ANALYSIS OF TRENDS AND VOLATILITY OF CRYPTOCURRENCIES IN THE GLOBAL MARKET

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DECLARATION

This project is my original work and has not been submitted for the award of a Masters degree in any other university.

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We declare that this project has been submitted with our approval as supervisors in its present form as satisfying the research requirements for the Degree of **Master of Science in Applied Statistics**

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DEDICATION

To all my colleagues who supported me and encouraged me to put more efforts in my career. I owe it all to you

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ACRONYMS

1. GARCH- Generalized AutoRegressive Conditional Heteroskedasticity
2. ARIMA-Autoregressive Integrated Moving Average
3. MA-Moving Average
4. AR-Auto Regression
5. GDP- Gross Domestic Product
6. CBDCS-Central Bank Digital Currencies
7. USD-United States Dollars
8. RMSE- Root Mean Square Error of Approximation
9. MAE- Mean Absolute Error
10. XRP - The Currency of the Ripple
11. AIC -Akaike Information Criterion
12. POW -Proof of Work
13. POS- Proof of Stake

ABSTRACT

The motivation of this study was to analyze trends, volatility and model identification for Bitcoin, Ethereum and Ripple cryptocurrencies in the global market.
The study utilized weekly price and cryptocurrency trading datasets from https://coinmarketcap.com. The study period was from 1st February 2015 to 26th December 2021. Two models, Arima and Garch models have been used in the study to determine the trends and volatility in the global market, trends have shown that cryptocurrencies have continued to increase in the market creating a worrying trends of overrunning both the domestic and international currencies, cryptocurrencies have remained unregulated in domestic markets and even in global markets, this have made it difficulty to establish the value of digital assets held by mostly the tech-savvy individuals amounting to billions that have affected the markets both locally and internationally. Model identification was also determined using akaike information criterion values, the models that reported the least akaike information criterion values were considered to be the best models. On volatility, the results revealed that cryptocurrencies prices varied with time positively, which means traders looking to capitalize on volatility for profits may use such indicators as a strength indexes, volumes and establish support and resistance levels.
The results from this study are important for market stability, investment and risk management purposes.

Chapter 1

INTRODUCTION

In this section the chapter was divided into the following: background information, types of cryptocurrencies used in the study, models, statement of the problem, objectives, significance of the study, justification of the methods used in the study and research questions.

1.1 Background Information

Money as a medium of exchange has been accepted by many economies in the world. Different economies have considered certain currencies as their medium of exchange. Their excess supply can cause inflation or reduced demand causes deflation. This, therefore, has called for different countries to put measures to control inflation or deflation. Fernandez-Villa Verde et al.(2020). stated that the introduction of Central Bank Digital Currency (CBDC) gives authority to Central banks to manage inflation or deflation. Many Countries in the world have concentrated on digital currency when handling transactions as stated by Bordo et al,(2017). This new currency has motivated many to come up with new innovations in technology. Cryptocurrency is a decentralized digital currency that uses encryption which is the process of converting data into codes to generate units of currency and validate transactions independent of a Central bank or government. Satoshi Nakamoto (2008), states that cryptocurrencies have no physical image, instead, cryptocurrencies are created, stored, and transacted electronically. Most of the cryptocurrencies are maintained by a community of cryptocurrency miners who are members of the public. Cryptocurrencies originate from two protocols, Proof of Work (POW) and proof of stake (POS). In the POW system, the probability of mining a block is dependent on how much work is done by a miner while in the POS system users can mine depending on how many coins they hold. In this study, three major cryptocurrencies were selected to carry out the research, Bitcoin, Ripple and Ethereum.

1.1.1 Bitcoin

Bitcoin is a digital currency that is decentralized and can be sent from user to user on a peer-to-peer payment protocol that operates on cryptography. This currency is transacted by broadcasting digitally signed messages to the network using bitcoin cryptocurrency wallet software. When trading transactions are verified by network nodes and recorded in a publicly distributed ledger called a blockchain. Bitcoin has several advantages as compared to other currencies. These currencies are easy to access and have liquidity, user anonymity and transparency are independent of central authority, have high return potential, volatility, no government regulations, irreversible, and limited use. However, this currency has also limitations Bitcoin has serious scalability issues and can be an extremely volatile investment.

1.1.2 Ethereum

Ethereum is a cryptocurrency that has decentralized blockchain technology. The technology has applications that help in communicating without being controlled by a central authority. It is the second largest currency after bitcoin by market capitalization. It has the advantages of building and deploying smart contracts and decentralized applications without fraud, controls, or interference from a third party. Ethereum is a software system that is part of a decentralized system, meaning not a single entity controls it, Ethereum was conceived in 2013 by programmer Vitalik Buterin.

1.1.3 Ripple

Ripple currency is a blockchain real-time gross digital payment network that is accepted for transactions and not discriminated between any fiat currency. This currency can use a consensus mechanism through a group of bank-owned servers to meet settlements of transactions. It has its own protocol called XRP. This currency has the following advantages, fast settlement and transaction confirmation is fast, it incurs low fees to complete a transaction, it has a versatile exchange network as compared to others, and it is accepted by large financial institutions. However, it has also its own limitation one of them being it is centralized.

1.1.4 Arima Model

The Arima model is a class of models that 'explains' a given time series based on its own past values, that is, its own lags and the lagged forecast errors, so that equation can be used to forecast future values. Any 'non-seasonal' time series that exhibits patterns and is not a random white noise can be modeled with Arima models. The model is characterized by 3 terms: p, d, q where p is the order of the Arima model is one of the methods used for forecasting. Arima model involves three steps: Identification of the model, estimation of the parameter in the identified model, and diagnostic checks of the model. Since it is an integrated process, it has to undergo differencing for stationary time series and the results of the model are integrated to produce final estimates and predictions. Arima Model is denoted by ARIMA (p,d,q) where p is the number of autos regressive terms, d is the number of nonseasonal differences needed for stationarity, and q is the number of lagged forecast errors in the prediction equation. Depending on the values of p, d and q, an Arima model can be a Moving Average (MA) model, the Auto-Regressive (AR) process, the Auto Regressive Moving Average (ARMA) process, or the Autoregressive Integrated Moving average(ARIMA) process term is the order of the MA term and d is the number of differences required to make the time series stationary.

1.1.5 Garch Model

The Garch model assumes that the error terms variance is determined by an autoregressive moving averages process. This model aids in the prediction of the volatility of returns of financial assets. Developing a Garch model involves three steps. The first step is to create an autoregressive model that fits the data the best. The second step is to calculate the error term's autocorrelations. The last step is to conduct a significance test. The Garch model is generally denoted by Garch (p,q) where p is the number of auto-regressive terms and q is the number of lagged forecast errors.

1.2 Statement of the Problem

Many economies in the global market are moving towards cashless transactions through innovations and digitizing trade possibly using e-wallets. This was one of the newest innovations in the money market. Unfortunately, these currencies are not being regulated by many states across the world including the Central banks of such states. If they were not monitored and regulated they could easily flood the market and replace domestic currency a process called cryptolization, which could Jeopardize the monetary severity of a country. Their continuous usage constantly increased the risk of instability in the majority of markets globally. It was for this noble reason that the study explored through determination of trends and volatility of these currencies in the market and came up with measures of regulating them from the market, and testing the correlation strength of these currencies with the US dollar that helped to understand their impact on the global market. To solve this gap the study used the Arima model and Garch model to determine the trends and volatility of these cryptocurrencies. To understand the correlation strengths, the study employed normality tests, the Shapiro-Wilk test and Dick Fuller test to test the null hypothesis that the unit root test is present in an autoregressive time series model and the Shapiro-Wilk normality test to detect all departures from the normality of the historical times series data under consideration.

1.3 Objectives

1.3.1 General Objective

The general objective of this study was to analyze the trends, volatility, and model identification of cryptocurrency in the global market.

1.3.2 Specific Objectives

1. To determine trends of Bitcoin, Ethereum and Ripple cryptocurrencies in the market.

2. To test correlation strength of Bitcoin, Ethereum and Ripple cryptocurrency and the US dollar in the global market.

3. To determine volatility of Bitcoin,Ethereum and Ripple cryptocurrency in the global market.

1.4 Significance of the Study

Cryptocurrency was a new technology in financial systems that close gaps in the financial sector and be able to help meet traditional banking problems by being a peer-to-peer system. A study by Kelley (2014), stated that cryptocurrencies are meant to reduce problems related to unbanked customers since significant portions of the population in developing countries do not keep money in banks.

Many businesses saw the need for cryptocurrencies for international transactions, for example whenever transactions needed to occur fast in response to an emergency. According to Team (2016) he stated that currencies can be sent internationally, but typically arrive days after being sent and not for the full amount.

The results of this study will help investors to foresee and manage risks while identifying opportunities for alternative diversified and profitable investments.

By studying trends of Bitcoin, Ethereum, and Ripple cryptocurrencies a framework for emerging technologies and a platform for future studies in this area of cryptocurrencies can be created.

The adoption of digital currencies will change the financial markets and improve the money transfer landscape in many economies across the world.

1.5 Statistical Justification for the Methods used in this Study

The Garch model was applied in this study because it provided the best fit in terms of modeling volatility in major cryptocurrencies, Bitcoin, Ethereum, and Ripple. A study by Coporale et al.(2003) indicated that arch model contained a conditional volatility process that was highly persistent. On the other hand, Arima model was used in this study because it provided predictive time series values based on past values. Arima, a parametric method and it should work better for relatively short series when the number of observations was not sufficient to apply more flexible methods.
The U.S. dollar was used in the study because it was accepted across the market globally. Other popular currencies were the euro and the yen. IMF defined the U.S. dollar as the major currency as of the fourth quarter of 2019. It contributed about 60 percent of all known Central bank foreign exchange reserves. That makes it the de-facto global currency.

1.6 Research Questions

This study aim to answer the following research questions:

1. What are the global trends of Bitcoin, Ethereum, and Ripple cryptocurrencies in the market?

2. What is the correlation strength of Bitcoin, Ethereum, and Ripple cryptocurrencies as compared to the US dollar in the global market?

3. What is the volatility of Bitcoin, Ethereum, and Ripple cryptocurrencies in the global market?

   The following chapter will be on literature review.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

In this section the literature was presented according to objectives.

2.1.1 Market Trends of Cryptocurrencies

Trends provided a clear command of any market stability in terms of the asset price. Additionally, trends were identified by trend lines or price actions that highlighted when the price was going up or down. There are three types of trends; uptrends, downtrends, and horizontal trends. It was important to study trends since trend analysis can improve business by helping identify which direction the business was going. It was equally important to study market trends of cryptocurrencies since they are drivers of any developing economies since they can change the economic and social status of any economy. Businesses get more control, thus access to capital becomes much easier due to the advent of blockchain technologies which contribute to the rise of economic activities.

