and transaction data. By the structure, block chains are intrinsically unaffected to alteration of the data. It is, in a supportable and stable way, an open, distributed ledger that can record transactions between two parties resourcefully.

For use as a distributed ledger, a blockchain is typically managed by a peer-to-peer network collectively observing to a protocol for confirming new blocks. Once recorded, without the modification of all subsequent blocks, the data in the given block cannot be changed retroactively. Block chains are protected by strategy and are an example of a distributed computing system with high Byzantine fault tolerance. Decentralized agreement has therefore been achieved with a blockchain.

2. Literature Review

Blockchain technology is perhaps the best technology for powerful corporate financial administration. It mirrors the change in the digitalization of business measures in actualizing advanced technology in the industrial enterprises, administrations, financial services, and government offices. Blockchain advances are continuously being presented in numerous areas of the economy as well as in the arrangement of policy implementation and other advertising [17].Cryptography is an area, which studies about the various advanced and complicated mathematical techniques. The mutual constituent of the different cryptocurrency systems is blockchain. Cryptocurrencies are considered to be a profitable investment tool in the long run for any investor. India levy Goods and Services Tax of 18% GST on the trading, since it is considered in service sector. The issue is that the Bitcoin exchanges are not yet legitimized and not supported by the SEBI and RBI. In India purchasing and selling of Bitcoin and exchanging them over to fiat money is prohibited by the RBI.

Market efficiency hypothesis (EMH) proposes that market prices fully reflect all available information and they are rational. Time and calendar anomalies oppose the weak form efficiency. But existence of monthly effects and seasonality oppose market efficiency [13]. The Bitcoin market isn't effective. In any case, the exact outcomes show that Bitcoin exchanges are turning out to be and can turn out to be more effective and the outcomes propose that Bitcoin returns will be irregular later on. For the different sorts of data, the offer will be dynamic and develops essentially over the time. Sound exchanging and boosting economies by means of Bitcoin is expected. Cryptocurrencies like LiteCoin, Ripple, and Dash are discovered not to show day of the week anomaly [9]. Utilizing a trading simulation approach it is shown that a trading procedure dependent on this anomaly is beneficial and these outcomes essentially contrast from the abnormal ones. In general, there is no efficiency.

The evidence for the day of the week calendar anomaly in Bitcoin returns and contends was found that not considering this anomaly brings about a one-sided gauge of the market efficiency [9]. Further, it likewise measures the level of market inefficiency of Bitcoin over the long time utilizing the procedure proposed by Ito and Sugiyama (2009). Cryptocurrency market is fairly new and might in any case be generally inefficient and it very well might be a decent reason for the Month of the Year Effect presence. For instance Caporale and Plastun(2019) investigate overreactions in the cryptocurrency market and discover proof of value pattern after overreaction. Chevapatrakul and Mascia (2019) utilizing the quantile autoregressive model show that days with high negative returns are probably going to be trailed by periods described by negative returns and week after week certain profits as Bitcoin costs keep on rising.

Bitcoin trades named in US dollars and euro show stronger patterns contrasted the exchanges in Japanese yen and Chinese yuan. The findings in volume likewise recommend that Bitcoin isn't exchanged by retail investors as it were furthermore, that institutional investors assume a critical role on US dollar and euro exchanges . The Bitcoin and Litecoin were utilized as objects since they were a cryptocurrency with a large market capitalization. The information utilized was monthly cryptocurrency returns for looking at the month of-the-year-effect and every day returns for analyzing the day-of-the-week-effect. The investors should purchase Bitcoin toward the end of January and they should sell them at the end of February. While, for the investors who exchanged day to day, can exchange Bitcoin Monday, Wednesday and Thursday in light of the fact that the Bitcoin can possibly create daily benefits [19].

The day-of-the-week effect consequently varies with test periods, while altogether high volatilities are seen on Monday and Thursday. Consequently, the altogether high mean return of Bitcoin for Monday is found as a reaction to higher volatility. In addition, both risk and return stays vigorous in the wake of representing financial exchange returns and gold market returns [11]. The day of the week effect in the cryptocurrency market was examined and it is found that most cryptocurrencies are discovered not to show this anomaly. The lone exemption is Bitcoin, for which returns on Mondays are fundamentally higher than those on different days of the week. Utilizing OLS and GARCH models with daily information for 2010–2017, the initial proof about the presence of the day-of-the-week effect anomaly in returns as well as in the volatility of Bitcoin was found. The presence of Monday Effect was found in stock and Treasury Bills happens in the Bitcoin market, which varies from other financial markets because of its continuous exchanging. The returns on Tuesday and Wednesday for Bitcoin are above average, which means evidence of market inefficiency. It additionally identifies that the returns on Wednesday and Saturday are influenced by the profit for earlier day [14].

To research the day-of-the-week effect of price clustering in Bitcoin, Mbanga (2018) acquire the two-digit decimals from every daily closing Bitcoin value (M-values). The recurrence of event of every M-value over the whole sample and for every day of the week was found. Next, to estimate regression, utilizing M assessment strategy with BiSquare weights[16]. As stated by Efficient Market Hypothesis (EMH), effective market was characterized as a market with enormous quantities of individuals, amplifying their benefit and effectively competing one another and attempting to anticipate future market estimation of specific securities, and where all relevant data is freely accessible to investors.There found a robust pattern in exchanging activity across the ten high market capital cryptocurrencies. Thus, exchanging volume, volatility and spreads are on normal lower in January, on ends of the week and throughout the mid-year months. The frequency of price overreactions in the cryptocurrency market on account of BitCoin over the period 2013–2018 was examined. In general, the outcomes recommend that it can give valuable data to anticipate price dynamics in the cryptocurrency market and for planning trading procedures, while there is no proof of seasonality [10].

