The Effect of Cryptocurrency Returns Volatility on Stock Prices and Exchange Rate Returns Volatility in Nigeria

Sodiq Olaiwola Jimoh[1], Oluwasegun Olawale Benjamin[2]

Abstract: The global usage and acceptability of bitcoin and other forms of cryptocurrencies as another means of payment have attracted the attention of financial and economic experts in recent times, but research on these means of payment and their relationship with economic and financial variables are scanty in Nigeria. This study, therefore, examined the nexus between the two key economic and financial variables (exchange rate and stock market price) and the most traded cryptocurrency (Bitcoin and Etherum) in Nigeria. The study used monthly data between August 2015 and December 2019 and employed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH 1,1), Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH 1,1), and Granger causality technique to estimate the reaction of the volatility of exchange rates and stock market prices to volatility in cryptocurrency prices. The result shows that the stock market price is more influenced by the instability of bitcoin and ethereum prices than the exchange rate in Nigeria. Further, there is evidence of a one-way causality from bitcoin and ethereum to all share index. Given these findings, there is a need for the stock market investors in Nigeria to pay rapped attention to the movement of cryptocurrency prices.

Keywords: Stock Prices; Bitcoin, Ethereum; Cryptocurrency; Exchange Rates; Univariate Volatility Models

JEL Classification: E41; G23; F31

1. Introduction

The payment system has evolved from the batter system, commodity money, fiat money, checks, and electronic money. These forms of money are generally acceptable as a means of payment, settlement of debts, and differed payments. Despite the general acceptability of the different forms of money, the quest for a new electronic payment system continues. In 2009, a software developer known as Satoshi Nakamoto invented another type of electronic money called bitcoin. Bitcoin

[1] University of Sains Malaysia, Penang, Malaysia, Address: 11800 Gelugor, Penang, Malaysia, Tel.: +2348066455922, Corresponding author: sodiqjimoh07@student.usm.my.
[2] Research and Data Analysis Department, Lightway Research and Technology Centre, Nigeria, Address: Royal Civic Center, Off Offa Garage Railway Line, Area, Ilorin, Nigeria, Tel.: +2348168850193, E-mail: meetbenjamin@lrtcworld.org.

is a widely known cryptocurrency that uses cryptographic methods to link peer-to-peer users without any intermediaries. Just like other cryptocurrencies, bitcoin is not controlled by the Central bank or authority, and it relies on the blockchain, an open-source software algorithm that verifies decentralised transactions.

The supply of Bitcoin is determined by a publicly known algorithm, while the expected price movement mainly influences its demand. The price of bitcoin and other cryptocurrencies is determined by the interplay of demand and supply, like every other commodity. Bitcoin has rapidly been used as a medium of exchange since 2013, possibly due to its lower cost of transaction compared to other forms of money, instant transaction, and faster international payment (Oh and Nguyen, 2018). However, its high volatility has prevented it from being used as a store of value and unit of account.

The demand for bitcoin has increased over the years despite its high volatility. The growing demand may be attributed to the anonymous bitcoin transaction. The anonymity of the revolutionary digital payment system preserves the privacy of the user and hence, makes it easier for users to engage in anti-governmental transactions such as money laundering, purchase of contra-bound drugs, and theft. No wonder countries like China outlawed bitcoin as a currency. The increasing controversies surrounding bitcoin use case, bitcoin price, users' intention, volatility, and global acceptability as a means of exchange have drawn the interest of financial experts and economists recently.

For instance, Fink and Johann (2014) analysed the price of bitcoin between January 2011 and May 2014. They found out that the liquidity rate of all bitcoin exchange rates is correlated and improving with time. In a similar spirit, Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) evaluated users' intention on the use of bitcoin, and their result shows that the users of bitcoin are not really after using it for transactions but as an alternative investment vehicle. Carrick (2016) analysed the use of bitcoin as a complement to the conventional currencies, and his result suggests that bitcoin possesses some characteristics that make it a complement.