For instance, according to an American basic cable business news channel in march 2021, Morgan Stanley an American investment bank started to offer Bitcoin funds to its wealth management clients. This enabled the company to improve its offerings. A significant amount of funds being raised by various venture capital firms in the market are expected to offer better growth opportunities.(https://cnb.cx/3vwOjou).

Similarly, according to Indian cryptocurrency exchange CoinSwitch Kuber in October 2021, CoinSwitchKuber (cryptocurrency exchange platform) raised over USD 260 million through investo Andreessens Andresen Horowitz a Coinbase venture. Additionally, the growing number of development by key players is anticipated to boost the cryptocurrency industry's growth.

Study by Hong MY et al, (2022). During the time of the COVID-19 pandemic, there was a substantial negative impact on the activities in the global market. As the virus spread many businesses were suppressed. However, against the uncertainties created by the virus, cryptocurrencies such as Bitcoin, Ethereum and Ripple gained more attention. Amid the pandemic, Banks started investing in cryptocurrencies platform for the first time. banks started creating their system (blockchain-based) to enable Business to Business cryptocurrency payments.

A report by Fortune business insight newspaper,the trend of cryptocurrency in the global market experienced tremendous growth. For example, the Market size rose to USD 826.6 million in 2020. The major factors that drive the market growth are the growth of distributed ledger technology and increasing digital investments in the venture capital market. Countries that are developed have started to incorporate cryptocurrency as a financial exchange medium. The rising use of cryptocurrencies like Bitcoin, Ripple, and Ethereum is likely to step up market growth in the near future. Moreover, cryptocurrency is also often utilized with the integration of blockchain technology to attain decentralization and controlled efficient transactions, blockchain offers decentralized, fast, transparent, secure, and reliable transactions. With these advantages of blockchain and digital currency companies, both are investing in cryptocurrencies and collaborating with companies to deliver efficient and quality services to users.
A study by Mubarak,H (2021), stated that because of the increase in information and communication technologies, many transactions in our daily lives transited to online activities and they have changed the way of doing things fast. The rise in the number of online users has brought in a new business opportunity that increased the facilitation of financial activities in trading. The use of digital money increased in many different systems in the past. Cryptocurrency, however, is not fully controlled or regulated hence most economies have not admitted this currency in their daily economic activities.

2.2 Correlation Strength of Cryptocurrencies and US Dollar in the Global Market

From their studies, Kristjanpoller et.al (2020) examined asymmetric multifractality and long rage cross-correlations between conventional currencies, including the Swiss franc, British pound, Euro, Australian dollar, and the main cryptocurrencies. they found significant asymmetric, persistent multifractal cross-correlations between these assets. Using the quantile cross-spectral approach, a study by Eduard (2019) analyzed the connectedness between forex and cryptocurrencies. This study reported negative dependencies between forex and cryptocurrencies from both the short- and long-term perspectives.

The findings from a report Carrick, (2016) indicated that there exist possibilities of using Bitcoin to complement emerging issues in market currencies.In addition to this, digital currency has characteristics that make it well-suited to work as a complement to emerging situations in the market currencies. Similarly, Corelli (2018) analyzed the correlation between major cryptocurrencies and a range of selected fiat currencies. The analysis reported evidence of bidirectional causality between fiat currencies with Bitcoin and Ethereum in most cases.

According to Chan et al, (2017). Bitcoin has the statistical properties of the largest cryptocurrency as demonstrated by market capitalization. in their study, they found out that Bitcoin is the major cryptocurrency characterized by exchange rates when compared to the US Dollar. After fitting the parametric distribution model to them they discovered that returns were non-normal, however, no single popular currency, Bitcoin and Litecoin, the generalized hyperbolic distribution gives the best fit and inverse Gaussian distribution, generalized to distribution, and Laplace distribution gave good fits. They reported that the result derived can be good for prospective investors in making an informed decision for investment and management of risks.
Bitcoin one of the popular cryptocurrencies was formed as a peer-to-peer cash

system and it works well as a currency since it bears the following characteristics. It is stable and backed by the state as stated by Nakamoto (2008). In his study, he noted that the volatility of Bitcoin prices is higher than the popular exchange rates of major currencies US dollar, Euro, and Yen. The increased volatility has adversely affected its potential role in portfolios. In his study, he indicated that Bitcoin cannot function properly as a medium of exchange since it has limited use as a risk diversifier. Contrary he used the deflationary design of Bitcoin since it displays the store of value characteristics over a long horizon.

2.3 Price and Volatility Models

A study by Emaeyak Xavier Udom, (2018), evaluated the performance of the hybrid ARIMA-GARCH model in forecasting Bitcoin daily price returns. In his, study Combined ARIMA and GARCH models with Normal, Student's t, and Skewed student's t distributions to make the series stationary, Bitcoin daily price data was transformed into bitcoin daily returns. By using the Box-Jenkins method, the appropriate model (Arima 2,0,1) as obtained, for capturing volatility of the return's series GARCH (1,1) models with Normal, Student's t and Skewed student's t distributions were used in his studies. It evaluated the performance of the models and the study employed two measures, root means a square error of approximation(RMSE) and mean absolute error(MAE). The results showed that ARIMA (2,0,1)-GARCH (1,1) with Normal distribution outperform the other models in terms of out-of-sample forecast with minimum RMSE and MAE. They proposed that their findings can aid investors, market practitioners, financial institutions, policymakers, and scholars in making informed decisions.

Raskin,(2012) noted that the cost of handling physical cash exceeds one percent of the global market's GDP. Virtual currency issuers similarly should be regulated by central banks by ensuring that digital money issued is also deposited with fully accredited financial institutions Reskin (2012). The theoretical roots of Bitcoin can be found in the Austrian school of economics and its criticism of the current fiat money system and interventions undertaken by governments and other agencies, which, in their view, result in aggravated business cycles and massive inflation. A famous name in this field is Hayek

(2013) who noted that government should not have a monopoly over the issuance of money. It was prudent that private banks should be allowed to issue non-interest-bearing certificates based on their registered trademarks. He argued that these certificates or currencies should be open to competition and would be traded at variable exchange rates. He also argued that currencies should be able to guarantee a stable purchasing power and remove other less stable currencies from the market and the result of this process of competition and profit increase would be a highly efficient monetary system where only stable currencies would remain in the market.

Chapter 3

RESEARCH METHODOLOGY

3.1 Introduction

In this section, research design,models used in the study and test statistics have been discussed.

3.1.1 Research Design

The main objective of this study was to analyze the volatility of Bitcoin, Ethereum, and Ripple cryptocurrencies in the global market their market trends, and their correlation strengths against the US dollar in the global market. Even though there were many other cryptocurrencies in the global market, three cryptocurrencies were selected based on their popularity in the market, their market share value, and the availability of their data. The period under consideration was from 1st of february 2015 to 26th december 2021. The source data was obtained from https//coinmarketcap.com.
This study implemented the arima model and garch model in the determination of the trends and volatility of the above-named cryptocurrencies. It also employed the statistical normality test Shapiro-Wilk method and Dickey-Fuller test to test the null hypothesis that a unit root test was present in an auto-regressive time series model.

3.2 Arima Model

The arima model was used for forecasting time series data that has a time series regression model in which the independent variables are lags of the dependent variable and also lags of the forecast errors. The equation was defined as follows.

$$y_t = C + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{3.1}$$

where, y_t was the differenced series, ϕ_1 was the coefficient of the first AR term, p was the order of the AR term, θ_1 was the coefficient of the first MA term, q was the order of the MA term and ϵ_t was the error.

The equation was regressed with its past values $y_{t-1}, y_{t-2} \cdots$. The order of lag was defined with p. Differencing the time series to make it stationary.

The model used time-series data and statistical analysis to interpret the data and make future predictions. It explained data by using time series data on its previous values and used linear regression to make predictions. The equation for p path was provided below and AR(p) model was defined as follow.

$$y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{3.2}$$

where y_t was the data on which the ARMA (p,q) model was to be applied. That means, the series was already power-transformed and differenced, in that order. The parameters ϕ_1, ϕ_2 are AR coefficients.
Equation for a q order moving average (MA) model is given below.

$$y_t = C + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_{t-q} \epsilon_{t-q} \tag{3.3}$$

where y_t was the differenced series and $\theta_1, \theta_2 \cdots$ and are MA coefficients

AR and MA models were combined to obtained the following equation

$$y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_{t-p} y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_{t-q} \epsilon_{t-q} \tag{3.4}$$

3.3 Garch Model

The garch model is a statistical modeling technique used to help predict the volatility of returns on financial assets. It was appropriate for time series data where the variance of the error term was serially autocorrelated following an autoregressive moving average process. The model was useful in assessing risk and expected returns for assets that exhibit clustered periods of volatility in returns.

The Garch Model is defined as follows.

$$y_t = \mu_t + Z_t \tag{3.5}$$

where μ_t is the conditional mean of y_t and Z is the shock at time t.

$$Z_t = \sigma_t \epsilon_t \tag{3.6}$$

where $\epsilon_t \rightarrow$independent and identically distributed N(0,1)

$$\sigma_t^2 = \alpha_0 \sum_{i=1}^{q} \alpha_i Z_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_j^2 \tag{3.7}$$

where σ_t^2 is the conditional variance of y_t. α_0 is the constant term. q is the order of the ARCH terms. p is the order of the Garch terms.

α_i and β_j are the coefficients of the ARCH and GARCH parameters respectively with constraints. $\alpha_0 > 0$, $\alpha_i \geq 0$ for i=1,2,$\cdots$,q, $\beta_j \geq 0$ for j=1,2,$\cdots$,p, $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$

The two models Arima and Garch models have been chosen over other models in this study because of the following , arima model was as a forecasting tool to predict how something will act in the future based on the past performance,it is more flexible than other statistical models.Garch model are widely used for modeling asset return and inflation, they minimize errors in forecasting by accounting for errors in prior forecasting and enhancing the accuracy of ongoing predictions,they are good for alysis and forecasting volatility.

3.3.1 Test of Normality

In this study, a statistical normality test, Shapiro-Wilk,(1965) and Dickey-Fuller,(1979) was implemented to check if a continuous variable follows a normal distribution, and the Dickey-Fuller test to test the null hypothesis that a unit root was present in an autoregressive time series model.

3.3.2 Shapiro-Wilk Test

The Shapiro-Wilk test was selected to analyze whether the distribution of variables follows normal distribution or non-normal distribution. The null hypothesis tested was that the population was normally distributed.
The null hypothesis of the Shapiro-Wilk test was
$H_0 : \theta = 0$(Variable is normally distributed in same population)
versus alternative hypothesis.
$H_1 : \theta < 0$.

Reject the null hypothesis if the p-value is less than 0.05. The test tests the null hypothesis that a sample $x_1, x_2, \cdots, x_n$ came from a normally distributed population.

The test statistics were given by

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{3.8}$$

where
$x_{(i)}$ was the order statistics which represents the smallest value in the sample.

