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CRYPTOCURRENCY SHOCK AND EXCHANGE RATE BEHAVIOUR IN NIGERIA

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ABSTRACT: *This study examined the relationship between cryptocurrency shocks and exchange rate behaviour in Nigeria. Selected cryptocurrencies for the study are Bitcoin, Ethereum, Litecoin, Ripple and Binance coin which are the most traded cryptocurrencies in Nigeria. Augmented Dickey-Fuller (ADF), Johansen Cointegration and Vector Autoregressive (VAR) tests were used to analyze the monthly data of exchange rate and selected cryptocurrencies for four years (45 months). The result of the cointegration test revealed the existence of a long-run relationship among the variables. ECM result showed that about 6% of the short-run disequilibrium are being corrected and integrated into the long-run equilibrium relationship. In addition, the Variance Decomposition result showed that Ripple has the highest variations to exchange rate in the short and long runs. The present value of exchange rate adjusts slightly to changes in cryptocurrency. Ripple and Bitcoin have the highest shocks on the exchange rate. Therefore, monetary authorities should give adequate attention to cryptocurrency transactions and make policy decisions on how to reduce the prevailing high exchange rate in Nigeria by integrating crypto transactions in their systems. Transaction in cryptocurrency is still at the early stage, especially in Nigeria; only five years data can be gotten on commonly traded cryptocurrencies in Nigeria. This is a limitation to the study in terms of the number of cryptocurrencies used in the study. More cryptocurrencies can be included in future studies.*

KEYWORDS: Cryptocurrency, Exchange rate, Bitcoin, Ripple, Monetary.

JEL Classification code: E42, G23, F31

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INTRODUCTION

Over the years, money, as a means of exchange for goods and services, has undergone different stages from the use of items like salt, clothes, arrows, cowry shell to metal coins and paper money, and thereafter to electronic currency. The latest form of money is the digital currency known as cryptocurrency which is a purely peer-to-peer version of electronic cash with the aid of crytography. Ari (2018) defined cryptocurrency as the intersection of game theory, cryptography, computer science, economics, venture capital, and public markets. With the aid of cryptocurrency, payments for goods and services can be made directly from one party to another without the involvement of financial institutions. Technically, crytocurrencies are not money but they derived their values from real world currencies, which puts them in a very precarious situation (Partanen, 2018). They are very volatile in nature and as such they cannot be used as store of value; therefore, they are referred to as fiat money. The inability to function as store of value can be seen in the recent fall in their values. In 2008, Satoshi Nakamoto launched the most popular cryptocurrency known as Bitcoin, mined by computers performing complex mathematical equations and recorded in a public distributed ledger called the blockchain. Other cryptocurrencies were developed among which are Ethereum, Ripple, Litecoin, Binance, Zcash, Monero and so on. As at June, 2021, there are 10 505 cryptocurrencies in the world with a total market cap of $1,493,789,040,578 (CoinMarketCap, 2021).

Over the years, bitcoin and other cryptocurrencies have recorded gains, with their suitability in hedging against inflation, coupled with access to other crypto assets that offer more viable options. Cryptocurrency is gaining popularity in Nigeria on daily bases as majority of the youths adopted it as a means of wealth creation and for business transaction; this has earned the country second place in the world for cryptocurrency trading with a volume of over $400m worth of transactions in 2020 and $2,912,371 (N1.13 billion) in March 2021 (Adesina 2021).

Initially, the argument behind the development of cryptocurrency was to avoid participation of a third party, like the financial institutions, in transaction and also regulatory authorities. This poses a serious challenge to monetary authorities all over the world, since atrocities like money laundry, terrorist financing, and so on are committed through the use of cryptocurrency. In order to regulate transactions using cryptocurrency, some countries like Australia, Canada, Denmark, Finland, Germany, Israel, New Zealand, Singapore, Sweden, Switzerland, Taiwan, and the Arab Emirates (UAE) apply existing laws. Whereas, other countries like Indonesia, Mauritius, Mexico and Venezuela have enacted new legislations. While some countries are at various stages of developing legislation that specifically governs cryptocurrency—countries such as France, Italy, Japan, Malaysia, Philippines, South Africa, and Ukraine—the usage of cryptocurrency as a means of payment was banned in China (Law Library of Congress, 2019). Also, the Central Bank of Nigeria on the 5th of February, 2021 banned transactions using cryptocurrency and threatened to sanction financial institutions which involve themselves in it. However, the CBN later lifted the ban and promised to create national cryptocurrency (Kalu, 2021). Nations of the world through their monetary authorities have started plans to develop national digital currency in which they will have control over. For instance, Ghana and Nigeria are on the way to roll out national digital currencies.