3. Research Methodologies

3.1 Problem Statement

The Cryptocurrency market is yet to be studied deeply and the studies and researches related to Anomalies are numbered. With the exception of Borowski and Matusewicz (2020), the studies related to Litecoins (Cryptocurrencies other than Bitcoin) are yet to be analyzed. There are more than 6000 cryptocurrencies are active around the world and many are soon to come into existence. Thus the need to study about the anomalies and efficiency of cryptocurrencies become a need of the global economy. This study will help the investors to make right trading strategies and investment decisions. It also ensures the potential growth of the cryptocurrency market. This study will help the investor to decide the best time to buy the coin and to sell it.

3.2 Research Gap

Since many countries around the world legalized cryptocurrency and except few, the remaining remains neutral to the new digital currency, cryptocurrency becomes the major topic for researchers. It has many application including, school or college fee payment, online money transfer, real estate and so on, the need to know the behavior of these digital currency becomes unavoidable. Bitcoin has the highest market share of 62% (September, 2020) and it also has the most number of investor. Thus, the studies related to it are higher than other coins. This study examines the day of the week effect (a calendar anomaly) of the top 15 (from the time period October 5, 2017 to September 5, 2020).

3.3 Objective of the study

1. To study the descriptive statistics of Cryptocurrency (From 2017 (Oct) to 2020(Sept))
2. To study the weekday and holiday effect of top 15 cryptocurrencies.
3. To prove whether the trading volume and price of the top 15 cryptocurrency is average on Tuesday and Wednesday

3.4 Need for the study

The Calendar anomalies in the cryptocurrency market are more volatile and it is important for any potential investor to know the behavior of the coins they are going to invest. Since there are only few studies examining this area of cryptocurrency, the need to study deep in this field is inevitable. This study will benefit the potential investors, researchers and the financial analyst.

3.6 Data

The closing price of the op 15 cryptocurrencies, namely Bitcoin, Ethereum, Tether, XRP, Litecoins, Bitcoin Cash, Binance Coin, Polkadot, Cardano, Chainlink, Stellar, Monero, EOS, NEM and TRON. These coins cover nearly 85% of the total cryptocurrency market capitalization. Secondary data is used for this study and they will be taken from coinmarketcap.com website. The time period of the study is from October 9, 2017 to September 8, 2020 contaning 1096 trading days. Since the cryptocurrencies EOS and TRON are introduced in September, 2017, the study will start from October 9, 2017.

3.7 Research Design

The study is divided in to three parts. The first part will examine the descriptive statistics (Normality check) of the 15 cryptocurrencies. It was done using JarqueBera Statistics. Since the cryptocurrency is expected to exhibit volatility, its Stationarity is tested using Augmented Dickey Fuller (ADF) method and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

The Augmented Dickey fuller method is only for the test of unit root, thus to confirm the stationarity, KPSS method is used. In ADF method, the null hypothesis that is 'the time series data is not stationary' alone is verified. Thus we are going for KPSS test, because though the time series data has unit root or not, there is possibility it is stationary. Thus in KPSS, we examine the stationarity of the time series data with null hypothesis that the series is stationary to the alternate hypothesis that the time is not stationary. The dummy variable regression is used to verify the presence of Autocorrelation and ARCH effect. If the ARCH effect is present, GARCH (1, 1) method is used. ARMA model is used for the other cryptocurrencies, if there are any insignificant values in the analyzed result. All the above analysis will be done for the closing price of the cryptocurrencies.

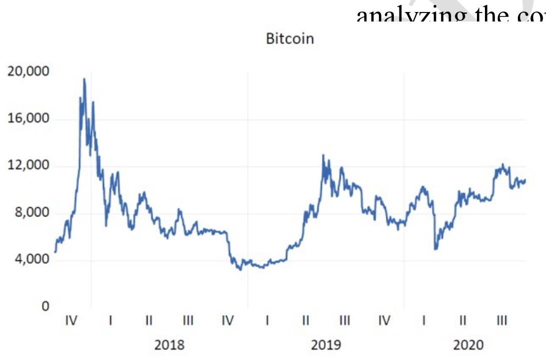
For the day of the week effect, the dummy variable regression formula is given by Equation (1), where LN(return) represents the natural log of return of the daily closing price of the corresponding coin, D1 up to Dn are the dummy variables equals to 1 for values corresponding to the respective day and 0 for other days and β1 to βn represents the mean return of the particular day. $Constant^{Sunday}$ examines the anomaly present in Sunday.

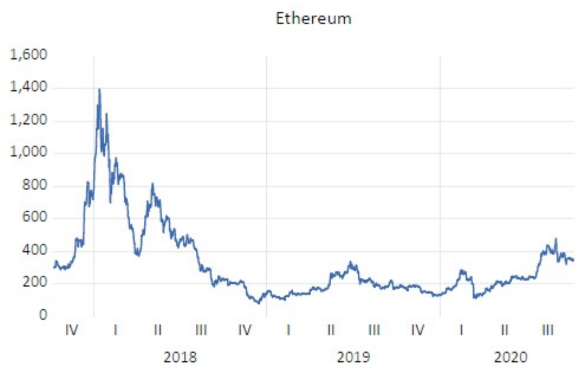
$$LN(Return) = D1\beta1+\ldots+Dn\beta n+Constant^{Sunday}+Error\ term \qquad (1)$$