$\bar{x} = \dfrac{x_1 + x_2 + \cdots + x_n}{n}$, sample mean.

a_i is a constant given by

$$(a_1, a_2, \cdots, a_n) = \frac{M^T V^{-1}}{\sqrt{M^T V^{-1} V^{-1} M}} \tag{3.9}$$

where $M = (m_1, m_2, \cdots, m_n)^T$
and $m_1, m_2, \cdots, m_n$ were expected values of the order statistics of iid random

variables sample from the standard normal distribution.

V was the covariance of order statistics
If the test statistic W was smaller the critical threshold (0.05) then the assumption of normality has to be rejected .

3.3.3 Dickey-Fuller Test

When the time series has a trend and was potentially scattered around the trend line, a line can be drawn on data, and use the following test equation:

$$\Delta Z_t = \alpha_0 + \theta Z_{t-1} + \gamma t + \alpha_1 \Delta Z_{t-1} + \alpha_2 \Delta Z_{t-2} + \cdots + \alpha_p \Delta Z_{t-p} + \epsilon_t \quad (3.10)$$

where Δ was the difference operator and y_t was variable of interest at time t.

It was noted that this equation (3.10) has an intercept term and a time trend. Additionally, the number of augmenting lags (p) was determined by minimizing the Schwartz Bayesian information criterion or reducing the Akaike information criterion or lags are dropped until the last lag was statistically significant.

The null hypothesis of the Augmented Dickey-Fuller t-test was
$H_0 : \theta = 0$(the data needs to be differenced to make it stationary)
against
$H_1 : \theta < 0$(The data was stationary and needs to be analyzed by means of using a time trend in the regression model instead of difference in the data)

3.4 Welch's t-Test

This test was used to test the difference in mean prices between different currencies (Bitcoin, Ripple, and Ethereum) and US currencies. Unlike standard student's t-test which assumes that the variance of two populations were equal, Welch's t-test was less restrictive since it does not assume equality of the variance.
The Welch t-statistics are defined as follows

$$t(computed) = \frac{M_A - M_B}{\sqrt{\left(\frac{S_A^2}{n_A} + \frac{S_B^2}{n_B}\right)}} \tag{3.11}$$

where M_A and M_B are means of the two groups and S_A and S_B are corresponding stadard deviations.
The degree of freedom of Welch's test was estimated as follows

$$df = \frac{\left(\frac{S_A^2}{n_A} + \frac{S_B^2}{n_B}\right)^2}{\left[\frac{S_A^4}{n_A^2(n_A-1)} + \frac{S_B^4}{n_B^2(n_B-1)}\right]} \tag{3.12}$$

where n_A and n_B are samples of the two groups.

Now the next chapter will entail data presentation, analysis and discussions.

Chapter 4

DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.1 Introduction

The following chapter provides Data presentations. analysis and discussion.

4.2 Descriptive Statistics

The data has been divided into measures of central tendency and measures of variability. Measures of central tendency are the mean, median, and mode. On the other hand, measures of variability include standard deviation, minimum and maximum variables, range, skewness, and kurtosis.

Table 4.1. Summary of Sample Data used in the Study

	XRP	**Ethereum**	**Bitcoin**
Character	**N=362**	**N=215**	**N=399**
Date	2015-1-25-2021-12-26	2017-11-06-2021-12-13	2015-02-01-2021-12-20
Median price	0.249	357	6399
IQR	0.01,0.46	189,1013	703,10452

In table 4.1, the price is summarized in terms of sample size, median and range.

The weekly data price and cryptocurrency trading datasets were obtained from https//coinmarketcap.com using apical dominance key into R studio. Cryptocurrency transaction closing weekly prices were outsourced from Yahoo finance database,this source was selected because of their reliability results from a similar study conducted by Jenkins Forecast, (2018) and also the data is valid as compared to other sources.

Table 4.2 Descriptive Statistics for Cryptocurrency Prices

Crypto	N	Mean	Sd	Median	Min	Max	Range	Skew	Kurtosis
Ripple	362	0.33	0.39	0.24	0	2.65	2.65	1.97	5.34
Ethereum	215	906.13	1158.51	357.44	85.26	4626.36	4541.1	1.72	1.8
Bitcoin	359	11242	15941	6398.9	223	65467	65243	1.95	2.67

In table 4.2, describes descriptive statistics for the three cryptocurrency prices under study. The table illustrates measure of central tendency, measure of variability and dispersion measures of the currency-specific prices.The standard deviation looks at the values and their deviations from the mean of the sample set, it measures how widely prices dispersed from the average price, if prices trade in a narrow trading range the standard deviation will return a low value that indicates low volatility. For this data set, all the three cryptocurrencies indicates a moderate skewness and kurtosis as exhibited by the degree of decay where the values moving a ways from the center to a positive side.

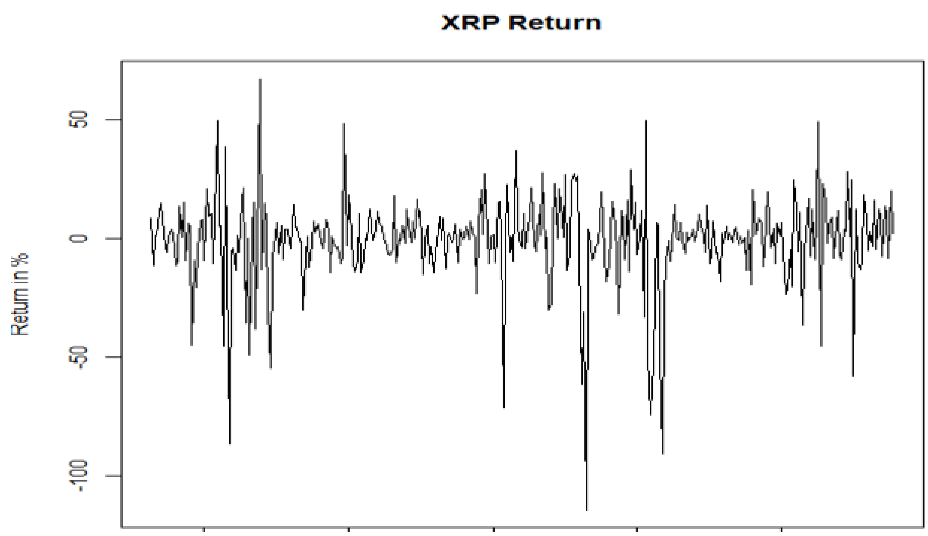
4.3 Price Trends and Volatility Graphs

Figure 4.1, Shows the time series of Ripple prices when applied to Ripple closing prices through the period from January 2015 to December 2021. From the plot volatility of the Ripple, prices were significantly highest in 2018 in comparison to other periods. This suggested that the autocorrelation and seasonality of the structure of Ripple prices under study were not seen. When the samr approach was applied to continuous compounding return of the Ripple prices to check the deviation of price variations through the period or any possibility of volatility. Continuous compounding return series of Ripple identified the changing variance of the prices over time or the possibility of volatility clustering

.

Figure 4.1.Weekly Time Series of Ripple Price.

In figure 4.1, it is clear that the trend of price with time was constant for the period starting 2015 to 2017, thus low volatility. However, prices varied with time from mid-2017 to December 2021 which implied that during this period the prices were highly volatile for this cryptocurrency.



\- 2015 2016 2017 2018 2019 2020 2021

Figure 4.2. Distribution of Ripple Weekly Price Returns.

The figure indicated that the prices were scattered around a constant trend line throughout the period. This implies that the prices were moderately volatile.

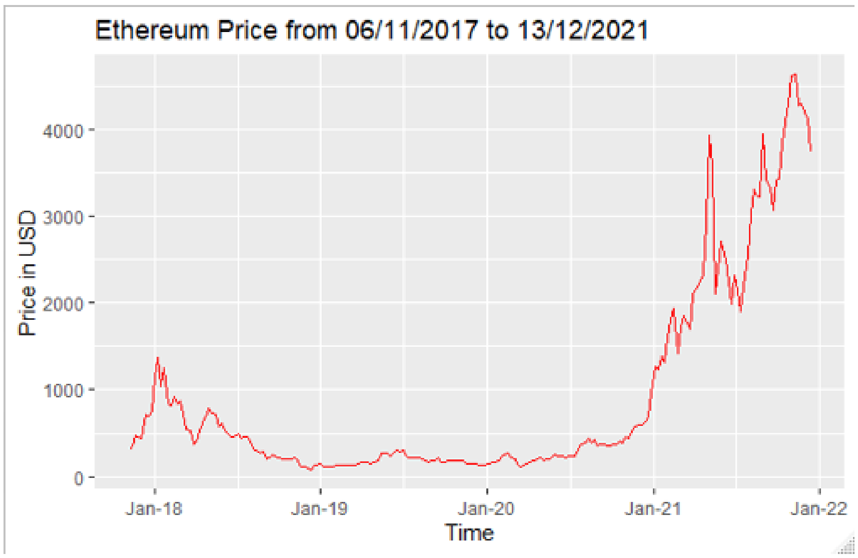


Figure 4.3 Weekly Time Series of Ethereum Prices.

In figure 4.3, it can be seen that the prices remained constant with time and from mid-2020 prices varied with time upwards. Evaluating the time series plot in terms of volatility, it can be seen that the prices were fairly volatile at a lower magnitude at the beginning of 2018 and thereafter prices increased with time, this was interpreted as the highly volatile nature of the market in 2021.

Figure 4.4. Plot time series for Bitcoin prices over the period 2015-2021.

The change of variance of Bitcoin prices is obvious and the time series trend of the prices was different over the periods, it can be observed that the prices were steadily volatile from 2015 to mid-year 2017 after which there was a slight increase in prices until late 2017, thereafter the prices slightly decreased further to late 2020, there was a radical increase in prices as seen in the figure which eventually increased from 10000 to 65000, this was interpreted as a highly volatile nature of the market in 2021.

4.4 Determining the Trends of Cryptocurrencies in the Global Market (Bitcoin, Ethereum and Ripple).

In this section,the analysis for each of the cryptocurrencies has clearly shown the trends, Auto Correlation function(ACF) and Partial Autocorrelation function (PACF) were used to evaluate the correlation among successive points of specific cryptocurrency price plots and the existence of trends among the time series plots.