On the other hand, the exchange rate, which is the price of one currency in terms of another currency, is an important instrument of economic management. Movements in the exchange rate pose serious worries not only to the monetary authorities who are faced with stabilization

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problem but also to firms and individuals that engage in foreign businesses, as a result of the consequences of exchange and political risk. Factually, fluctuations in exchange rate are formidable bed rocks for all economic activities all over the world. In the past years, the value of the naira has been fallen, this made the Central Bank to come up with policies aimed at promoting exchange rate stability.

However, the price of cryptocurrency according to Ciaian, Rajcaniova and Kancs (2014) is determined by the interaction between demand and supply, macroeconomic conditions and financial developments, and attractiveness to investors. While Yanuar and Yoda (2017) argued that there is a difference in the nature of cryptocurrency to the normal currency in the sense that currencies such as dollar and euro are affected by economic conditions like trade, inflation, politics and crises, which enable easy determination prices unlike cryptocurrencies which are more difficult to determine. Chu, Chan, Nadarajah and Osterrieder (2017) opined that the acceptance of cryptocurrency has increased significantly. It is a known fact that cryptocurrencies are very volatile compared to normal currencies. Therefore, the exchange rates are not expected to be independently distributed. Tarasovaa, Usatenkob, Makurinb, Ivanenkoc, and Cherchatad (2020) observed cryptocurrency to be the easiest and riskiest investment asset with decentralization, code openness, secrecy, emission, and dependability as benefits while instability, lack of assurance, risk of proscription and possible loss are the cons.

Evidence from literature indicates a dearth of empirical studies on cryptocurrency and exchange rate due to the slow global acceptability of cryptocurrency as a medium of exchange. Most studies analyze cryptocurrency theoretically without in-depth statistical evidences which this study takes quintessential. Meanwhile, recent developments in the world of cryptocurrency necessitate the need for more empirical investigations on cryptocurrency, especially its relationship with exchange rate.

Nigerian economy is presently facing a predominant high exchange rate which the monetary authority is looking for ways to reduce. With the advent of crytocurrency in recent years, it is essential to investigate the nature of relationship existing between cryptocurrency and exchange rate and the response of exchange rate to shocks coming from cryptocurrency.

THEORETICAL BACKGROUND

Mises Regression Theorem

The Mises regression theorem was propounded by Ludwig von Mises in his 1912 book titled The Theory of Money and Credit. The theory assumes that all money must ultimately derive their purchasing power from a historical tie to a commodity that was valued in a state of barter. According to Jeffrey (2014), cited in Mckenzie (2018), the theory of the value of money is able to trace the objective exchange value of money only to that point where it is no longer the value of money but merely the value of a commodity.

Empirical Review

It has been established that there are few empirical studies on cryptocurrency. This study will review a handful of related studies like the study conducted by Riska Dwi and Nadia (2018)

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that investigated the effect of cryptocurrency on exchange rate of Yuan with interest on the effect of Bitcoin on China's exchange rate. The study adopted ARDL to analyze the monthly date from 2012 to 2017. It was discovered that in the long run, volatility of Bitcoin price exhibited significant effect on the exchange rate of Chinese currency. Oh (2018) examined the roles of exchange rates using cryptocurrency as a foreign currency in the international economy. Interest rate parity condition was used to refer to the price of a cryptocurrency as the absolute price in terms of a country's currency so as to investigate its movement. The study identified three sources of premium referred to as "Kimchi premium" in South Korea which include the difference in the rates of return of the cryptocurrency, interest rates of the regular currencies and the projected cryptocurrency exchange rates. With the aid of money market and the foreign exchange market models, the study established that the introduction of a new cryptocurrency in one country would lead to high exchange rate.

The study of Sodiq and Oluwasegun (2020) assessed the effect of cryptocurrency returns volatility on stock prices and exchange rate returns volatility in Nigeria from 2015 to 2019. They employed GARCH, EGARCH and Granger causality techniques to analyse the data. Findings from the study revealed that stock market price is mostly affected by the price fluctuation in bitcoin and ethereum than the exchange rate in Nigeria. There was a unidirectional causality from bitcoin and ethereum to stock market index. The study therefore established a significant effect between volatility of bitcoin and ethereum on the stock market price in Nigeria. In addition, Chu, Chan, Nadarajah and Osterrieder (2017) developed twelve GARCH models for seven cryptocurrencies with the aim of assessing their fitness to each cryptocurrency based on five criteria. Findings revealed that the IGARCH and GJRGARCH models gave the best fits in modelling the volatility of cryptocurrencies. In their conclusion, cryptocurrencies were found to be highly volatile mostly in daily prices.