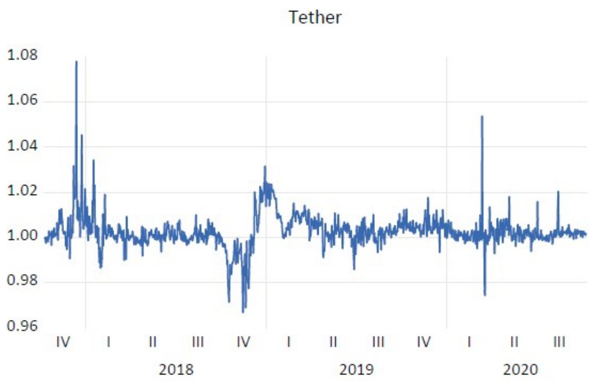
4. Results and Interpretations

4.1 Daily Closing Price Graph

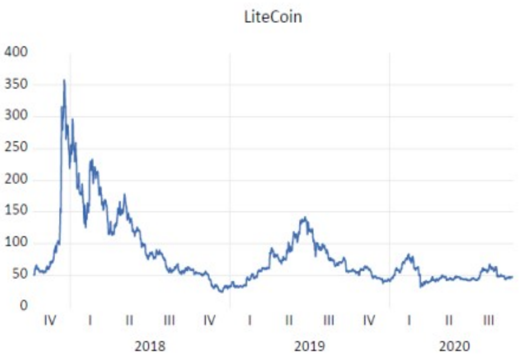
The behavior of the selected cryptocurrenciescan be studied with the help of the graphs and its descriptive statistics analyzed for its closing price. From the graph (Figure 4.1), we can say that except Binance Coin and TRON all the coins have their peaks in both 2017 4th quarter and 2018 1st quarter. Those two coins have their peaks in 2019 2nd Quarter and 2020 2nd quarter respectively. Also, only Bitcoin has a gradual increase all the quarters in the considered time period except in 2018 4th and 20191st quarter, where there is a sudden dip in its prices. Tether though it somehow resembles Bitcoin, we can see price clustering throughout the considered period. Thus we have a proof that, there will be insignificant values while analyzing the correlati

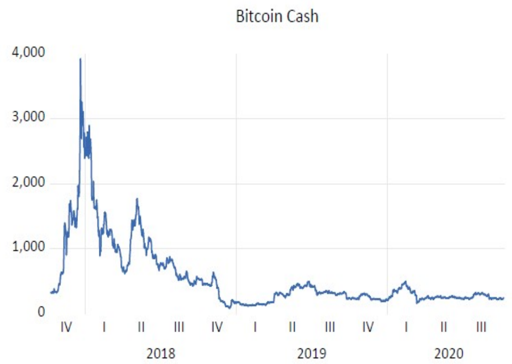


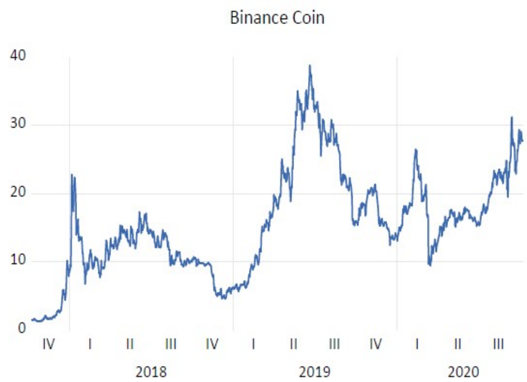



Tether
1.08
1.06
1.04
1.02
1.00
0.98
0.96
IV I II III IV I II III IV I II III
2018
2019
2020


XRP
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
IV I II III IV I II III IV I II III
2018
2019
2020


LiteCoin
400
350
300
250
200
150
100
50
0
IV I II III IV I II III IV I II III
2018
2019
2020


Bitcoin Cash
4,000
3,000
2,000
1,000
0
IV I II III IV I II III IV I II III
2018
2019
2020


