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Analysis of Volatility of Cryptocurrencies in the Global Market

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Abstract: The motivation of this study was to analyze the volatility of Bitcoin, Ethereum, and Ripple cryptocurrencies in the global market. The weekly price and cryptocurrency trading datasets were outsourced from https.//Coinmarketcap.com. The period under study was from 1st February 2015 to 26th December 2021. Descriptive statistics for each cryptocurrency were analyzed and produced the following results. The mean for Ripple is 0.33, with a standard deviation of 0.39, a skewness of 1.97, and a kurtosis of 5.34 while the mean for Ethereum is 906.13, with a standard deviation of 1158.51, a skewness of 1.72 and kurtosis 1.8. The Mean for Bitcoin is 11242.34, standard deviation 15941.38, skewness 1.95, and kurtosis 2.67. This study was subjected to Garch Model analysis to determine the market volatility of Bitcoin, Ripple, and Ethereum cryptocurrencies. The analysis showed that ripple prices were constant from the years 2015 to 2017 low volatile then rose to high prices in the same year, the price variation with time was seen after 2017 to 2021, which means the prices were highly volatile. This suggested that the autocorrelation and seasonality of the structure of ripple cryptocurrency are not determinable. However, when data was subjected to compounding the return for ripple prices to check if there is any deviation in price variation through the study period, The result revealed that the highest volatility was presented in the year 2018. Ethereum price maintained a constant trend from 2018 to mid-2020 volatile and the prices increased with time to 2021 highly volatile as seen in figure 3. Bitcoin presented price variation with time as seen in figure 4, this shows a volatile market. By using Akaike Information Criterion was possible to identify the best Garch Models fitted to individual cryptocurrencies. This study has provided vital information to businesses, investors, and Governments to consider when making an informed decision regarding the type of cryptocurrencies to consider when making investment decisions, the price variability, and the volatility of cryptocurrencies in the market.

Keywords: Cryptocurrency, Volatility, Technology

1. Introduction

1.1. Background

In many states, money has been given priority for any economy to grow, because all economies have accepted certain currencies as a medium of exchange. The money supply causes inflation as well as deflation in economies by its excess supply or reduced demand, hence currencies of different countries are regulated by states to control inflation or deflation situations [1]. The introduction of Central Bank Digital Currency (CBDC) allows Central banks to mitigate such runs. Countries in the world have continued to focus on digital currency when dealing with transactions [2]. This has led to increased innovations in new currencies such as cryptocurrency, cryptocurrency is decentralized digital money that uses encryption the process of converting data into code to generate units of currency and validate transactions independent of a Central bank or government. Cryptocurrencies have no physical image in sense, Instead Cryptocurrencies are created, stored, and transacted electronically [3]. Most of the cryptocurrencies are maintained by a community of cryptocurrency miners who are members of the public. Cryptocurrencies are derived from two protocols, proof of work (POW) and proof of stake (POS). In the POW system, the probability of mining a block is depended 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, there are three major cryptocurrencies, Bitcoin, Ripple, and Ethereum have been considered.

1.2. Statement of the Problem

Many economies in the global market are moving towards cashless transactions through innovations and making buying and trading possible using e-wallets. This is one of the newest innovations in the money market. Unfortunately. These currencies are not being regulated by many states across the globe including the Central banks of such states, their continuous usage has constantly continued to pose a greater risk of instability in the majority of markets, for this main reason that the study seeks to determine the price trends and volatility of this digital currencies to determine the impact of effects in the markets. To bridge this gap the study has considered the Garch Models in the data analysis to show the volatility and trends of Bitcoin, Ripple, and Ethereum cryptocurrencies in the global market. Data has also been subjected to the normality test and Augmented DickFuller Tests to test the null hypothesis that the unit root test is present in an auto-regressive 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. Significance of the Study