Furthermore, Chiu and Koeppl (2017) used a general equilibrium monetary model based on bitcoin to analyse the optimal design of a cryptocurrency system. Their study managed to relate the value of cryptocurrency systems to the volume of transactions. Similarly, Caporale and Zekokh (2019) estimated alternative models to measure the volatility of cryptocurrencies. Their finding revealed that a large number of users globally hold bitcoin for speculative reasons as an alternative to investment in the stock market and foreign exchange market. They attributed the increasing desire to hold the first and most widely known cryptocurrency to its rapidly increasing market capitalisation, most notably the surge in market capitalisation from 18 billion US dollars to about 200 billion US dollars between January and December 2017 (Caporale and Zekokh, 2019).

Few other studies have also analysed the relationship between cryptocurrency, exchange rates, and stock prices. For instance, Oh (2018) incorporated cryptocurrency into the money supply equation to explain the channels through which cryptocurrency induces a rise in the level of the exchange rate. According to the study, an increase in cryptocurrency adoption increases the monetary base of the economy and subsequently raises the money supply level. The increase in the totality of the money in circulation is accompanied by a fall in interested rate and an upward movement in the exchange rate. Similarly, Erdas and Caglar (2018) submitted that there is a one-way causality from bitcoin prices to Standard and Poor's (S&P) 500 index.

Despite the growing literature on the prices, adoption, and implications of cryptocurrencies, not much has been done in the most populous and the largest economy among African countries. Nigeria, which is operating a managed floating exchange rate, has witnessed a rapid increase in bitcoin trading recently. As of 2017, Nigeria was in the second position in bitcoin trading in the world (Hope, 2017), and in 2019, Nigeria ranked first in global online search for bitcoin volume (Cryto David, 2019). Also, Binance, which is the leading cryptocurrency exchange, added Nigerian currency to her growing list of fiat-to-cryptocurrency trading pairs recently (Binance, 2019). In the spirit of Erdas and Caglar (2018), the rapid adoption of cryptocurrencies in Nigeria may influence the behaviour of the stock and exchange rate market. Given the form of exchange rate system in Nigeria, coupled with the influence of speculations on bitcoin prices and its implication on the exchange rate and the stock market, the relationship between exchange rates, cryptocurrencies, and stock prices become an empirical exercise in Nigeria. This study intends to examine how the volatility of bitcoin and ethereum prices influence the exchange rate and the stock market volatilities in Nigeria. These two cryptocurrencies were selected because they are the most used and most traded cryptocurrency in Nigeria.

Following the above background, the remaining parts of this paper consist of theoretical and empirical review, methodology and techniques of data analysis, presentation and interpretation of results, discussion of findings as well as conclusion and recommendations.

2. Theoretical and Empirical Review

Bitcoin is a recent innovation in the payment system, a lot of computer and engineering experts have written on the technicality of bitcoin in relations to Cyber-security and the legal aspects. Economists and financial experts have argued on weather bitcoin has a fundamental economic barking. The price of bitcoin cannot be explained by any economic theories because some certain characteristics of demand and supply of currencies are missing in the bitcoins market (Kristoufek, 2013).

Bouoiyour and Selmi (2015) also stressed that bitcoin is largely detached from macroeconomic fundamentals and rather behaves as a ‘speculative bubble’. Ciaian, Rajcaniora, and Kancs (2016) applied the traditional Fisher’s equation to the formation of bitcoin price treated bitcoin as only means of payment and not for speculative motive as shown in the following equation;

$$P^B = \frac{PG}{VB},$$

Where P^B is the price of bitcoin, P is the general price level, V is the velocity of bitcoin, G is the size of bitcoin and B is the stock of bitcoin. Price of bitcoin is expected to increase with the general price level and the size of bitcoin in the economy and decreases with the velocity of bitcoin and the stock of bitcoin in the system. Ciaian, et al (2016) analysed the intentions of new and uninformed users of bitcoin with the Generalized Autoregressive Conditional Heteroscedasticity (GARCH 1,1). Their result shows that users demand for bitcoin for speculative reasons and it is influenced by the volume of exchange rate, bitcoin traffic, the lag of network volume, and the daily controls of bitcoin.