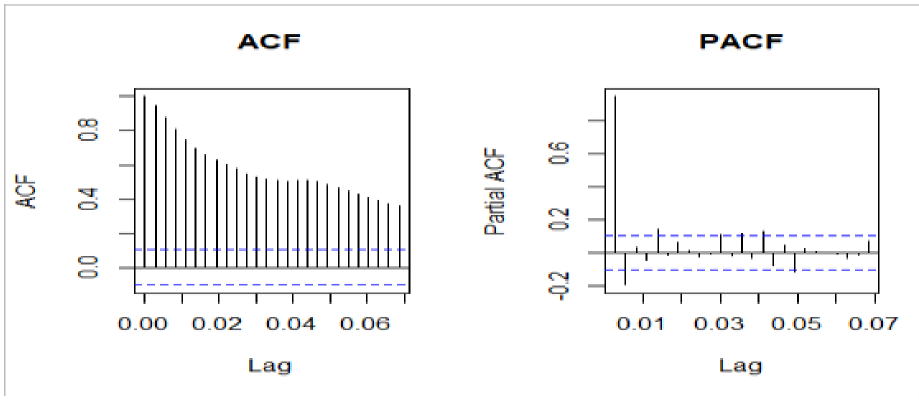


Figure 4.5. ACF and PACF Plot for Ripple Time Series.

The ACF plots in figure 4.5, suggests relatively high correlation between Ripples successive prices points, this indicates a strong evidence of seasonal trends from the time series plots, the PACF plot indicates significant correlation on the Ripple prices time series plots over the period under study.

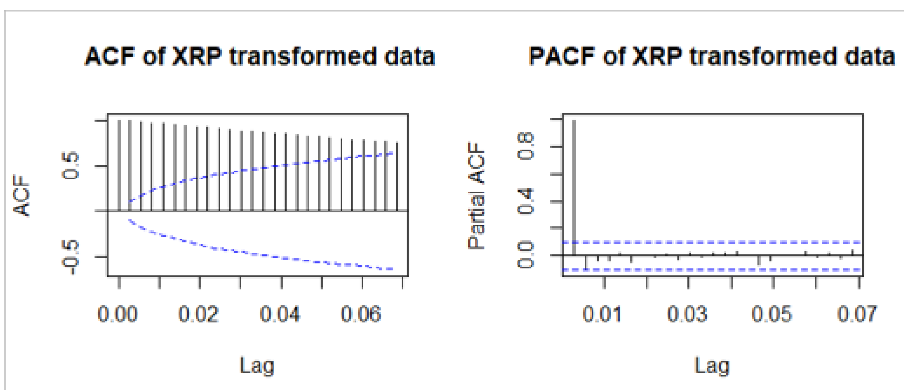


Figure 4.6. ACF and PACF Plot for Ripple Time Series Transformed Data

Natural logarithm transformation was applied to the price data to further explore the stationarity characteristic of the time series, the ACF and PACF plots as shown in figure 4.6, is different from the original series and we can suspect the non-stationarity characteristics of the series have been leveraged and this is also supported by the unit root test.

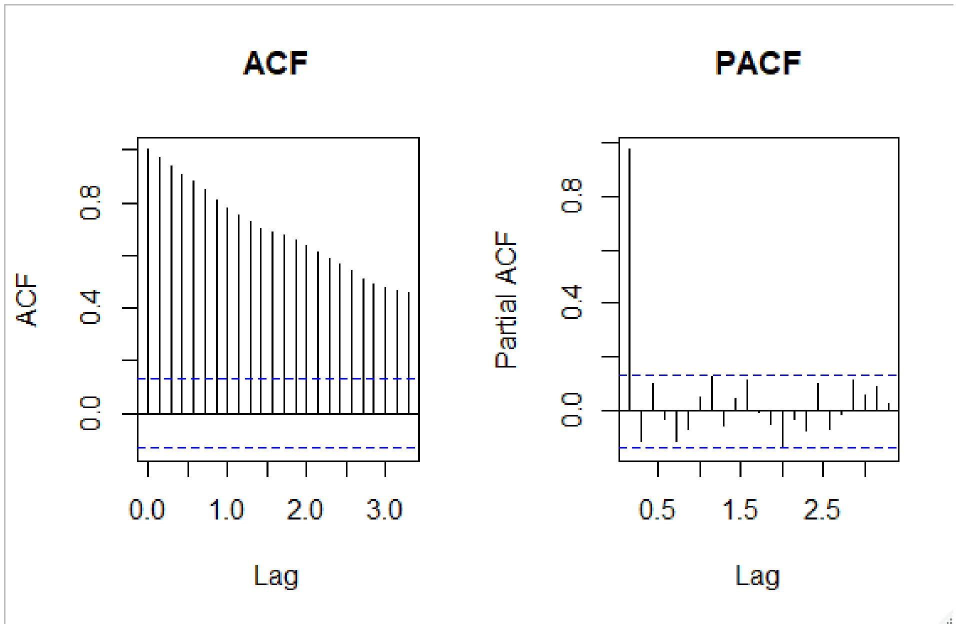


Figure 4.7. ACF and PACF Plot for Ethereum Weekly Price Time Series.

The ACF and PACF in figure 4.7 indicates a strong autocorrelation between successive price points on the Ethereum time series, there was no indication of seasonal trends in the time series data, using Dickey-Fuller test p-value to evaluate the seasonality characteristic(p-value=0.1151) indicates the existence of a seasonality trend among the data points.

Application of the Augmented Dickey-Fuller test on the data reported the results, Dickey-Fuller was -3.0988, Lag order was 5, p-value was 0.1151 The p-value was 0.1151 for the Dickey-Fuller test showed that there was not enough evidence to reject the null hypothesis. This clearly implied existence of non-stationarity, the P-value was 0.000 for the Shapiro test was less than 0.05 which means that null hypothesis was rejected. Hence, the data does not exhibit normality. Shapiro-Wilk normality test W was 0.69018, p-value less than 2.2e-16.

Bitcoin Trend Analysis and Results

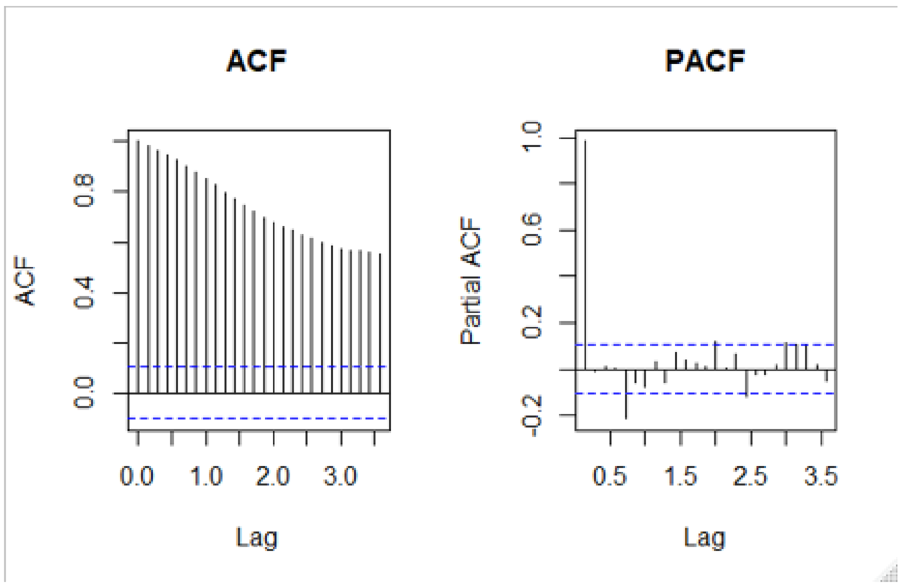


Figure 4.8. ACF and PACF Plot for Bitcoin Time Series

In figure 4.8, there was an existence of a trend which indicates that Bitcoin prices was stable over the period, the stationality assumption is confirmed through Augmented Dickey-Fuller test where p-value was 0.08, which indicates significance as it was less than 0.05. Normality and Stationarity assumptions tests were also applied to each of the cryptocurrency to understand the results.

Application of the Augmented Dickey-Fuller test provided the following results, Dickey-Fuller was -4, Lag order was 7, p-value was 0.03826. alternative hypothesis: stationary the p-value was 0.04 for the Dickey-Fuller test shows that there was enough evidence to reject the null hypothesis. This implies the nonexistence of non-stationarity, similarly, p-value was 0.0 for the Shapiro test is less than 0.05 which means that the null hypothesis was rejected, hence, the data does not exhibit normality characteristics. Shapiro-

Wilk normality test w was 0.67083, p-value< 2.2e-16.

4.5 Using AIC to Test Arima Models

The Akaike information criteria (AIC) was a statistical tool that was used to measure the performance of statistical models. It puts together the goodness of fit and simplicity of the model into a single statistic. When comparing the two models the one that reports the lowest AIC was considered to be the best model.

4.5.1 Model fitted to Bitcoin Data

Table 4.3 present different Arima models fitted and their corresponding AIC.

Arima (p,d,q)	AIC Value
(1,2,1)	453.21
(1,2,2)	453.71
(2,2,1)	452.09
(2,2,2)	451.86

In table 4.3, Arima (2,2,2) has reported the least AIC value, therefore it was selected as the best fit for Bitcoin.
The following was a time series equation which was obtained to predict the current values based on the past time series values.

$$Bitcoin(X_t) = -0.9506X_{t-2} - 0.3883X_{t-3} - 0.2673\epsilon_{t-1} - 0.7525\epsilon_{t-2} \quad (4.1)$$

4.5.2 Model fitted to Ethereum Data

Table 4.4 presents different Arima models fitted and their corresponding AIC Value.

Arima (p,d,q)	AIC Value
(1,0,1)	469.75
(2,0,1)	472.83
(2,0,2)	470.27
(1,1,1)	456.88
(1,1,2)	455.89
(2,1,2)	456.84

In table 4.4, Arima (1,1,2) has recorded the least AIC value, therefore it was selected as the best fit for Ethereum data. The equation below was a predictive model which was used to get the current values based on the past time series values.

$$Ethereum(X_t) = -0.6233X_{t-1} + 0.4395X_{t-2} - 0.3385\epsilon_{t-2} \tag{4.2}$$

4.5.3 Model fitted to XRP Data

The table 4.5 present different Arima models fitted and their corresponding AIC Value.

Arima (p,d,q)	AIC Value
(1,0,1)	-55.5
(2,0,1)	-57.17
(2,0,2)	-55.94
(1,1,1)	57.31
(2,1,1)	-57.58
(2,1,2)	-55.66

From Table 4.5, the Arima (2,1,1) has reported the least AIC value and therefore it was picked as the best fit for Ripple data.

The following equation was derived from the a bove data to help predict the current time series values based on the past values.

$$XRP(X_t) = -0.9982(X_{t-1}) - 0.1408(X_{t-2}) + \epsilon_{t-1} \tag{4.3}$$

4.6 Garch(p,q) Models for Volatility

Garch models were estimated by fitting models into individuals data. After investigating the data it shows that all data have ARCH effects (data was volatile) as shown in the Table 4.6.

Table 4.6:ArchTest results

Data	Chi-square	df	p-value
XRP	250.27	12	< 0.00001
Etherum	160.28	12	< 0.00001
Bitcoin	198.47	12	< 0.00001

In table 4.6, the p-values are small indicating that there exist the arch effects therefore garch model (p,q) should be fitted.
Different Garch (p,q) are fitted to different data and the AIC was used to determine the suitable model fit given data.