Cryptocurrency is a forerunner in a possibly transformative technology to long-standing financial systems. By its very nature, it can fill gaps in current financial technologies and help solve traditional banking problems by being a peer-to-peer system. Cryptocurrencies are poised to help solve the problems related to unbanked consumers since significant portions of the population in developing countries are unbanked [4]. Businesses are beginning to see the value in using cryptocurrencies for international transactions, especially when transactions need to occur quickly in response to an emergency. Money can be wired internationally, but typically arriving days after being sent and not for the full amount [4]. This study provides a basis for creating a framework that will help markets to identify gaps in not controlling these currencies in the market. The results of this study will also help investors to foresee and manage risks while identifying opportunities for alternative diversified and profitable investments. The study will propose a platform to evaluate some of the challenges and opportunities of central bank digital currencies (CBDCS) and blockchain technologies. By Studying the volatilities 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.

1.4. Research Objectives

1.4.1. General

Analysis of volatility of cryptocurrencies in the global market.

1.4.2. Specific Objective

To determine the volatility of Bitcoin, Ethereum, and Ripple.

Cryptocurrencies in the global market.

The study aim to answer the following research question:

Can the volatility of Bitcoin, Ethereum, and Ripple cryptocurrencies affect global market growth?

2. Price and Volatility Models

A study by Emaeyak evaluated the performance of the hybrid ARIMAGARCH model in forecasting Bitcoin daily price returns [5]. The 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 ARIMA model (Arima 2,0,1) was 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 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. Research shows that the cost of handling physical cash exceeds one percent of the global market the GDP [6]. Digital money issuers should be regulated by central banks by ensuring that digital money issued is deposited with fully accredited financial institutions. 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. One of the foremost names in this field is Hayek who noted that government should not have a monopoly over the issuance of money [7]. It was suggested that private banks should be allowed to issue non-interest-bearing certificates based on their registered trademarks. Hayek also argued that these certificates or currencies should be open to competition and would be traded at variable exchange rates. The study found that currencies should be able to guarantee a stable purchasing power and eliminate other less stable currencies from the market and the result of this process of competition and profit maximization would be a highly efficient monetary system where only stable currencies would coexist Hayek [7]. A study by Gil-Alana reported that cryptocurrencies are susceptible to speculative bubbles since it is characterized by anonymity [10] The impact may be aggravated even during times of severe economic shocks, especially, during the COVID-19 pandemic. As reported by Yarovaya and Asafo-Adjei, Owusu Junior the speculative bubbles in the cryptocurrency markets may, in turn, increase contagion and weaken financial stability. [11] This calls for an increased assessment of the cryptocurrencies' mechanism in terms of volatility [12].

3. Statistical Models

3.1. GARCH Model

Tim Bollerslev studied the Garch model [8] as a statistical modeling technique used to help predict the volatility of returns on financial assets [9]. It is appropriate for time series data where the variance of the error term is serially autocorrelated following an autoregressive moving average process. The model is useful to assess risk and expected returns for assets that exhibit clustered periods of volatility in returns. The GARCH Model is as follows:

$$y_t = \mu_t + Z_t \tag{1}$$

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

$$Z_t = \sigma_t \varepsilon_t \tag{2}$$

where ε_t $_t$→iid N(0,1)

$$\sigma_t^2 = \alpha_0 \sum_{i=1}^{q} \alpha_i Z_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_j^2 \tag{3}$$

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,· · ·,q, $\beta_j \geq 0$ for j=1,2,· · ·,p, $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$.

3.2. Normality Test

The study implemented statistical normality tests namely the Shapiro-Wilk and Dickey-Fuller. The Shapiro-Wilk test is used to check if a continuous variable follows a normal distribution and the Dickey-Fuller test tests the null hypothesis that a unit root is present in an autoregressive time series model.

3.2.1. Shapiro-Wilk Test

The Shapiro-Wilk test is selected to analyze whether the distribution of variables follows normal distribution or non-normal distribution. The null hypothesis tested is that the population is normally distributed. The null hypothesis of the Shapiro-Wilk test is:

H_0: θ = 0 (Variable is normally distributed in some populations) versus the alternative hypothesis.

H_1: θ < 0 (Reject the null hypothesis if p is less than 0.05).