Binance Coin
40
30
20
10
0
IV I II III IV I II III IV I II III
2018
2019
2020


Cardano
1.2
1.0
0.8
0.6
0.4
0.2
0.0
IV I II III IV I II III IV I II III
2018
2019
2020


Chainlink
20
16
12
8
4
0
IV I II III IV I II III IV I II III
2018
2019
2020

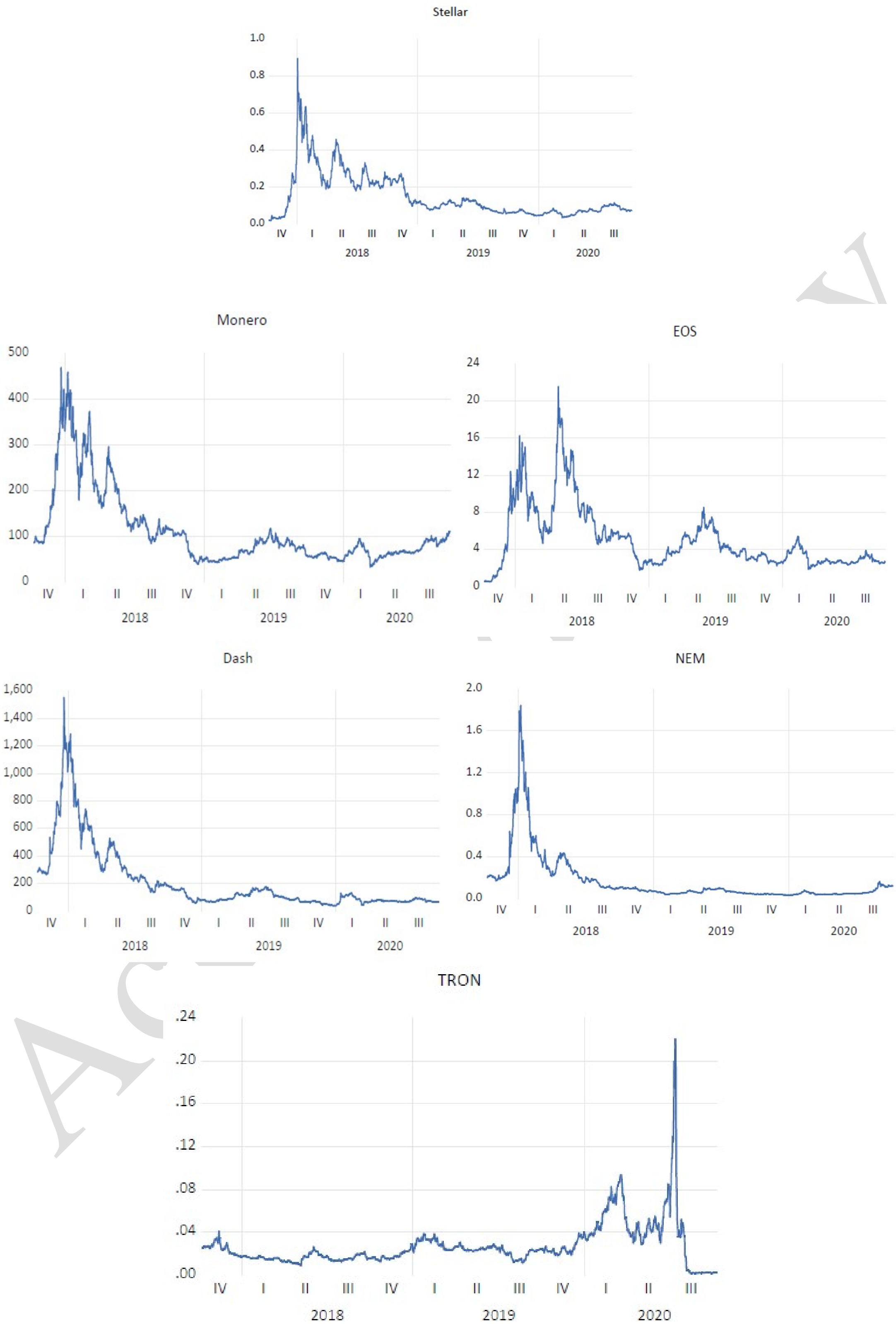


Figure 4.1 Graph of closing price of selected cryptocurrencies

4.2 Descriptive Statistics

The fluctuations and price variability behavior of the selected 15 cryptocurrencies can be observed form the descriptive statistics results. Mean shows the average value of the 1096 observations, Median reflects the middle value, the maximum and minimum value shows the lowest and highest value in the taken time series data. The standard deviation shows the deviation for the sample mean. Kurtosis and Skewness will help us to understand whether the data will be normally distributed or not. For normal distribution the skewness value will be around 0 and kurtosis value will be around 3. For the daily close price normality values, skewness values are above 3 for all considered currencies. Thus they don't follow the normal curve. But while we take the log return normality results, we can say that they are normally distributed, since their values are around 0. The kurtosis value for all is above 3, thus if there is any skewness in the curve, they will have positive skewness(leptokurtic) in the daily closing price as well as log return data.
The same goes for the Jarque-Bera normality result. From the table 4.1, we can infer that the Jarque-Bera value is always greater than the probability value which is zero in all the cases. It means, that the times series data in not normally distributed. Thus, if we take the natural logarithm of the time series data, we can make the series close to normal distribution.

Table 4.1 Descriptive Statistics test result of the selected cryptocurrencies

Descriptive Statistics at Daily Close Price						
	Bitcoin	**Ethereum**	**Tether**	**XRP**	**Litecoin**	**Bitcoin Cash**
Mean	8127.252	319.6168	1.002559	0.416564	80.98281	543.4128
Median	8099.115	228.6543	1.00187	0.307492	59.89181	314.9215
Maximum	19497.4	1396.42	1.07788	3.37781	358.336	3923.07
Minimum	3236.762	84.3083	0.966644	0.139635	23.46433	77.36578
Standard Deviation	2707.337	230.1577	0.777309	0.35287	53.85998	536.9412
Skewness	0.591866	1.849488	1.457021	4.096943	2.059117	2.397252
Kurtosis	4.180167	6.345178	18.91936	25.60934	7.598693	9.678109
Jarque-Bera	127.5935	1135.851	11960.91	26410.05	1740.258	3086.355
Probability	0	0	0	0	0	0
	Binance Coin	**Cardano**	**Chainlink**	**Stellar**	**Monero**	**EOS**
Mean	15.44234	0.117767	2.207911	0.149252	110.8561	4.993291
Median	14.95834	0.072615	0.677269	0.100027	84.42279	3.775409
Maximum	38.81592	1.11412	19.09875	0.896227	469.198	21.5426
Minimum	1.15257	0.020635	0.145255	0.017522	33.01032	0.493225
Standard Deviation	7.776561	0.142995	3.140458	0.123197	81.27206	3.324527
Skewness	0.453659	3.412776	2.705191	1.895201	2.016602	1.723314
Kurtosis	2.95473	17.05949	10.93577	7.335387	6.637386	6.209682
Jarque-Bera	37.68765	11154.42	4212.686	1514.431	1347.044	1012.946
Probability	0	0	0	0	0	0
	NEM	**TRON**	**Dash**			