Georgoula, Pournarakis, Bilanakos, Sotiropoulos, and Giaglis (2015) used sentiment analysis to examine the economic and technological determinants of bitcoin prices. The short-run analysis shows that twitter sentiment ratio, mining difficulties, and the degree of public interest are positively related to bitcoin prices while exchange rate is negatively related to bitcoin prices. The long-run analysis shows that bitcoin price is positively related to the total stock of bitcoin and negatively related to the stock market index. Chiu and Koeppl (2017) used bitcoin to develop a generalised equilibrium monetary model to analyse the optimal design of cryptocurrencies.

Corelli (2018) assessed the relationship and causality between cryptocurrencies and fiat currencies of Europe, Australia, Indian, Malaysia, Thailand, Taiwan, South Africa, New Zealand, China and Japan. The study considers only six cryptocurrencies namely Bitcoin, Etherium, Ripple, Litecoin, Monero and Dash. The study adopts a Ganger Causality test and Vector Autoregressive model to examine the relationship and causality between the cryptocurrencies and fiat currencies of the selected countries. The result shows that the cryptocurrencies have some dependence on the selected national fiat currencies. Riska-Dwi and Nadia (2018) analysed the effect of cryptocurrency on the exchange rate of china using monthly data over the period of November 2012 to July 2017. The study used Autoregressive distributive lag model to analyse the data. The result suggests that bitcoin price volatility has a significant effect on exchange rate in China. This implies that investors prefer to invest in real currency when there is high volatility in bitcoin price.

However, based on the above literature, it is obvious that much work have been done on cryptocurrencies in recent time but the economic and finance aspect of the relationship between cryptocurrencies and its impact on exchange rate and stock market volatility have not been properly explored.

3. Methodology

In this section, the study uncovered the natural and sources of data, model specification, and techniques of analysis employed in the study

3.1. Nature and Sources of Data

The variables used for the analysis include nominal exchange rate, all share index, bitcoin prices and ethereum prices. Monthly data on nominal exchange rate and all share were obtained from the Central Bank Statistical Bulletin (2019), while the data on bitcoin and ethereum were sourced from the CoinMarketCap[1] which is the central historical data bank for all cryptocurrency. The secondary data spans from August 2015 to December 2019. The analysis is limited to this period because of the scarcity of data on ethereum.

3.2. Model Specification

To analyze the impact of cryptocurrency volatility on stock and exchange rate volatility in Nigeria, the study specified a simple linear models which can be traced to the work of Riska-Dwi and Nadia (2018). These two models are expressed as follows;

$$\ln asir_t = f(\ln btcr_t, \ln ethr_t) \qquad 1$$

$$\ln exrr_t = f(\ln btcr_t, \ln ethr_t) \qquad 2$$

where $asir_t$ is stock prices returns at time t, $btcr_t$ represents bitcoin price returns at time t, $ethr_t$ denotes ethereum price returns at time t, $exrr_t$ stands for exhchange rates returns at time t and ln is the natural logarithm. The returns series were calculated using the following formula: $r_t=\ln P_t-\ln P_{t-1}$ where r_t denotes returns at time t, $\ln P_t$ represents the natural logarithm of the observed price at time t while $\ln P_{t-1}$ is the observed prices at time t-1. The returns formula is simply the first differences of the prices (Darne and Charles, 2019).

[1] The historical data can be found on https://coinmarketcap.com/historical/.