The test tests the null hypothesis that a sample,

X_1 X_2, X_3, · · ·, X_n came from a normal distribution population. The test statistics are given by

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{4}$$

Where

M = (m_1 m_2, · · ·, m_n) T m_1 m_2, · · ·, m_n) are expected values of the order statistics of iid random variables sample from the standard normal distribution V is the covariance of those order statistics If the test statistic W is small then the critical threshold (0.05) then the assumption of normal distribution has to be rejected.

3.2.2. Dickey-Fuller Test

When the time series has a trend in it and is potentially slow-turning around a trend line, you would draw through the data, and use the following test equation:

$$\begin{aligned} &\Delta z_t = \alpha_0 + \theta\ z_{t-1} + y_t + \alpha_1 \Delta z_{t-1} + \\ &\alpha_2 \Delta z_{t-2} + \dots \alpha_p \Delta z_{t-p} + \varepsilon_t \end{aligned} \tag{5}$$

Where delta is the difference operator and i_t is variable interest at time t. We notice that this equation has an intercept term and a time trend. Again, the number of augmenting lags (p) is determined by minimizing the Schwartz Bayesian information criterion or minimizing the Akaike Information Criterion, or lags are dropped until the last lag is statistically significant. You then use the t-statistic on the θ coefficient to test whether you need to differentiate the data to make it stationary or you need to put a time trend in your regression model to correct for the variables' determinable trend. Notice the test is left-tailed. The null hypothesis of the Augmented Dickey-Fuller t-test is:

H0: θ = 0 (the data needs to be differenced to make it stationary) versus the alternative hypothesis.

H1: θ < 0 (The data is trend stationery and needs to be analyzed using a time trend in the regression model instead of a difference in the data).

4. Results and Discussion

This study collected the weekly cryptocurrency price data from https:/coinmarketcap.com. [13] Weekly closing transaction prices were used in this study since this is a new area in the global market and most of the data is unavailable. The study utilized the data that covered the period from 1st February 2015 to 26th December 2021 to perform the analysis. However, The cryptocurrencies under study Ripple, Ethereum, and Bitcoins were selected due to their popularity in the market, their market share value, and the availability of their data.

4.1. Time Series Trend Graphs

Figure 1, shows the time series of Ripple price when applied to closing prices through the period January 2015 to December 2021. From the plots volatility of Ripple, prices were significantly higher in 2018 in comparison to other periods. This suggested that the autocorrelation and seasonality of the structure of XRP prices under study were not seen. When applying the same approach of continuous compounding return of the XRP prices to check the deviation of price variations through the period or any possibility of volatility, the Continuous compounding return series of Ripple identified the changing variance of the prices over time or the possibility of volatility clustering.

Weekly Time Series of Ripple Prices

Figure 1. *Weekly Time Series of Ripple Prices.*

From figure 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.

Distribution of Ripple Weekly Price Returns

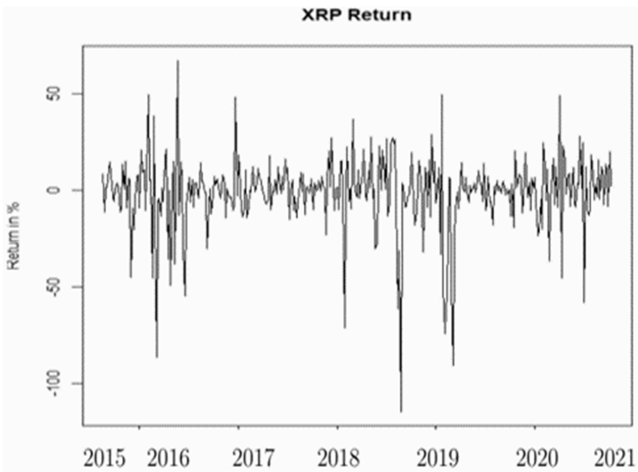

Figure 2. *Distribution of Ripple Weekly Price Returns.*

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

Weekly Time Series of Ethereum Prices

Figure 3. *Weekly Time Series of Ethereum Prices.*

From figure 3 We see 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.