Mean	0.161055	0.02684	211.9288
Median	0.071616	0.022567	109.669
Maximum	1.84272	0.220555	1550.85
Minimum	0.031043	0.001783	39.87371
Standard Deviation	0.241676	0.020373	237.3759
Skewness	3.66422	3.629928	2.487498
Kurtosis	18.60215	25.77147	9.50933
Jarque-Bera	13572.03	26086.87	3065.236
Probability	0	0	0

Descriptive Statistics of Log Returns						
	Bitcoin	**Ethereum**	**Tether**	**XRP**	**Litecoin**	**Bitcoin Cash**
Mean	0.000745	5.571824	0.00253	-0.0000972	-0.0000526	-0.000347
Median	0.001387	5.432211	0.001869	-0.001619	-0.001097	-0.002664
Maximum	0.225119	7.241667	0.074996	0.606885	0.389321	0.431577
Minimum	-0.46473	4.43448	-0.033925	-0.398968	-0.449062	-0.561348
Standard Deviation	0.042182	0.594	0.007255	0.059671	0.055376	0.069151
Skewness	-1.096242	0.643595	1.290411	1.636467	0.405064	0.094278
Kurtosis	18.85247	2.68168	17.65644	24.00794	12.90103	13.43862
Jarque-Bera	11695.59	80.29056	10113.88	20643.41	4506.695	4977.686
Probability	0	0	0	0	0	0
	Binance Coin	**Cardano**	**Chainlink**	**Stellar**	**Monero**	**EOS**
Mean	0.002615	0.001412	0.002901	0.001252	0.000196	0.001336
Median	0.000615	0.0003	-0.001061	-0.000739	0.000274	0.00031
Maximum	0.481792	0.861543	0.480615	0.666779	0.24825	0.350812
Minimum	-0.543084	-0.50364	-0.614577	-0.409951	-0.494243	-0.504227
Standard Deviation	0.060362	0.074495	0.076995	0.066847	0.055405	0.067816
Skewness	0.145322	2.364168	0.076423	1.384293	-0.782764	0.189096
Kurtosis	16.96003	29.99378	10.15697	17.85144	10.58779	10.12907
Jarque-Bera	8903.484	34296.64	2340.217	10422.52	2742.672	2327.477
Probability	0	0	0	0	0	0
	NEM	**TRON**	**Dash**			
Mean	-0.000446	-0.00224	-0.001383			
Median	0.000238	-1.6E-05	-0.001464			
Maximum	0.995577	0.523147	0.43775			

Minimum	-0.36145	-0.78667	-0.459331
Standard Deviation	0.068555	0.080889	0.057618
Skewness	2.927396	-2.17355	0.411026
Kurtosis	46.71821	26.19964	14.37925
Jarque-Bera	88847.24	25441.83	5944.11
Probability	0	0	0

4.3 Stationarity

For the Stationaity test, we have used ADF and KPSS unit root test and we have compared it with the Mackinnon (1996) standard values. In this paper, the defined probability value (for ADF) is compared with the resulted probability value for each coin. From the result (Table 4.2), we can infer that most of the times, the resulted probability is lower than the defined probability for daily closing price data. Thus this proves that the data is not stationary. But while considering the log return of the close price data, we can say that all the resulted probability is higher than the defined probability, thus making the data stationary.

Table 4.2 Stationarity test (ADF and KPSS) result of the selected Cryptocurrencies

ADF for daily Close price								
	Bitcoin	**Ethereum**	**Tether**	**XRP**	**Litecoin**	**Bitcoin Cash**	**Binance Coin**	
t statistics	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	
Probability defined	0.1162	0.417	0	0.0049	0.0577	0.2892	0.2938	
Probability	0.012	0.1497	0	0.0036	0.0211	0.1624	0.0296	
Hypothesis	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	
	Cardano	**Chainlink**	**Stellar**	**Monero**	**EOS**	**NEM**	**TRON**	**Dash**
t statistics	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284
Probability defined	0.0316	0.5488	0.0986	0.3718	0.0793	0.0132	0.0578	0.1517
Probability	0.0451	0.1487	0.0412	0.1293	0.0221	0.0619	0.0289	0.1463
Hypothesis	Accept H0	Reject H0	Reject H0	Reject H0	Reject H0	Accept H0	Reject H0	Reject H0
ADF for Log Return								
	Bitcoin	**Ethereum**	**Tether**	**XRP**	**Litecoin**	**Bitcoin Cash**	**Binance Coin**	
t statistics	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	
Probability defined	0	0	0	0	0	0	0	
Probability	0.5421	0.5794	0.0065	0.9913	0.9732	0.9007	0.1519	
Hypothesis	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	
	Cardan	**Chainlink**	**Stellar**	**Monero**	**EOS**	**NEM**	**TRON**	**Dash**

	o							
t statistics	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284	-2.284
Probability defined	0	0	0	0	0	0	0	0
Probability	0.604	0.1908	0.5286	0.8742	0.4841	0.766	0.4949	0.4367
Hypothesis	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0

KPSS for daily Close price

	Bitcoin	**Ethereum**	**Tether**	**XRP**	**Litecoin**	**Bitcoin Cash**	**Binance Coin**
t statistics	0.463	0.463	0.463	0.463	0.463	0.463	0.463
P value	0	0	0	0	0	0	0
Hypothesis	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0

	Cardano	**Chainlink**	**Stellar**	**Monero**	**EOS**	**NEM**	**TRON**	**Dash**
t statistics	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463
P value	0	0	0	0	0	0	0	0
Hypothesis	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0