Tarasovaa, Usatenkob, Makurinb, Ivanenkoc, and Cherchatad (2020) employed mathematical modeling to forecast cryptocurrency exchange rate. It was opined that the higher the speed of mining cryptocurrency, the more difficult it is to predict future cryptocurrency exchange rates. It was observed that cryptocurrency exchange rates are affected by trade wars of the USA with other export countries like China, the introduction of IEO as the alternative for ICO and new drivers linked with the interest in cryptocurrency, recommendations of FATF for market control, the development of the stablecoin market and the entry of world giants such as Facebook into the crypto-market. Nashirah and Sofian (2017) used Autoregressive integrated moving average (ARIMA) to predict future exchange rate of bitcoin in high volatility environment. The parameter of ARIMA model was determined by autocorrelation function (ACF) and partial autocorrelation function (PACF). Findings from the study revealed that 5.36% ex-post forecasting error was found between actual data and forecasting value. It was observed that forecasting in a high volatility environment was characterized with larger errors which need special consideration of error diagnostics.

Also, Sahoo, Sethi and Acharya (2019) studied the relationship between price and volume of bitcoin near-stock properties. Linear and non-linear causality tests were adopted in the study. Findings from linear causality test revealed that return on bitcoin cannot be predicted by trade volume while the non-linear causality test indicated the existence of non-linear responses amid trade volume and returns on bitcoin. The study concluded that investment decision in bitcoin should not be based on linear but on non-linear dynamics in the market. Sahoo (2021) investigated the effect of the coronavirus pandemic on cryptocurrency market returns. The study employed linear Toda and Yamamoto and nonlinear Diks and Panchenko Granger

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causality test for data analysis. The result from the study revealed that there is unidirectional causal relation from confirmed cases and death cases of COVID-19 to returns on cryptocurrency price. Findings from post-break period further confirmed the existence of unidirectional linear causality from COVID-19 confirmed cases to returns of cryptocurrency price. It was concluded that information on COVID-19 spread is a determinant factor for the return on cryptocurrency.

Research Questions

The pertinent questions addressed by this study are

i. Is there any relationship between cryptocurrency and exchange rate?

ii. How does the exchange rate respond to changes in cryptocurrency?

Data and Methods

Secondary data obtained from the Central Bank of Nigeria (CBN) Statistical Bulletin and Coincodex Exchange from August 2017 to June 2021 was used in the study. Monthly exchange rate of Naira in relation to US Dollar was used as the dependent variable and the most traded cryptocurrencies in Nigeria were selected as the independent variables.

Model Specification

The model specified below shows the relationship between cryptocurrency and exchange rate in Nigeria.

$$
\left[\begin{array}{l}
EXR_t = Y_{10} + y_{11}BTC_{t-1} + y_{12}ETH_{t-1} + y_{13}XRP_{t-1} + y_{14}BNB_{t-1} + y_{15}LTC_{t-1} + U_{10t} + \sum EXR_t \\
BTC_t = Y_{20} + y_{21}EXR_{t-1} + y_{22}ETH_{t-1} + y_{23}XRP_{t-1} + y_{24}BNB_{t-1} + y_{25}LTC_{t-1} + U_{20t} + \sum BTC_t \\
ETH_t = Y_{30} + y_{31}EXR_{t-1} + y_{32}BTC_{t-1} + y_{33}XRP_{t-1} + y_{34}BNB_{t-1} + y_{35}LTC_{t-1} + U_{30t} + \sum ETH_t \\
XRP_t = Y_{40} + y_{41}EXR_{t-1} + y_{42}BTC_{t-1} + y_{43}ETH_{t-1} + y_{44}BNB_{t-1} + y_{45}LTC_{t-1} + U_{40t} + \sum XRR_t \\
BNB_t = y_{50} + y_{51}EXR_{t-1} + y_{52}BTC_{t-1} + y_{53}ETH_{t-1} + y_{54}XRP_{t-1} + y_{55}LTC_{t-1} + U_{50t} + \sum BNB_t \\
LTC_t = y_{60} + y_{61}EXR_{t-1} + y_{62}BTC_{t-1} + y_{63}ETH_{t-1} + y_{64}XRP_{t-1} + y_{65}BNB_{t-1} + U_{60t} + \sum LTC_t \ldots 1
\end{array}\right]
$$