Weekly Time Series of Bitcoin Prices

Figure 4. *Weekly Time Series of Bitcoin Prices.*

Figure 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. It can be noticed A radical increase in prices can be noticed which eventually increased from 10000 to 65000. This was interpreted as a highly volatile nature of the market at the time in 2021.

4.2. Garch (p,q) Models for Volatility

The Garch Models were estimated by fitting models into individual data. After investigating the data it shows that all data have ARCH effects (data is volatile) as shown in the table.

Table 1. *ArchTest results.*

Data	Chi-Square	Df	P-value
XRP	250.27	12	<0.00001
Ethereum	160.28	12	<0.00001
Bitcoin	198.47	12	<0.00001

From Table 1 since all p-value is less than, it can be concluded that all data have arch effects hence Garch model (p,q) should be fitted. Different Garch (p,q) are fitted to different data and the AIC is used to determine which suitable model fits the given data.

4.2.1. Fitting Garch (p,q) Model to BITCOIN Data

Table 2 presents different Garch model fitted and their corresponding AIC value.

Table 2. *Bitcoin Data.*

Garch (p,q)	AIC Value
(1,1)	4744.619
(1,2)	4760.340
(1,3)	4773.430
(2,1)	4752.564
(2,2)	4752.676

This study, therefore, selected Garch (1,1) model as a suitable model since it reported the smallest value of AIC. Thus, the fitted model is given by

$$\sigma_t^2 = 9567.6108 + 0.5463 z_{t-1}^2 + 0.1949\sigma_{t-1}^2 \quad (6)$$

Where $Z_t = \sigma_t \varepsilon_t$.

4.2.2. Fitting Garch (p, q) Model to Ethereum Data

Table 3 presents different Garch models fitted and their corresponding AIC values.

Table 3. *Ethereum Data.*

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

From Table 3, Garch (2,1) reported the least AIC value, here the study concludes that the fit was the best.

The fitted model is given by,

$$\sigma_t^2 = 3289 + 0.7883 z_{t-1}^2 + 5.046e^{-11}\sigma_{t-1}^2 + 0.01626\sigma_{t-2}^2 \quad (7)$$

Where $Z_t = \sigma_t \varepsilon_t$.

4.2.3. Fitting Garch (p,q) Model to XRP Data

Table 4 Garch models fitted and their corresponding AIC value.

Table 4. *XRP Data.*

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 Garch (1,1) model reported the least AIC value, the study concludes that this was the best fit.

The fitted model is given by

$$\sigma_t^2 = 1.070e^{-14} + 1.039 z_{t-1}^2 + 0.06784\sigma_{t-1}^2 \quad (8)$$

Where $Z_t = \sigma_t \varepsilon_t$.

4.3. Discussion

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 is 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. Conclusion

Since the inception of cryptocurrencies, markets have transformed into new platforms for trading with new technologies. Naturally, as cryptocurrencies continue to gain popularity in these markets, there is a need to study and understand the volatility of these cryptocurrencies. From this study, Garch models were applied to determine market volatilities. The analysis reported that Ripple prices were constant from the years 2015 to 2017 low volatile then rose to high prices in the same year, the price varied with time, as observed in figure 1 which means the prices were highly volatile. This indicated that the autocorrelation and seasonality of the structure of ripple cryptocurrency are not determinable. However, when data was subjected to compounding the return for ripple prices to check if there is any deviation in price variation through the study period, the result indicated that the highest volatility was reported in the year 2018. Ethereum price maintained a constant trend from 2018 to mid-2020 volatile and the prices increased with time to 2021 highly volatile as can be observed in figure 3. Bitcoin reported price variation with time as seen in figure 4, this shows a volatile market. Volatility is an important metric and the most common risk measure in finance. Accessing stable and reliable volatility information is of fundamental interest to investors and risk managers alike.

By using Analyzing 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. By doing so it rewards models that achieve a high goodness-of-fit score. Recommendation, the study recommends further study of the volatiles of cryptocurrency with other fiat currencies to understand their strengths in market growth.

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