KPSS for Log Return

	Bitcoin	**Ethereum**	**Tether**	**XRP**	**Litecoin**	**BitcoinCash**	**Binance Coin**
t statistics	0.463	0.463	0.463	0.463	0.463	0.463	0.463
P value	0.5587	0.5076	0.876	0.957	0.9749	0.8681	0.5518
Hypothesis	Accpet H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0

	Cardano	**Chainlink**	**Stellar**	**Monero**	**EOS**	**NEM**	**TRON**	**Dash**
t statistics	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463
P value	0.5305	0.4825	0.5355	0.907	0.5143	0.8294	0.5602	0.4962
Hypothesis	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0	Accept H0

The same can be explained for the KPSS test result. For the daily closing price the resulted probability value is zero for all instances, thus making it lower than the defined probability of 0.463. But for the natural log return value for closing prices, in all cases the resultant probability is greater than the defined probability (0.463), thus making all the coins stationary. We can also test the stationarity of the given data with the help of defined and resultant t-statistics value at 5% significant level.

4.4 Day of the week effect

With the help of the dummy variable regression day of the week anomaly will be studied. In Equation (1), one will be allocated to the dummy variables for all Mondays and 0 for other days. Correspondingly, 1 will be allocated as dummy variable value to all Tuesdays and 0 for other day. The same will be followed for all days except Sunday, that is, 1 will be allocated for dummy variable for the corresponding day and 0 for the remaining days. No dummy variable value will be allocated for Sunday, because it taken as reference variable and it will be represented by the constant term (Equation (1)).

The OLS model is used to check the heteroskedasticity of the time series. From the result, it is proved that all the coins are Heteroskedastic, thus to find the day of the week anomaly GARCH(1,1) model is used. To get the accurate result, we are going to test the presence of Autocorrelation, ARCH test is done and it proves that Autocorrelation is present in all the coins. To be assured about the accuracy of the result, the Ljung-Box test is done with the maximum lag and found out that the residuals are uncorrelated at 1% significant(the LB value should be above 0.010) except for Tether.Thus Tether to get the accurate result, we go for GARCH(1,1) ARMA (1,1) model was used to test the day of the week anomaly.

Table 4.3 GARCH (1,1) and GARCH(1,1) ARMA(1,1) model results for the selected Cryptocurrencies

	Bitcoin		Ethereum		Tether	
Variable	**Coefficient**	**Probability**	**Coefficient**	**Probability**	**Coefficient**	**Probability**
	Mean Equation					
Monday	0.003559	0.3637	0.010333	0.3509	-0.000464	0.5
Tuesday	-0.002067	0.619	0012869	10.2450	-0.000278	0.6121
Wednesday	-0.001929	0.5805	**0.025844**	**0.0150**	-0.000453	0.4539
Thursday	**-0.007406**	**0.0354**	0.012895	0.3108	0.000347	0.5486
Friday	0.000308	0.9424	0.0007555	0.5801	-0.000071	0.9104
Saturday	0.001589	0.7671	0.008216	0.5402	0.00027	0.6525
C	0.002018	0.4532	5.347826	0	**0.002577**	**0.0451**
AR(1)					0.933048	0
MA(1)					-0.564413	0
	Variance Equation					
C	0.000113	0	0.00186	0	0.0000805	0
ARCH Term	0.135601	0	1.067627	0	0.37255	0
GARCH Term	0.815253	0	-0.067166	0	0.695861	0
Adjusted R Squared	-0.004502	0	-0.134964	0	-0.00975	0
Durbin-Watson Stat	2.051126	0	2.004894	0	2.060256	0
LB (Q)	0.987	0	0.128	0	0	0
LB (Q2)	1	0	0.547	0	0	0

	XRP		Litecoin		Bitcoin Cash	
Variable	**Coefficient**	**Probability**	**Coefficient**	**Probability**	**Coefficient**	**Probability**
	Mean Equation					
Monday	0.005958	0.1457	-0.000606	0.917	0.007646	0.231
Tuesday	0.004809	0.2834	0.003049	0.5755	-0.000876	0.8873
Wednesday	-0.000718	0.8781	-0.002152	0.7116	-0.001392	0.8827

Thursday	**-0.008935**	**0.0255**	-0.006765	0.1927	**-0.014892**	**0.0081**
Friday	0.001124	0.8236	0.008704	0.1393	0.006353	0.3136
Saturday	0.006267	0.241	0.011041	0.0715	0.011857	0.1231
C	-0.002346	0.4716	-0.002054	0.6187	-0.00144	0.7496
	Variance Equation					
C	0.000122	0	0.000248	0	0.000369	0
ARCH Term	0.152438	0	0.094224	0	0.134718	0
GARCH Term	0.820656	0	0.821947	0	0.798721	0
Adjusted R Squared	-0.012137	0	0.00884	0	0.001438	0
Durbin-Watson Stat	1.942105	0	2.046237	0	1.949277	0
LB (Q)	0.387	0	0.859	0	0.975	0
LB (Q2)	0.838	0	0.228	0	0.719	0