4.6.1 Fitting Garch (p,q) Model to Bitcoin Data

Table 4.7, Comparing AIC of Bitcoin data and Garch models.

Garch (p,q)	AIC Value
(1,1)	4744.619
(1,2)	4760.340
(1,3)	4773.430
(2,1)	4752.564
(2,2)	4753.676

This study therefore, selected Garch (1,1) model as suitable model since it reported the smallest value of AIC. Thus, the fitted model was given below to predict the current values.

$$\sigma_t^2 = 9567.6108 + 0.5463 z_{t-1}^2 + 0.1949 \sigma_{t-1}^2 \tag{4.4}$$

$$where\ z_t = \sigma_t \epsilon_t$$

where σ_t^2 is the conditional variance of z_t, and $\epsilon_t.iswhitenoise.$

4.6.2 Fitting Garch (p,q) Model to Ethereum Data

Table 4.8, Comparing AIC of Ethereum data and Garch models.

Garch (p,q)	AIC Value
(1,1)	2613.52
(1,2)	2620.653
(1,3)	2625.81
(2,1)	2600.873
(2,2)	2618.741

In table 4.8, Garch (2,1) reported the least AIC value , here the study concludes that the fit was the best. The fitted model was given below to predict the current values based on the past time series values.

$$\sigma_t^2 = 3289 + 0.7883 z_{t-1}^2 + 5.046e^{-11}\sigma_{t-1}^2 + 0.01626\sigma_{t-2}^2 \tag{4.5}$$

$$where\ z_t = \sigma_t \epsilon_t$$

where σ_t^2 is the conditional variance of z_t, and $\epsilon_t.iswhitenoise.$

4.6.3 Fitting Garch (p,q) Model to XRP Data

The table 4.9 Comparing AIC of XRP data and Garch models.

Garch (p,q)	AIC Value
(1,1)	-548.657
(1,2)	-520.7709
(1,3)	-515.6812
(2,1)	-541.9975
(2,2)	-512.093

From Table 4.9 Garch(1,1) model reported the least AIC value , the study concludes that this was the best fit. The fitted model is given below to predict the current time series values.

$$\sigma_t^2 = 1.070e^{-14} + 1.039 z_{t-1}^2 + 0.06784\sigma_{t-1}^2 \tag{4.6}$$

$$where\ z_t = \sigma_t \epsilon_t$$

where σ_t^2 is the conditional variance of z_t, and $\epsilon_t.iswhitenoise.$

4.7 Testing the Correlation Strength of Cryptocurrencies and the US dollar in the Global Market

The analysis was performed on Bitcoin, Ethereum, and Ripple cryptocurrencies against the US dollar to test if there is any significant relationship between the cryptocurrency and the US dollar currencies. The data wwas analyzed using Welch's t-test since there was an unequal sample size for the study. Welch's t-test is an adaptation of the student t-test and it is more reliable when the two samples have unequal variance or unequal sample size.

Table 4.10 provides welch two sample t-test of Ripple and US dollar prices.The statistical test was used to evaluate statistical difference between XRP cryptocurrency and US dollar prices in the market over the period.

Table 4.10: Two sample t-test between Ripple and US dollar prices.

Welch two sample t-test			
statistics t-value	df	p-value	95% confidence interval
-603.82	376.22	1.000	(-95.53019,Inf)

In table 4.10, t-test statistic between the two prices as presented depicts no statistical difference at 95% Confidence interval between XRP prices and US dollar prices in the market for the period 2015-2021.This indicates that the prices for Ripple(XRP) and US dollar prices were fairly same throughout the period, a P value is greater than 0.05 which means no effect was observed.

Table 4.11 Two Sample t-test between Ethereum Prices and US dollar Prices.

Welch two sample t-test			
statistics t-value	df	p-value	95% confidence interval
10.258	214	2.2 e^{-16}	(679.9974,Inf)

In table 4.11, t-test statistics suggest that Ethereum prices was higher than US dollar prices over the period.There is a significant statistical difference between the cryptocurrency price and dollar price at 95% CI, its true since p-value was less than 0.05 meaning there was a significance effect.

Table 4.12 Two Sample t-test between Bitcoin Prices and US dollar Prices

Welch two sample t-test			
statistics t-value	df	p-value	95% confidence interval
13.249	358	2.2 e^{-16}	(9759.243,Inf)

In table 4.12, t-test statistics, a p-value was less than 2.2e-16), therefore it suggest that Bitcoin prices were higher that US dollar prices over the period, there was a significant statistical difference between the cryptocurrency price and dollar price at 95% CI evidenced by p-value was 0.000 which was less than 0.05.

The following chapter will entail the summary, conclusions and recommendations.

Chapter 5

SUMMARY,CONCLUSION AND RECOMMENDATION

5.1 Introduction

In this chapter, we presents a detailed summary,conclusions and recommendation from the study.

5.1.1 To Determine Trends of Cryptocurrencies in the Global Market.

The selected cryptocurrencies; Bitcoin, Ethereum, and Ripple were analyzed separately to clearly show the trends of individual cryptocurrencies. This was necessitated so because of unequal periods in the datasets of inceptions of each cryptocurrency.

The trends of Ripple, the auto-correlation function, and partial auto-correlation functions were subjected to the datasets of the prices of ripple cryptocurrency to determine the possibility of trends among the time series plots. The ACF plots in figure 4.5 indicated a relatively high correlation between ripple cryptocurrency successive price points. In conclusion, there was strong evidence of seasonal trends from the time series plots. We further subjected the data to an augmented Dickey-Fuller test to determine if the null hypothesis has a unit root present in the time series sample. The Shapiro-Wilk Normality test has also been applied to test if the variables used are normally distributed. The results indicated that the p-value clearly shows that there was enough evidence to reject the null hypothesis and conclude that there was nonexistence of nonstationarity. Similarly, the p–value of Shapiro-Wilk Normality test was 2.2e-16 which was less than a 0.05 significance level. In this case, we reject the null hypothesis and therefore conclude that the data doesn't show normality behavior.

The trends of Ethereum, the ACF, and PACF plots in figure 4.7 indicate a strong autocorrelation between successive Ethereum time series data. There was no clear indication of seasonal trends in the time series data. Evaluating the Augmented Dickey-Fuller test, the P-Value was 0.1151 which indicates the existence of seasonality trends among the data series. The P-value of the Shapiro- Wilk Normality test was 2.2e-16 which was less than a 0.05 significance level. In this case, we reject the null hypothesis and conclude that the Ethereum Data does not exhibit normality.

The trends of Bitcoin, the ACF, and PACF plots in figure 4.8 shows the existence of trends. Bitcoin prices were stable for some time. The stationarity assumption is confirmed through the Augmented Dickey-Fuller test, the P-value is 0.03826, Shapiro Wilk Normality test P-value is 2.2e-16.In this case, Since the p-value is less than 0.05 significance level, we reject the null hypothesis and conclude that Bitcoin data doesn't show normality behavior.

The significance of these results will help investors to make better-informed decisions in selecting appropriate investment funds that contribute better returns and lower risks. Also, the government may use the results to come up with a framework on how to regulate digital money in the economy. To the Academia fraternity, it will form a basis for further research and studies.

5.1.2 Correlation Strength of Cryptocurrencies and the USD in the Global Market

The statistical relationship between XRP and US dollar prices when analyzed, at 95% confidence interval, there is no statistical difference between XRP and US dollar prices in the global market for the period between 2015 to 2021. This indicates that the two currency prices are fairly the same.
On the other hand the analysis of Ethereum prices and the US dollar at a

95% confidence interval shows that the prices of Ethereum are much higher than those of the US dollar. This was shown by the P-value which is less than the 5% significance level

Similarly, the analysis of Bitcoin and the US dollar showed that there was a statistical difference between the US dollar and Bitcoin. This was evidenced by the p-value which was less than 5% significance level.

The importance of these results will provide an opportunity to end over-dependency on the US Dollar by various Central banks across the world. This is so because any fluctuation in the value of the US Dollar will likely affect the entire market.

5.1.3 To Determine Volatility of Cryptocurrencies in the Global Market

The volatility of XRP prices was significantly higher in 2018 in comparison to other years. This suggested that the autocorrelation and seasonality structure of XRP prices under this study was not determinable. However, after further subjecting the data to continuous compounding, the return on XRP prices to check if there was any deviation of price variation in the study, the results showed that the highest volatility was reported in 2018 and until 2021 the price variation was quite stable and only changed with time after some time. The volatility of Ethereum was fairly volatile at a lower magnitude at the beginning of 2018 and thereafter there was a steady decrease in prices with time at the global market at the end of 2020 Beyond this period prices started increasing again which eventually rose from USD 500 to 5200. This reported a highly volatile market in 2021. The volatility of Bitcoin prices was volatile from 2015 to midyear 2017 after which there was a slight increase in prices until late 2017. Beyond this period prices negatively increased through 2020 after which prices started to increase positively from USD 10000 to 65000. This presents a highly volatile nature of the global market in 2021.

5.2 Answers to Research Questions

The following section will provide answers to all research questions in chapter one.

5.2.1 What is the global trends of Bitcoin,Ethereum and Ripple cryptocurrencies in the market?

Cryptocurrencies are one of the recent revolutionary innovations in the global market.The study have revealed that there was the existence of seasonality trends from ACF and PACF plots.This means that cryptocurrency trends in the global market has continued to occur. There was mixed periods of increase and periods of decrease in prices variations.

5.2.2 What is the Correlation Strength of Bitcoin,Ethereum and Ripple Cryptocurrencies as Compared to USD in the Global Market?

To provide more detailed information between cryptocurrencies and the US dollar, Welch's t-test to test the variables in these cryptocurrencies was implemented, Bitcoin, Ethereum, and Ripple and the US dollar to find out if there is any statistical difference. The results generally indicated that the Ripple cryptocurrency and the US dollar are fairly the same but Bitcoin and Ethereum are not correlated with the US dollar which means Bitcoin and Ethereum have a strong correlation strength than the US dollar.

In this study, results go in the direction of the evident significant bidirectional negative causal relationship between digital and conventional currencies. Therefore, it was recommended that investors who are more interested in trading in the US dollar market should closely follow the cryptocurrency prices.

5.2.3 What is the volatility of Bitcoin,Ethereum and Ripple cryptocurrencies in the global market?

Cryptocurrencies have become extremely popular due to the ideals of decentralization they convey,along with potentially outside gains, but their volatility remain high and these assets carry a greater risk of loses than many other asset. For instance from the study it can be seen how indeterminable these cryptocurrencies Bitcoin, Ripple and Ethereum occur.They show upward and downward swings over time. However through predictive models that have been developed they can be predicted.