3.3. Techniques of Analysis

Different techniques of analysis were used in this study. Specifically, the article used descriptive statistics to examine the attributes of the secondary data. At the same time, the correlation matrix was employed to determine the strength and nature of the association among the variables. Further, the study adopted three different unit root tests, namely Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for robust stationary analysis. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH 1,1) and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH 1,1) were used to establish the impact of cryptocurrency returns volatility on stock prices and exchange rate returns volatility in Nigeria. Also, the study utilized the Granger causality volatility test to determine the directional causality among the variables. A brief explanation of the GARCH (1,1) and EGARCH (1,1), which are the core techniques of analysis is provided below:

The mean equation of GARCH and EGARCH are the same, and the estimated mean equation of stock prices and exchange rate model is presented in Equation 3 as follows;

$$r_{it} = c + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

where r stands for returns, i is stock prices returns and exchange rate returns, c is constant, Ɛ is the error term and t represents time series.

The estimated GARCH and EGARCH variance equation is presented in Equation 4 and 5 as follow:

$$\ln h_t = c + \alpha_i \varepsilon_{t-i}^2 + \beta_i \ln h_{t-i} + \delta \ln btcr_t + \psi \ln ethr_t \ldots\ldots\ldots\ldots 4$$

$$\ln h_t = c + \omega \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \phi \ln h_{t-1} + \delta \ln btcr_t + \psi \ln ethr_t \ldots\ldots\ldots 5$$

The estimated parameters in the GARCH variance equation that is, Equation 4 are α, β, δ, and ψ. The constant is denoted by c, the ARCH effect is represented by α and it measures the extent to which present volatility shock feeds through into the next period volatility, and β which is the GARCH effect is a measure of the last period's forecast variance. The summation of α and β which is expected to be less than one measures the persistence of volatility. The parameters δ and ψ measures the effect of bitcoin and ethereum volatility on exchange rate volatility respectively while the error term is represented by ε. The variance equation of the EGARCH model is expressed in Equation 5 and the natural logarithm of the conditional variance at time t is denoted by $\ln h_t$. The volatility spill over effect of cryptocurrency market on the stock market is measured by ω such that if ω is statistically significant, then stock market volatility is influenced by cryptocurrency volatility.

The parameter γ captures the asymmetric effect of the shocks in cryptocurrency on the stock market volatility. If $\gamma=0$ or insignificant, shocks in the cryptocurrency market will not have any asymmetry effect on the stock market volatility. This implies that both positive and negative shocks have similar impact on stock market volatility as in the case of GARCH framework. Meanwhile, if $\gamma>0$ and significant, then there is asymmetry effect meaning that positive shocks (good news) in the cryptocurrency market will have a higher impact on stock market volatility than negative shocks (bad news) but if $\gamma<0$ and significant, negative shocks in the cryptocurrency market will have a larger impact on stock market volatility than positive shocks. Persistence in the conditional variance is captured by ϕ. A large positive ϕ indicates a high persistence which means that volatility will not die out quickly in the event of a shock in the cryptocurrency market vice versa. The effect of bitcoin returns volatility and etherum returns volatility on stock prices returns volatility is represented by δ and ψ respectively while ε denotes the error term.

4. Presentation and Discussion of Results

This section presents the results of the preliminary analysis, unit root, univariate volatility results and Granger causality test.

4.1. Preliminary Analysis

Table 1 shows the descriptive statistics and the correlation matrix of all the variables used for the analysis. The average value of bitcoin, which is the major traded cryptocurrency in the world, is above every other economic and financial variables such as exchange rate and all share index. Also, the average value of bitcoin is greater than the mean of ethereum, which authenticate the fact that bitcoin is the most traded cryptocurrency in the world. Further, it can be seen that all share index has the highest values compared to other variables, which suggests that all share index is the most volatile variable. Bitcoin is more volatile compared to ethereum, while the exchange rate is the least volatile variable. The correlation matrix reveals the positive relationship among exchange rates volatility, stock prices volatility, bitcoin prices volatility and ethereum prices volatility. By implication, all the variables move in the same direction over the period of study.