	Binance Coin		**Cardano**		**Chainlink**	
Variable	**Coefficient**	**Probability**	**Coefficient**	**Probability**	**Coefficient**	**Probability**
	Mean Equation					
Monday	0.00387	0.4444	0.002488	0.6926	0.004196	0.5822
Tuesday	0.000373	0.9353	0.001087	0.8514	0.01282	0.0867
Wednesday	0.000188	0.9689	0.000672	0.9149	0.0091	0.2239
Thursday	-0.004907	0.2729	**-0.011353**	**0.0239**	-0.00486	0.4789
Friday	**0.010445**	**0.0293**	0.0083	0.2062	0.008292	0.2906
Saturday	0.008688	0.1408	0.013332	0.0607	0.013387	0.144
C	-0.000914	0.7989	-0.00246	0.5657	-0.002545	0.6656
	Variance Equation					
C	0.0000987	0	0.000159	0	0.0000933	0
ARCH Term	0.133782	0	0.10062	0	0.08554	0
GARCH Term	0.848883	0	0.862937	0	0.906849	0
Adjusted R Squared	0.003762	0	-0.001562	0	-0.002875	0
Durbin-Watson Stat	1.906528	0	2.006976	0	2.072186	0
LB (Q)	0.925	0	0.198	0	0.895	0
LB (Q2)	1	0	0.728	0	0.74	0

	Stellar		**Monero**		**EOS**	
Variable	**Coefficient**	**Probability**	**Coefficient**	**Probability**	**Coefficient**	**Probability**
	Mean Equation					
Monday	0.00069	0.9021	-0.000595	0.934	0.007582	0.2305
Tuesday	-0.004538	0.4048	-0.005405	0.3102	0.00482	0.3919

Wednesday	-0.000861	0.8728	0.00353	0.4834	0.004963	0.4024
Thursday	**-0.01342**	**0.0056**	**-0.012264**	**0.0062**	-0.009835	0.0798
Friday	0.003849	0.527	0.00168	0.7528	0.012636	0.0695
Saturday	0.00199	0.7656	0.002549	0.7144	0.013048	0.0657
C	0.00071	0.8579	0.002688	0.4715	-0.004599	0.2997
	Variance Equation					
C	0.0000818	0	0.000111	0	0.0000757	0
ARCH Term	0.061903	0	0.104247	0	0.055147	0
GARCH Term	0.910991	0	0.865695	0	0.929	0
Adjusted R Squared	-0.002888	0	0.001168	0	0.001624	0
Durbin-Watson Stat	1.948936	0	2.232655	0	2.0239	0
LB (Q)	0.602	0	0.204	0	0.123	0
LB (Q2)	0.481	0	0.986	0	0.734	0

	NEM		**TRON**		**Dash**	
Variable	**Coefficient**	**Probability**	**Coefficient**	**Probability**	**Coefficient**	**Probability**
	Mean Equation					
Monday	0.012565	0.0134	0.005443	0.3572	-0.002407	0.6229
Tuesday	0.003907	0.431	**0.017956**	**0.0023**	-0.007581	0.1108
Wednesday	**0.012166**	**0.0211**	**0.015251**	**0.0088**	-0.002491	0.5637
Thursday	0.008529	0.1057	0.006351	0.2779	**-0.014534**	**0.0006**
Friday	**0.013459**	**0.0186**	0.007095	0.2319	-0.001017	0.8462
Saturday	**0.014311**	**0.0128**	**0.013566**	**0.0317**	0.002982	0.509
C	**-0.009776**	**0.0104**	-0.008268	0.0881	0.000166	0.962
	Variance Equation					
C	0.000484	0	0.000167	0	0.000166	0
ARCH Term	0.383506	0	0.26437	0	0.235576	0
GARCH Term	0.587679	0	0.7466	0	0.760104	0
Adjusted R Squared	-0.002658	0	-0.007082	0	-0.002554	0
Durbin-Watson Stat	2.298236	0	1.844075	0	2.034937	0
LB (Q)	0.33	0	0.452	0	0.903	0
LB (Q2)	1	0	0.859	0	0.686	0

From Table 4.3, we can infer that Litecoin, Chainlink and EOS have no significant day of the week anomalies for any weekdays at 5% significance. Bitcoin, XRP, Bitcoin Cash, Cardano, Stellar, Monero and Dash have negative coefficient and significant at 5% significance. Ethereum, Tether, Binance Coin, NEM and TRON have positive coefficient on different days. Ethereum has on Wednesday, Tether has on Sunday (Indicated by C (constant)), Binance Coin has on Friday, NEM has on Wednesday, Friday and

Saturday and TRON has on Tuesday and Wednesday. Also, NEM has negative coefficient and significant on Sunday. Table 4.4 shows the summarization of the day of the week anomaly for each coin along with its corresponding Coefficient and Probability. The positive and negative signs of coefficient indicate that the return will be positive and negative respectively on those days. These days have high volatility that is price fluctuations.

Table 4.4 Summarization Table of the day of the week anomaly of the 15 selected cryptocurrencies

Coin	Coefficient		Probability	Days
Bitcoin	+			
	-	-0.007406	0.0354	Thursday
Ethereum	+	0.025844	0.0150	Wednesday
	-			
Tether	+	0.002577	0.0451	Sunday
	-			
XRP	+			
	-	-0.008935	0.0255	Thursday
Litecoin	+	**No day of the week anomaly for any days**		
	-			
Bitcoin Cash	+			
	-	-0.014892	0.0081	Thursday
Binance Coin	+	0.010445	0.0293	Friday
	-			
Cardano	+			
	-	-0.011353	0.0239	Thursday
Chainlink	+	**No day of the week anomaly for any days**		
	-			
Stellar	+			
	-	-0.01342	0.0056	Thursday
Monero	+			
	-	-0.012264	0.0062	Thursday
EOS	+	**No day of the week anomaly for any days**		
	-			
NEM	+	0.012166, 0.013459, 0.014311	0.0211, 0.0186, 0.0128	Wednesday, Friday, Saturday
	-	-0.009776	0.0104	Sunday
TRON	+	0.017956, 0.015251	0.0023, 0.0088	Tuesday, Wednesday
	-			
Dash	+			
	-	-0.014534	0.0006	Thursday