5.3 Conclusions

In objective one, trends provide a clear command of any market stability in terms of asset price. The analysis have revealed that cryptocurrencies have continued to increase in the market, creating a worrying trends of overrunning the both the domestic and international currencies, a process called crystallization. Cryptocurrencies have remained unregulated in domestic markets and even in global markets, this have made it difficulty to establish the value of digital assets held by mostly the tech-savvy individuals amounting to billions that can affect the markets both locally and internationally.

In objective two, studying correlation facilitates the decision-making in the business world. It reduces the range of uncertainty as predictions based on correlation are likely to be more reliable and near to reality. The results generally indicated that the Ripple cryptocurrency and the US dollar are fairly the same but Bitcoin and Ethereum are not correlated with the US dollar which means Bitcoin and Ethereum have a strong correlation strength than the US dollar.

In objective three,determining volatility of cryptocurrencies in the global market. Investing was inherently about risk, but risk works both ways, each trade carries with it the risk both of failure and success without volatility, there was a lower risk either. In this study, the results revealed that cryptocurrencies prices varied with time positively, which means traders looking to capitalize on volatility for profits may use such indicators as a strength indexes, volumes and establish support and resistance levels.

By application of Akaike Information Criterion, the best Garch Models were fitted to individual cryptocurrencies. It was important to do this because AIC minimizes outliers in a given data. In doing so it rewards models that achieve a high goodness-of-fit score.

5.4 Recommendations

1. Cryptocurrencies have remained unregulated in domestic markets and even in global markets, this have made it difficulty to establish the value of digital assets held by mostly the tech-savvy individuals amounting to billions that can affect the markets both locally and internationally. It was for this reason that it has been recommended the need to develop rules that limit the use of digital currencies without stifling innovation.

2. It was important to note that cryptocurrencies are expected to continue to make strides to become an accepted currency globally, in fact, this result can reinforce and support the fact that cryptocurrencies can occupy a more interesting place in the global market and therefore replace traditional currencies in most of the international transactions. Therefore there was a need to regulate and monitor its use in the market

3. In this study, the results revealed that cryptocurrencies prices varied with time positively, which means traders looking to capitalize on volatility for profits may use such indicators as a strength indexes, volumes and establish support and resistance levels.

4. A future work was to fit multivariate GARCH-type models to describe the joint behavior of the exchange rates of Bitcoin, Ethereum, Litecoin, Maidsafecoin, Monero and Ripple. This will require methodological, as well as empirical developments.

5. Finally a paper was published based on objective three, analysis of volatility of cryptocurrencies in the global market.

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Appendix 1

```
Dat1<-read.csv("ETH.csv")
Dat1
attach(Dat1)
Etherum.ts = ts(Dat1$ETHEREUM, frequency = 12,
                 start=c(2017,11), end=c(2021,12))
plot.ts(Etherum.ts,ylab="ETHERUM")
ArchTest(ETHEREUM)
garch(ETHEREUM,,order = c(2,1))
AIC(garch(ETHEREUM,,order = c(2,1)))
fit<-arima(Etherum.ts,order=c(1 ,0, 1))
fit
residuals(fit)
plot(residuals(fit),main="residual plot")
abline(h=0)
#####fitting ARIMA(2,0,1)
fit1<-arima(Etherum.ts,order=c(2 ,0, 1))
fit1
residuals(fit1)
plot(residuals(fit1),main="residual plot")
abline(h=0)
#####fitting ARIMA(2,0,2)
fit2<-arima(Etherum.ts,order=c(2 ,0, 2))
fit2
residuals(fit2)
plot(residuals(fit2),main="residual plot")
abline(h=0)
#####fitting ARIMA(1,1,1)
fit4<-arima(Etherum.ts,order=c(1 ,1, 1))
fit4
residuals(fit4)
plot(residuals(fit4),main="residual plot")
abline(h=0)
#####fitting ARIMA(1,1,2)
fit3<-arima(Etherum.ts,order=c(1 ,1, 2))
fit3
residuals(fit3)
plot(residuals(fit3),main="residual plot")
abline(h=0)
####fitting ARIMA(2,1,2)
fit5<-arima(Etherum.ts,order=c(2 ,1, 2))
fit5
residuals(fit5)
plot(residuals(fit5),main="residual plot")
abline(h=0)
####fitting ARIMA(3,1,2)
fit6<-arima(Etherum.ts,order=c(3 ,1, 2))
fit6
residuals(fit6)
plot(residuals(fit6),main="residual plot")
abline(h=0)
####fitting ARIMA(3,1,2)
fit7<-arima(Etherum.ts,order=c(0 ,1, 2))
fit7
residuals(fit7)
plot(residuals(fit7),main="residual plot")
abline(h=0)
```

Appendix 1

```
BE<-read.csv("BIT.csv")
BE
attach(BE)
plot.ts(BE)
ArchTest(x=BITCOIN)
BITCOIN.ts = ts(BE$BITCOIN, frequency = 12,
                start=c(2015,2), end=c(2021,12))
plot.ts(BITCOIN.ts,ylab="BITCOIN")
ArchTest(BITCOIN)
garch(BITCOIN,order = c(1,1))
AIC(garch(BITCOIN,order = c(1,1)))
fit<-arima(BITCOIN.ts,order=c(1 ,0, 1))
fit
residuals(fit)
plot(residuals(fit),main="residual plot")
abline(h=0)
#####fitting ARIMA(2,0,1)
fit1<-arima(Etherum.ts,order=c(1 ,1, 1))
fit1
residuals(fit1)
plot(residuals(fit1),main="residual plot")
abline(h=0)
#####fitting ARIMA(2,0,2)
fit2<-arima(Etherum.ts,order=c(2 ,1, 1))
fit2
residuals(fit2)
plot(residuals(fit2),main="residual plot")
abline(h=0)
#####fitting ARIMA(1,1,1)
fit4<-arima(Etherum.ts,order=c(1,1, 2))
fit4
residuals(fit4)
plot(residuals(fit4),main="residual plot")
abline(h=0)
#####fitting ARIMA(1,1,2)
fit3<-arima(Etherum.ts,order=c(2 ,2, 2))
fit3
residuals(fit3)
plot(residuals(fit3),main="residual plot")
abline(h=0)
####fitting ARIMA(2,1,2)
fit5<-arima(Etherum.ts,order=c(2 ,1, 2))
fit5
residuals(fit5)
plot(residuals(fit5),main="residual plot")
abline(h=0)
####fitting ARIMA(3,1,2)
fit6<-arima(Etherum.ts,order=c(3 ,1, 2))
fit6
residuals(fit6)
plot(residuals(fit6),main="residual plot")
abline(h=0)
####fitting ARIMA(3,1,2)
fit7<-arima(Etherum.ts,order=c(0 ,1, 2))
fit7
residuals(fit7)
plot(residuals(fit7),main="residual plot")
abline(h=0)
```

Appendix 2

JAN 2015 TO DEC 2021		NOV 2017 TO DEC 2021		FEB 2015 TO JAN 2021	
DURATION	***XRP IN $***	***DURATION***	***ETHEREUM IN $***	***DURATION***	***BITCOIN in $***
26-Dec-21	0.85001	13-Dec-21	3,745.44	20-Dec-21	50,809.52
19-Dec-21	0.92525	6-Dec-21	4,134.45	13-Dec-21	46,707.02
12-Dec-21	0.82643	29-Nov-21	4,198.32	6-Dec-21	50,098.34
5-Dec-21	0.83722	22-Nov-21	4,294.45	29-Nov-21	49,368.85
28-Nov-21	0.84697	15-Nov-21	4,269.73	22-Nov-21	57,248.46
21-Nov-21	0.94547	8-Nov-21	4,626.36	15-Nov-21	58,730.48
14-Nov-21	1.09614	1-Nov-21	4,620.55	8-Nov-21	65,466.84
7-Nov-21	1.18937	25-Oct-21	4,288.07	1-Nov-21	63,326.99
31-Oct-21	1.1512	18-Oct-21	4,087.90	25-Oct-21	61,318.96
24-Oct-21	1.08406	11-Oct-21	3,847.10	18-Oct-21	60,930.84
17-Oct-21	1.09354	4-Oct-21	3,425.85	11-Oct-21	61,553.62
10-Oct-21	1.134	27-Sep-21	3,418.36	4-Oct-21	54,771.58
3-Oct-21	1.15945	20-Sep-21	3,062.27	27-Sep-21	48,199.95
26-Sep-21	1.0362	13-Sep-21	3,329.45	20-Sep-21	43,208.54
19-Sep-21	0.94014	6-Sep-21	3,410.13	13-Sep-21	47,260.22
12-Sep-21	1.07557	30-Aug-21	3,952.13	6-Sep-21	46,063.27
5-Sep-21	1.07882	23-Aug-21	3,227.00	30-Aug-21	51,753.41
29-Aug-21	1.25482	16-Aug-21	3,242.12	23-Aug-21	48,829.83
22-Aug-21	1.14492	9-Aug-21	3,310.50	16-Aug-21	49,321.65
15-Aug-21	1.21663	2-Aug-21	3,013.73	9-Aug-21	47,047.00
8-Aug-21	1.28015	26-Jul-21	2,561.85	2-Aug-21	43,798.12
1-Aug-21	0.81666	19-Jul-21	2,191.37	26-Jul-21	39,974.89
25-Jul-21	0.74434	12-Jul-21	1,895.55	19-Jul-21	35,350.19
18-Jul-21	0.60665	5-Jul-21	2,139.66	12-Jul-21	31,796.81
11-Jul-21	0.58164	28-Jun-21	2,321.72	5-Jul-21	34,240.19
4-Jul-21	0.62511	21-Jun-21	1,978.89	28-Jun-21	35,287.78
27-Jun-21	0.67644	14-Jun-21	2,246.36	21-Jun-21	34,649.64
20-Jun-21	0.61663	7-Jun-21	2,508.39	14-Jun-21	35,698.30
13-Jun-21	0.75977	31-May-21	2,715.09	7-Jun-21	39,097.86
6-Jun-21	0.83121	24-May-21	2,390.31	31-May-21	35,862.38
30-May-21	0.92274	17-May-21	2,109.58	24-May-21	35,678.13
23-May-21	0.83041	10-May-21	3,587.51	17-May-21	34,770.58
16-May-21	0.90502	3-May-21	3,928.84	10-May-21	46,456.06
9-May-21	1.48591	26-Apr-21	2,952.06	3-May-21	58,232.32
2-May-21	1.56237	19-Apr-21	2,316.06	26-Apr-21	56,631.08
25-Apr-21	1.65073	12-Apr-21	2,237.14	19-Apr-21	49,004.25
18-Apr-21	1.05015	5-Apr-21	2,157.66	12-Apr-21	56,216.18
11-Apr-21	1.54064	29-Mar-21	2,093.12	5-Apr-21	60,204.96