Table 1. Descriptive Statistics and Correlation Matrix

Descriptive Statistics				
	asi	Exr	btc	eth
Mean	31029.87	359.0628	4429.252	207.7788
Median	29597.79	360.9400	3792.948	141.2768
Maximum	44343.65	494.7000	14156.44	1246.010
Minimum	23916.15	216.6400	228.7600	0.610000
Std. Dev.	5214.317	56.38780	3867.665	254.1742
Skewness	0.849046	-0.376309	0.519610	1.926910
Kurtosis	2.803286	4.647581	2.075058	7.252695
Jarque-Bera	6.453214	7.245448	4.274217	72.73665
Probability	0.039692	0.026710	0.117996	0.000000
Obs.	53	53	53	53
Correlation Matrix				
	lnasir	Lnexrr	lnbtcr	Lnethr
Lnasir	1	0.074	0.280	0.218
Lnexrr		1	0.0168	0.023
Lnbtcr			1	0.422
Lnethr				1

The study used the untransformed variables for descriptive analysis for ease of interpretation. In contrast, the natural logarithm of the variables was used for the correlation matrix to establish the association among the variables.

Source: Authors' computation

4.2. Unit Root Test

The study employed ADF to check if the means and the variances of all share index returns, exchange rate returns, bitcoin price returns and ethereum price returns are constant over time. As it can be seen from the result of the test presented in Table 2, all the variables are stationary at level, which suggest that the mean and the variance of each of the variables is constant over time. To authenticate the result of the ADF, the study employed the PP and KPSS unit root tests. The empirical evidence reported in Table 2 validated the ADF outcome. Hence, the study concluded that all the variables are integrated of order zero, that is, I(0).

Table 2. Non-Stationary Results

Test	Variables	Level		Order of Integration
ADF	lnasir	-7.939(0.000)*		I(0)
	lnexrr	-6.697(0.000)*		I(0)
	lnbtcr	-7.128(0.000)*		I(0)
	lnethr	-6.710(0.000)*		I(0)
	Test Critical Values	1% level (-4.080)	5% level (-3.468)	10% level (-3.161)
PP	lnasir	-7.983(0.000)*		I(0)
	lnexrr	-6.669(0.000)*		I(0)
	lnbtcr	-7.129(0.000)*		I(0)
	lnethr	-6.669(0.000)*		I(0)
	Test Critical Values	1% level (4.0800)	5% level (-3.468)	10% level (-3.161)
KPSS	lnasir	0.084*		I(0)
	lnexrr	0.146*		I(0)
	lnbtcr	0.073*		I(0)
	lnethr	0.123*		I(0)
	Test Critical Values	1% level (0.216)	5% level (0.146)	10% level (0.119)

*ADF, PP, and KPSS represent Augmented Dickey-Fuller, Phillips-Perron, and Kwiatkowski-Phillips-Schmidt-Shin, respectively. Schwarz Info Criterion with default maximum lags was used for ADF while the Spectral estimation method: Default (Bartlett kernel) and Automatic selection (Newey-West Bandwidth) was used for PP and KPSS. All the tests were conducted with trend and intercept, and * denotes stationary at level.*

Source: Authors' computation

4.3. Univariate Volatility Results

The results of the mean and variance equation of the univariate volatility models are presented in Table 3. For the stock prices returns model, the stationarity and ergodicity conditions of the EGARCH model were satisfied. The intercepts of the mean and variance equation are negative and significant at one percent level. Similarly, the value of the volatility spillover effect (ω) is negative and significant at one percent, which suggests that the Nigerian stock market is susceptible to the changes in the cryptocurrency market, that is, an unexpected change in the behaviours of the cryptocurrency investors in the previous period drives the stock market volatility. The asymmetric effect (γ) is also negative and significant at one percent. The implication is that volatility in the stock market rises more in response to negative shocks to cryptocurrency prices than positive shocks of the same magnitude. In other words, bad news which affects the prices of the cryptocurrency increases stock market volatility than a similar magnitude of good news.