5. Conclusions

The Cryptocurrency is an emerging blockchain technology in Finance and it becomes the topic of interest for most investors and researchers in present time. The day of the week of top 15 Cryptocurrencies, that was introduced before October 2017 has been examined in this paper using GARCH Dummy variable regression. For the time period October 9, 2017 to October 8, 2020 covering 1096 trading days, the presence of day of the week anomaly 12 out of 15 cryptocurrencies is proved with evidence.
The behavior of the cryptocurrencies during the sample period was studied with the help of Normality test. The stationarity of the coins has been studied with the help of ADF and KPSS test. In both the cases the natural logarithmic of the daily closing price is more close to normal distribution and Stationary. Thus the log return of closing price is taken for the further analysis for getting more accurate results. Then with the help of dummy variable regression (Equation (1)), the ARCH effect is verified and GARCH model is used to verify the presence of day of the week anomaly for the samples taken.
From the Table 4.3, we can conclude that most of the coins like Bitcoin, XRP, Bitcoin Cash, Cardano, Stellar, Monero and Dashhave negative returns and significant at 5%. The reason for the negative return on Thursday may be due to it being on the middle of the week and the investors assumed that since it is the middle of the week and the return would be low. The investors presume that the return will be high on the beginning or the end of the week. So this may be the reason, why these coins have negative return on Thursday. The other coins exhibit positive returns on the other days than Thursday are either the beginning or the end of the week. But this assumption is based on the mindset of the investors and there is no valid evidence to prove this assumption and the result may change based on the considered time period. The study related to cryptocurrencies other than Bitcoin in very few. Considering growing momentum of the cryptocurrency market, this study will help the potential investor and trader to take right trading decision regarding the time of purchase and sales, and also it will help them to understand the market efficiency of a particular coin as this study will cover nearly 85% of the whole cryptocurrency market.

Reference

[1]. Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. Finance Research Letters, 31.
[2]. AMANULLAH, K. BitcoinsIn India–An Overview (2020). ISSN: 0474-9030, Vol-68.
[3]. Banwari, V. (2017). CRYPTOCURRENCY-SCOPE IN INDIA. International Research Journal of Management Sociology & Humanities, 8(12), 82-92.
[4]. Baur, D. G., Cahill, D., Godfrey, K., & Liu, Z. F. (2019). Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. Finance Research Letters, 31, 78-92.
[5]. Borowski, K., & Matusewicz, M. (2017). THE DAY-OF-THE-WEEK EFFECT ON THE EXAMPLE OF 82 CRYPTOCURRENCIES. Journal of Applied Finance & Banking, 7(3), 57-64.
[6]. Caporale, G. M., & Plastun, A. (2019). The day of the week effect in the cryptocurrency market. Finance Research Letters, 31.
[7]. Caporale, G. M., Plastun, A., & Oliinyk, V. (2019). Bitcoin fluctuations and the frequency of price overreactions. Financial Markets and Portfolio Management, 33(2), 109-131.
[8]. Decourt, R., Chohan, U. W., & Perugini, M. L. (2019). Bitcoin Returns and the Weekday Effect. Available at SSRN 3435176.
[9]. Durai, S. R. S., & Paul, S. (2018). Calendar anomaly and the degree of market inefficiency of Bitcoin. Madras School of Economics working paper, (168).
[10]. Kaiser, L. (2019). Seasonality in cryptocurrencies. Finance Research Letters, 31.

[11]. Kavitha, P., Mohanasundari, M., Vidhyapriya, P., & Sundharesalingam, P. (2020). An Analysis of the Relationship between Risk and Return in the Gold Market of Asian Countries. International Journal of Scientific & Technology Research , 9(3), 6850-6859

[12]. Kinateder, H., & Papavassiliou, V. G. (2019). Calendar effects in Bitcoin returns and volatility. Finance Research Letters, 101420.

[13]. Kurihara, Y., & Fukushima, A. (2017). The market efficiency of Bitcoin: A weekly anomaly perspective. Journal of Applied Finance and Banking, 7(3), 57.

[14]. Ma, D., & Tanizaki, H. (2019). The day-of-the-week effect on Bitcoin return and volatility. Research in International Business and Finance, 49, 127-136.

[15]. Latif, M., Arshad, S., Fatima, M., & Farooq, S. (2011). Market efficiency, market anomalies, causes, evidences, and some behavioral aspects of market anomalies. Research journal of finance and accounting, 2(9), 1-13.

[16]. Mbanga, C. L. (2019). The day-of-the-week pattern of price clustering in Bitcoin. Applied Economics Letters, 26(10), 807-811.

[17]. Mohania, S., & Singh, S. AN ANALYSIS OF CRYPTOCURRENCY AND ITS CHALLENGES. EPRA International Journal of Multidisciplinary Research (IJMR), 104.

[18]. Plastun, A., Drofa, A. O., &Klyushnik, T. V. (2019). Month of the year effect in the cryptocurrency market and portfolio management. European Journal of Management Issues, 27(1-2), 29-35.

[19]. Robiyanto, R., Susanto, Y. A., &Ernayani, R. (2019). Examining the day-of-the-week-effect and the-month-of-the-year-effect in cryptocurrency market. JurnalKeuangan Dan Perbankan, 23(3), 361-375.