21-Jun-20	0.17514	8-Jun-20	234.11	7-Jun-20	9,471.30
14-Jun-20	0.18793	1-Jun-20	245.17	31-May-20	9,669.60
7-Jun-20	0.19241	25-May-20	230.98	24-May-20	9,692.50
31-May-20	0.2037	18-May-20	202.37	17-May-20	9,177.00
24-May-20	0.20703	11-May-20	207.16	10-May-20	9,379.50
17-May-20	0.19883	4-May-20	188.6	3-May-20	9,554.60
10-May-20	0.19981	27-Apr-20	210.93	26-Apr-20	8,966.30
3-May-20	0.21647	20-Apr-20	197.32	19-Apr-20	7,540.40
26-Apr-20	0.22371	13-Apr-20	181.61	12-Apr-20	7,230.80
19-Apr-20	0.1942	6-Apr-20	161.14	5-Apr-20	6,867.80
12-Apr-20	0.19532	30-Mar-20	143.55	29-Mar-20	6,857.40
5-Apr-20	0.18841	23-Mar-20	125.58	22-Mar-20	6,233.70
29-Mar-20	0.18122	16-Mar-20	123.32	15-Mar-20	6,186.20
22-Mar-20	0.17545	9-Mar-20	125.21	8-Mar-20	5,182.70
15-Mar-20	0.15788	2-Mar-20	200.69	1-Mar-20	8,887.80
8-Mar-20	0.14596	24-Feb-20	218.97	23-Feb-20	8,543.70
1-Mar-20	0.23624	17-Feb-20	273.75	16-Feb-20	9,655.70
23-Feb-20	0.22902	10-Feb-20	259.89	9-Feb-20	9,907.70
16-Feb-20	0.27492	3-Feb-20	228.58	2-Feb-20	9,895.50
9-Feb-20	0.30754	27-Jan-20	188.62	26-Jan-20	9,381.60
2-Feb-20	0.27763	20-Jan-20	168.08	19-Jan-20	8,341.60
26-Jan-20	0.24132	13-Jan-20	166.97	12-Jan-20	8,916.30
19-Jan-20	0.2196	6-Jan-20	145.87	5-Jan-20	8,024.10
12-Jan-20	0.2435	30-Dec-19	136.28	29-Dec-19	7,376.80
5-Jan-20	0.21138	23-Dec-19	134.76	22-Dec-19	7,321.50
29-Dec-19	0.19311	16-Dec-19	132.37	15-Dec-19	7,156.20
22-Dec-19	0.19309	9-Dec-19	143.11	8-Dec-19	7,080.80
15-Dec-19	0.19146	2-Dec-19	151.26	1-Dec-19	7,510.90
8-Dec-19	0.21631	25-Nov-19	151.19	24-Nov-19	7,546.60
1-Dec-19	0.22708	18-Nov-19	142.83	17-Nov-19	7,324.10
24-Nov-19	0.22548	11-Nov-19	185.12	10-Nov-19	8,497.30
17-Nov-19	0.234	4-Nov-19	189.48	3-Nov-19	8,804.50
10-Nov-19	0.26219	28-Oct-19	182.43	27-Oct-19	9,300.60
3-Nov-19	0.27987	21-Oct-19	184.24	20-Oct-19	9,230.60
27-Oct-19	0.29469	14-Oct-19	175.53	13-Oct-19	7,957.30
20-Oct-19	0.29375	7-Oct-19	182.08	6-Oct-19	8,304.40
13-Oct-19	0.29133	30-Sep-19	173.06	29-Sep-19	8,127.30
6-Oct-19	0.27236	23-Sep-19	170.5	22-Sep-19	8,208.50
29-Sep-19	0.25318	16-Sep-19	211.55	15-Sep-19	9,993.00
22-Sep-19	0.24186	9-Sep-19	189.79	8-Sep-19	10,337.30
15-Sep-19	0.28968	2-Sep-19	181.36	1-Sep-19	10,461.10

8-Sep-19	0.26128	26-Aug-19	171.63	25-Aug-19	9,594.40
1-Sep-19	0.25999	19-Aug-19	186.84	18-Aug-19	10,131.00
25-Aug-19	0.25759	12-Aug-19	194.49	11-Aug-19	10,218.10
18-Aug-19	0.27137	5-Aug-19	216.09	4-Aug-19	11,314.50
11-Aug-19	0.26544	29-Jul-19	222.67	28-Jul-19	10,815.70
4-Aug-19	0.29925	22-Jul-19	211.19	21-Jul-19	9,492.10
28-Jul-19	0.31601	15-Jul-19	225.63	14-Jul-19	10,826.70
21-Jul-19	0.30993	8-Jul-19	227.58	7-Jul-19	11,364.90
14-Jul-19	0.33286	1-Jul-19	305.7	30-Jun-19	11,268.00
7-Jul-19	0.33206	24-Jun-19	290.7	23-Jun-19	11,906.50
30-Jun-19	0.39022	17-Jun-19	307.83	16-Jun-19	10,721.70
23-Jun-19	0.42673	10-Jun-19	269.22	9-Jun-19	8,812.50
16-Jun-19	0.47707	3-Jun-19	233.09	2-Jun-19	7,901.40
9-Jun-19	0.40947	27-May-19	270.23	26-May-19	8,545.70
2-Jun-19	0.40721	20-May-19	267.07	19-May-19	8,027.40
26-May-19	0.42894	13-May-19	261.29	12-May-19	7,262.60
19-May-19	0.38536	6-May-19	187.33	5-May-19	7,190.30
12-May-19	0.37194	29-Apr-19	163.45	28-Apr-19	5,830.90
5-May-19	0.32189	22-Apr-19	157.3	21-Apr-19	5,265.90
28-Apr-19	0.30368	15-Apr-19	170.05	14-Apr-19	5,290.20
21-Apr-19	0.29895	8-Apr-19	167.84	7-Apr-19	5,051.80
14-Apr-19	0.32735	1-Apr-19	174.53	31-Mar-19	5,046.20
7-Apr-19	0.32482	25-Mar-19	141.51	24-Mar-19	4,111.80
31-Mar-19	0.35256	18-Mar-19	136.99	17-Mar-19	4,002.50
24-Mar-19	0.31104	11-Mar-19	140	10-Mar-19	4,006.40
17-Mar-19	0.31171	4-Mar-19	136.76	3-Mar-19	3,944.30
10-Mar-19	0.31871	25-Feb-19	132.25	24-Feb-19	3,823.10
3-Mar-19	0.31388	18-Feb-19	135.85	17-Feb-19	4,120.40
24-Feb-19	0.31411	11-Feb-19	133.6	10-Feb-19	3,616.80
17-Feb-19	0.33285	4-Feb-19	124.81	3-Feb-19	3,661.40
10-Feb-19	0.30083	28-Jan-19	107.49	27-Jan-19	3,502.50
3-Feb-19	0.3122	21-Jan-19	113.41	20-Jan-19	3,570.90
27-Jan-19	0.31034	14-Jan-19	119.47	13-Jan-19	3,677.80
20-Jan-19	0.31304	7-Jan-19	116.9	6-Jan-19	3,597.20
13-Jan-19	0.32855	31-Dec-18	157.75	30-Dec-18	3,785.40
6-Jan-19	0.32715	24-Dec-18	139.86	23-Dec-18	3,706.80
30-Dec-18	0.35106	17-Dec-18	130.77	16-Dec-18	3,964.40
23-Dec-18	0.35945	10-Dec-18	85.26	9-Dec-18	3,228.70
16-Dec-18	0.36033	3-Dec-18	95.14	2-Dec-18	3,430.40
9-Dec-18	0.28549	26-Nov-18	116.39	25-Nov-18	4,196.20
2-Dec-18	0.30414	19-Nov-18	116.45	18-Nov-18	3,920.40

25-Nov-18	0.37328	12-Nov-18	177.07	11-Nov-18	5,621.80
18-Nov-18	0.37942	5-Nov-18	211.34	4-Nov-18	6,427.10
11-Nov-18	0.4976	29-Oct-18	207.49	28-Oct-18	6,386.20
4-Nov-18	0.50845	22-Oct-18	205.37	21-Oct-18	6,494.20
28-Oct-18	0.45684	15-Oct-18	205.14	14-Oct-18	6,572.20
21-Oct-18	0.45973	8-Oct-18	195.71	7-Oct-18	6,321.70
14-Oct-18	0.46712	1-Oct-18	226.12	30-Sep-18	6,596.30
7-Oct-18	0.42235	24-Sep-18	232.85	23-Sep-18	6,603.90
30-Sep-18	0.48883	17-Sep-18	244.33	16-Sep-18	6,729.60
23-Sep-18	0.56983	10-Sep-18	220.59	9-Sep-18	6,519.00
16-Sep-18	0.57338	3-Sep-18	196.92	2-Sep-18	6,184.30
9-Sep-18	0.28041	27-Aug-18	294.37	26-Aug-18	7,189.60
2-Sep-18	0.27673	20-Aug-18	275.2	19-Aug-18	6,734.80
26-Aug-18	0.34691	13-Aug-18	300.83	12-Aug-18	6,379.10
19-Aug-18	0.32725	6-Aug-18	319.57	5-Aug-18	6,231.60
12-Aug-18	0.32838	30-Jul-18	410.52	29-Jul-18	7,014.30
5-Aug-18	0.29757	23-Jul-18	466.67	22-Jul-18	8,234.10
29-Jul-18	0.42969	16-Jul-18	459.66	15-Jul-18	7,408.70
22-Jul-18	0.45675	9-Jul-18	449.85	8-Jul-18	6,254.80
15-Jul-18	0.45501	2-Jul-18	489.12	1-Jul-18	6,765.50
8-Jul-18	0.43849	25-Jun-18	453.92	24-Jun-18	6,398.90
1-Jul-18	0.4857	18-Jun-18	457.67	17-Jun-18	6,167.30
24-Jun-18	0.46486	11-Jun-18	500.45	10-Jun-18	6,505.80
17-Jun-18	0.48983	4-Jun-18	526.48	3-Jun-18	7,515.80
10-Jun-18	0.53297	28-May-18	618.33	27-May-18	7,646.60
3-Jun-18	0.6586	21-May-18	572.67	20-May-18	7,361.30
27-May-18	0.64286	14-May-18	715.37	13-May-18	8,245.10
20-May-18	0.60878	7-May-18	733.5	6-May-18	8,459.50
13-May-18	0.67391	30-Apr-18	792.31	29-Apr-18	9,853.50
6-May-18	0.68317	23-Apr-18	688.88	22-Apr-18	9,352.40
29-Apr-18	0.90121	16-Apr-18	621.86	15-Apr-18	8,923.10
22-Apr-18	0.86288	9-Apr-18	531.7	8-Apr-18	8,004.40
15-Apr-18	0.86585	2-Apr-18	400.51	1-Apr-18	6,905.70
8-Apr-18	0.64046	26-Mar-18	379.61	25-Mar-18	6,938.20
1-Apr-18	0.48562	19-Mar-18	524.29	18-Mar-18	8,547.40
25-Mar-18	0.50089	12-Mar-18	538.64	11-Mar-18	7,874.90
18-Mar-18	0.62913	5-Mar-18	723.34	4-Mar-18	8,762.00
11-Mar-18	0.62952	26-Feb-18	866.68	25-Feb-18	11,402.30
4-Mar-18	0.77546	19-Feb-18	844.81	18-Feb-18	9,704.30
25-Feb-18	0.89855	12-Feb-18	923.92	11-Feb-18	11,073.50
18-Feb-18	0.90218	5-Feb-18	814.66	4-Feb-18	8,559.60