Table 3. Results of the Volatility Models

EGARCH: Stock Prices Model				EGARCH: Exchange Rates Model			GARCH: Exchange Rates Model		
	Coef.	**z-Stat**	**Prob.**	**Coef.**	**z-Stat**	**Prob.**	**Coef.**	**z-Stat**	**Prob**
Mean Equation									
c	-0.027	-8.719	0.000*	0.001	0.403	0.687	0.001	0.190	0.849
Variance Equation									
c	-0.886	-54.369	0.000*	-7.150	-34.259	0.000*	0.001	1.344	0.180
α	-	-	-	-	-	-	0.093	1.690	0.091***
β	-	-	-	-	-	-	0.557	2.333	0.020**
ω	-0.774	-15.570	0.000*	2.251	5.740	0.000*	-	-	-
γ	-0.562	-3.162	0.002*	0.136	0.3896	0.697	-	-	-
ϕ	0.760	5.500	0.000*	0.275	5.990	0.000*	-	-	-
δ	2.019	2.745	0.006*	-1.224	-0.944	0.345	-0.002	-2.178	0.029**
ψ	0.644	1.853	0.064***	2.805	5.947	0.000*	0.0002	1.986	0.047**
Conditions (Stationarity and Ergodicity) of GARCH and EGARCH Models									
|ϕ|<1	√	-	-	√	-	-	-	-	-
γ≠0^	√	-	√	√	-	X	-	-	-
c, α, β>0	-	-	-	-	-	-	√	-	-
α+ β<1	-	-	-	-	-	-	√	-	-

****, ** and * represents significant at 10, 5, and 1% level of significance. GARCH technique was used to analyze the exchange rate model because of the failure of the EGARCH results to satisfy the stationarity and ergodicity condition of the EGARCH model*

Source: Authors' computation

Further, the volatility persistence (ϕ) is significant, and the magnitude is 0.70. This means that the volatility in the stock market will die out slowly through time. The coefficients of bitcoin and ethereum return volatility are positive and significant at one percent and 10 percent level of significance, respectively. By implication, a one percent increase in bitcoin and ethereum returns volatility fuels stock market returns by 2.019 and 0.644 percent respectively. In other words, cryptocurrency returns do not displace the stock market in Nigeria; rather, it improves it. This result departs from the submission of Georgoula et al. (2015), who reported that bitcoin price harms the stock market index. The rationale for the positive association between the cryptocurrency and the stock market can be explained by the fact that the cryptocurrency investors in Nigeria invest more of their gains in the conventional market. The global acceptability of cryptocurrency also justify the positive contribution of bitcoin and ethereum returns to the financial market in Nigeria.

Unlike the stock prices returns model, the asymmetry parameter of the exchange rates returns model was not significant at 10 percent level of significance. This departs from the ergodicity condition of the EGARCH model, and it implies that shocks in the cryptocurrency market did not have an asymmetric effect on the exchange rate market. The study, therefore, estimated GARCH (1,1) model which assumes a symmetry relationship between cryptocurrency and exchange rates volatility. As can be seen from the result, the GARCH and the ARCH parameters satisfy the non-negative condition. Specifically, the ARCH parameter is significant, and it suggests that the past volatility shock to the cryptocurrency market influences the present volatility in the exchange rate market. Further, the significant GARCH parameter implies that the last forecast variance has a high persistence effect on the model. The sum of the two parameters is less than one (0.65), which shows that the volatility fades away slowly over time.