11-Feb-18	1.17811	29-Jan-18	834.68	28-Jan-18	9,241.10
4-Feb-18	1.02892	22-Jan-18	1,246.01	21-Jan-18	11,467.50
28-Jan-18	0.95978	15-Jan-18	1,049.58	14-Jan-18	12,858.90
21-Jan-18	1.22142	8-Jan-18	1,366.77	7-Jan-18	14,292.20
14-Jan-18	1.60149	1-Jan-18	1,153.17	31-Dec-17	17,172.30
7-Jan-18	2.04008	25-Dec-17	756.73	24-Dec-17	12,531.50
31-Dec-17	2.65	18-Dec-17	694.15	17-Dec-17	14,396.50
24-Dec-17	1.86	11-Dec-17	719.97	10-Dec-17	19,345.50
17-Dec-17	1.01	4-Dec-17	441.72	3-Dec-17	14,843.40
10-Dec-17	0.7397	27-Nov-17	465.85	26-Nov-17	10,912.70
3-Dec-17	0.2353	20-Nov-17	471.33	19-Nov-17	8,754.70
26-Nov-17	0.2441	13-Nov-17	354.39	12-Nov-17	7,780.90
19-Nov-17	0.2488	6-Nov-17	307.91	5-Nov-17	6,339.90
12-Nov-17	0.2275			29-Oct-17	7,363.80
5-Nov-17	0.2092			22-Oct-17	5,726.60
29-Oct-17	0.2015			15-Oct-17	6,006.60
22-Oct-17	0.1982			8-Oct-17	5,824.70
15-Oct-17	0.2097			1-Oct-17	4,435.80
8-Oct-17	0.2556			24-Sep-17	4,360.60
1-Oct-17	0.2397			17-Sep-17	3,788.00
24-Sep-17	0.1999			10-Sep-17	3,698.90
17-Sep-17	0.1791			3-Sep-17	4,335.10
10-Sep-17	0.1828			27-Aug-17	4,573.80
3-Sep-17	0.213			20-Aug-17	4,352.30
27-Aug-17	0.2252			13-Aug-17	4,150.50
20-Aug-17	0.2097			6-Aug-17	3,871.60
13-Aug-17	0.1526			30-Jul-17	3,262.80
6-Aug-17	0.1716			23-Jul-17	2,733.50
30-Jul-17	0.1848			16-Jul-17	2,836.50
23-Jul-17	0.169			9-Jul-17	1,975.10
16-Jul-17	0.1977			2-Jul-17	2,564.90
9-Jul-17	0.172			25-Jun-17	2,424.60
2-Jul-17	0.23			18-Jun-17	2,590.10
25-Jun-17	0.2386			11-Jun-17	2,655.10
18-Jun-17	0.2775			4-Jun-17	2,900.30
11-Jun-17	0.2597			28-May-17	2,545.40
4-Jun-17	0.2598			21-May-17	2,052.40
28-May-17	0.2921			14-May-17	2,040.20
21-May-17	0.21			7-May-17	1,763.70
14-May-17	0.3449			30-Apr-17	1,545.30
7-May-17	0.2102			23-Apr-17	1,336.30

30-Apr-17	0.1001			16-Apr-17	1,240.90
23-Apr-17	0.05383			9-Apr-17	1,177.00
16-Apr-17	0.0316			2-Apr-17	1,180.80
9-Apr-17	0.03381			26-Mar-17	1,086.10
2-Apr-17	0.03575			19-Mar-17	966.3
26-Mar-17	0.022			12-Mar-17	971.4
19-Mar-17	0.00888			5-Mar-17	1,179.20
12-Mar-17	0.00688			26-Feb-17	1,264.30
5-Mar-17	0.00625			19-Feb-17	1,149.10
26-Feb-17	0.0062			12-Feb-17	1,052.30
19-Feb-17	0.00563			5-Feb-17	1,008.30
12-Feb-17	0.00554			29-Jan-17	1,031.80
5-Feb-17	0.00638			22-Jan-17	918.5
29-Jan-17	0.00644			15-Jan-17	919.8
22-Jan-17	0.00639			8-Jan-17	819.6
15-Jan-17	0.00684			1-Jan-17	888.9
8-Jan-17	0.00679			25-Dec-16	963.4
1-Jan-17	0.00636			18-Dec-16	891.1
25-Dec-16	0.00651			11-Dec-16	787.2
18-Dec-16	0.00644			4-Dec-16	774
11-Dec-16	0.00649			27-Nov-16	764.2
4-Dec-16	0.00674			20-Nov-16	734.1
27-Nov-16	0.00666			13-Nov-16	747.9
20-Nov-16	0.00697			6-Nov-16	704.3
13-Nov-16	0.00769			30-Oct-16	702.1
6-Nov-16	0.00811			23-Oct-16	715
30-Oct-16	0.00821			16-Oct-16	655.5
23-Oct-16	0.00773			9-Oct-16	637
16-Oct-16	0.00888			2-Oct-16	617.7
9-Oct-16	0.008			25-Sep-16	613.4
2-Oct-16	0.00745			18-Sep-16	602.6
25-Sep-16	0.00798			11-Sep-16	607.1
18-Sep-16	0.0075			4-Sep-16	624.5
11-Sep-16	0.00708			28-Aug-16	598.8
4-Sep-16	0.00592			21-Aug-16	570.3
28-Aug-16	0.00603			14-Aug-16	582.6
21-Aug-16	0.0059			7-Aug-16	584.6
14-Aug-16	0.0062			31-Jul-16	586.5
7-Aug-16	0.00618			24-Jul-16	654.7
31-Jul-16	0.0063			17-Jul-16	655.2
24-Jul-16	0.0062			10-Jul-16	660.7

17-Jul-16	0.0064			3-Jul-16	651.8
10-Jul-16	0.00671			26-Jun-16	698.1
3-Jul-16	0.00655			19-Jun-16	663.5
26-Jun-16	0.00661			12-Jun-16	753.8
19-Jun-16	0.00648			5-Jun-16	591.6
12-Jun-16	0.00651			29-May-16	572
5-Jun-16	0.00569			22-May-16	524.2
29-May-16	0.00589			15-May-16	443.6
22-May-16	0.00485			8-May-16	456.4
15-May-16	0.00595			1-May-16	458.5
8-May-16	0.00605			24-Apr-16	448.5
1-May-16	0.00634			17-Apr-16	450.1
24-Apr-16	0.00688			10-Apr-16	430
17-Apr-16	0.00736			3-Apr-16	418
10-Apr-16	0.00655			27-Mar-16	418.5
3-Apr-16	0.00622			20-Mar-16	416.5
27-Mar-16	0.00757			13-Mar-16	408.7
20-Mar-16	0.00813			6-Mar-16	410.4
13-Mar-16	0.00782			28-Feb-16	399
6-Mar-16	0.00814			21-Feb-16	431.3
28-Feb-16	0.00734			14-Feb-16	440.1
21-Feb-16	0.0078			7-Feb-16	390.1
14-Feb-16	0.0079			31-Jan-16	376.7
7-Feb-16	0.00844			24-Jan-16	377.8
31-Jan-16	0.008			17-Jan-16	388.6
24-Jan-16	0.00633			10-Jan-16	385
17-Jan-16	0.00512			3-Jan-16	448.3
10-Jan-16	0.00489			27-Dec-15	433.7
3-Jan-16	0.004			20-Dec-15	415.4
27-Dec-15	0.00513			13-Dec-15	461.2
20-Dec-15	0.0058			6-Dec-15	432.3
13-Dec-15	0.0055			29-Nov-15	386.7
6-Dec-15	0.00613			22-Nov-15	355.8
29-Nov-15	0.00425			15-Nov-15	324.7
22-Nov-15	0.004			8-Nov-15	331.8
15-Nov-15	0.00406			1-Nov-15	385.1
8-Nov-15	0.0048			25-Oct-15	311.2
1-Nov-15	0.00445			18-Oct-15	282.6
25-Oct-15	0.00503			11-Oct-15	269.6
18-Oct-15	0.0046			4-Oct-15	245.4
11-Oct-15	0.00505			27-Sep-15	238.6

4-Oct-15	0.00825			20-Sep-15	234.3
27-Sep-15	0.00525			13-Sep-15	231.1
20-Sep-15	0.0066			6-Sep-15	235.6
13-Sep-15	0.0077			30-Aug-15	233.7
6-Sep-15	0.00755			23-Aug-15	228.5
30-Aug-15	0.008			16-Aug-15	229.5
23-Aug-15	0.00873			9-Aug-15	260.5
16-Aug-15	0.00801			2-Aug-15	258.6
9-Aug-15	0.00801			26-Jul-15	280.5
2-Aug-15	0.009			19-Jul-15	288.7
26-Jul-15	0.00841			12-Jul-15	274
19-Jul-15	0.0077			5-Jul-15	292
12-Jul-15	0.008			28-Jun-15	260.5
5-Jul-15	0.00825			21-Jun-15	250.7
28-Jun-15	0.0109			14-Jun-15	245
21-Jun-15	0.011			7-Jun-15	232.5
14-Jun-15	0.0141			31-May-15	224.7
7-Jun-15	0.0079			24-May-15	233.2
31-May-15	0.00892			17-May-15	238.9
24-May-15	0.0081			10-May-15	236.2
17-May-15	0.0071			3-May-15	241.4
10-May-15	0.00648			26-Apr-15	235.3
3-May-15	0.0078			19-Apr-15	226.1
26-Apr-15	0.00844			12-Apr-15	223.4
19-Apr-15	0.00802			5-Apr-15	236.5
12-Apr-15	0.00827			29-Mar-15	252.9
5-Apr-15	0.008			22-Mar-15	252
29-Mar-15	0.00937			15-Mar-15	259.7
22-Mar-15	0.00895			8-Mar-15	281.6
15-Mar-15	0.01011			1-Mar-15	274.9
8-Mar-15	0.01112			22-Feb-15	254.1
1-Mar-15	0.0103			15-Feb-15	244.4
22-Feb-15	0.01178			8-Feb-15	258.6
15-Feb-15	0.01307			1-Feb-15	227.7
8-Feb-15	0.012				
1-Feb-15	0.01468				
25-Jan-15	0.01499				