Bitcoin prices return volatility exerts a significant adverse effect on exchange rates volatility while ethereum prices returns have a significant and plausible relationship with exchange rates volatility. Holding ethereum returns volatility constant, a one percent increase in bitcoin returns volatility gives rise to 0.002 percent appreciation in the value of Nigeria currency. This is in line with the finding of Dwi and Nadia (2018), and it also justifies the argument that instability in bitcoin prices at a point will make investors switch from bitcoin to local currency, which will in turn strengthen the domestic currency. On the contrary, a one percent increase in ethereum returns volatility fuels 0.0002 percent depreciation in exchange rates volatility in Nigeria. Even though ethereum returns volatility adversely influences the foreign exchange market, it is apparent that the impact is minimal as it is far from one percent.

4.4. Granger Causality Results

The Granger causality result presented in Table 4 shows a one-way causality from bitcoin to all share index. This implies that the volatility of bitcoin, which is the main form of cryptocurrency granger causes a change in the all share index in Nigeria. Even though the technique of analysis differ, the result agrees with the submissions of Erdas and Caglar (2018) that bitcoin Granger causes the S&P 500 index. Similarly, the empirical evidence reveals a unidirectional causality flowing from ethereum to all share index. This means that the behaviours of the cryptocurrency prices influence the investment decision of the stock market investors. In other words, the price of the cryptocurrency has a significant influence on the volatility of the stock market in Nigeria.

On the contrary, the result suggests the absence of directional causality between cryptocurrency prices and foreign exchange in Nigeria during the period under review. What this implies is that the foreign exchange market is not affected by the movement in the cryptocurrency prices. This is not a surprise because the result of the GARCH model earlier reported indicated that instability in cryptocurrency prices have a minimal impact on the exchange rate market in Nigeria.

Table 4. Granger Causality Results of the Volatility Series

Null Hypothesis	F-Stat	Prob.	Decision
Stock Prices Model			
lnbtcr does not Granger cause lnasir lnasir does not Granger cause lnbtcr	3.438 1.075	0.068*** 0.303	One-way Causality
lnethr does not Granger cause lnasir lnasir does not Granger cause lnethr	5.242 0.547	0.027** 0.463	One-way Causality
lnethr does not Granger cause lnbtcr lnbtcr does not granger cause lnethr	0.009 1.111	0.924 0.297	No Causality
Exchange Rates Model			
lnbtcr does not Granger cause lnexrr lnexrr does not Granger cause lnbtcr	0.43002 2.16155	0.5140 0.1457	No Causality
logethr does not Granger cause lnexrr lnexrr does not Granger cause lnethr	1.037 1.97695	0.3135 0.1662	No Causality
lnethr does not Granger cause lnbtcr lnbtcr does not Granger cause lnethr	0.00928 1.11070	0.9237 0.2972	No Causality

**** and ** indicate significance at 10 and 5 percent level of significance respectively.*

Source: Authors' computation

5. Conclusions

The use and acceptability of cryptocurrencies globally as another means of exchange have generated the attention of financial and economic experts in recent times. It is assumed that the bitcoin and other cryptocurrencies would be the money of the future due to its popularity and similar features of money it possesses. This study, however, examined the nexus between the most used cryptocurrency (Bitcoin and Etherum) and the volatility of exchange rate and all share index in Nigeria between August 2015 and December 2019. Generalized Autoregressive Conditional Heteroscedasticity and Exponential Generalized Autoregressive Conditional Heteroscedasticity and Granger causality tests were used for the analysis. The result of the EGARCH (1,1) revealed that volatility in the stock market response more to bad news in cryptocurrency market than the good news of the same magnitude and that the volatility in the stock market dies out slowly through time. It was also found that cryptocurrency returns volatility plays a significant role in the financial market in Nigeria. Further, the estimates of GARCH (1,1) indicate that bitcoin returns volatility leads to a very small appreciation in the domestic currency. The Granger causality test shows a unidirectional causal relationship from bitcoin to the stock market index in Nigeria. Based on the above, the study concludes that the volatility of bitcoin and ethereum has a significant impact on the stock market price in Nigeria. Therefore, we recommend that stock market investors in Nigeria should pay rapt attention to the movement of cryptocurrency prices.

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