Where:

EXR represents Exchange rate

BTC represent Bitcoin

ETH represents Ethereum

XRP represents Ripple

LTC represents Litecoin

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BNB represents Binance coin

F represents Functional denotation

$Y_{10} - Y_{60}$ = Intercept / Constant Parameter

$Y_{11} - Y_{61}$ = Coefficients of Estimates

U = Stochastic Term

The exchange rate used in the study was calculated using the following formula:

EXRt = EXRt - EXRt-1

where EXRt denotes exchange rate at time t, while EXRt-1 is the observed exchange rate at time t-1.

Estimation Techniques

The study employed Augmented Dickey-Fuller (ADF) test to test for stationarity of the variables, Johansen Cointegration test and Vector Autoregressive (VAR) through ECM, and impulse response test for the response of the variables to shock.

RESULT AND DISCUSSION OF FINDINGS

Descriptive Analysis

Descriptive analysis explains the nature of the distribution of the data as seen in the table below.

Table I: Result of the Descriptive Statistics

	logEXR	logBTC	logETH	logXRP	logLTC	logBNB
Mean	2.289839	15.19504	5.844384	4.985768	10.34903	8.831881
Median	0.001250	15.04788	5.670993	4.837682	10.22334	8.794332
Maximum	34.37500	16.99912	7.927902	6.489013	11.72493	12.41719
Minimum	-30.00000	14.17106	4.502800	4.156230	9.360899	5.800684
Std. Dev.	9.415169	0.697301	0.826205	0.543535	0.610075	1.261354
Skewness	1.005561	1.059230	0.850551	0.929933	0.628072	0.454528
Kurtosis	8.905344	3.793683	3.018776	3.285809	2.497354	4.700505
Jarque-Bera	74.59226	10.02236	5.667618	6.934047	3.584824	7.281281
Probability	0.000000	0.006663	0.058789	0.031210	0.166558	0.026236
Sum	105.3326	714.1667	274.6861	234.3311	486.4046	415.0984

Source: Author's Computation (2021)

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Table I presents the summary of several statistics indicating different distributions of the variables. Skewness statistic revealed that all the variables are positively skewed. The kurtosis statistic shows that EXR, BTC, ETH, XRP and BNB are leptokurtic (fat tailed) in nature while LTC is platykurtic (tin tail) in nature. The normality test from Jarque-Bera (JB) showed that EXC, BTC, XRP and BNB were not normally distributed while other variables such as ETH and LTC were normally distributed.

Unit Root Test

Table II below presents the results of Augmented Dickey-Fuller for unit root test.

Table II: Augmented Dickey Fuller (ADF)

Variables	ADF Test at Level	Critical Values at 5%	Critical Values at 10%	ADF Test at 1st Diff	Critical Values at 5%	Critical Values at 10%	Decision
logEXR	-2.950699	-2.931404	-2.60394	-12.29007	-2.931404	-2.603944	1(1)
logBTC	-0.918182	-2.926622	-2.601424	-5.616777	-2.928142	-2.602225	1(1)
logETH	-0.197334	-2.926622	-2.601424	-5.999426	-2.928142	-2.602225	1(1)
logXRP	-2.675332	-2.926622	-2.601424	-7.806087	-2.928142	-2.602225	1(1)
logLTC	-2.202017	-2.931404	-2.603944	-6.476788	-2.928142	-2.602225	1(1)
logBNB	-0.848681	-2.926622	-2.601424	-6.550106	-2.928142	-2.602225	1(1)

Source: Author’s Computation (2021)

The unit root test result revealed that the variables were not stationary at level I(0) but became stationary at first differencing I(1). This shows that the variables hold innovative shock passed on them for short period of time then let go. This therefore establishes the presence of non-stationary variables in the series; this explains the possibility of a spurious relationship in the short run as a result of the presence of random walk.

Lag Length Selection

The lag selection criteria is another pre-condition for the Vector Autoregressive (VAR) model after the unit root test. Therefore, this study applied different criteria, for optimal lag selection, i.e., Likelihood Ratio Test (LR), Final Prediction Error Criteria (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn Information Criteria (HQIC).

Table III: Lag Length Selection Criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-279.0729	NA	0.023098	13.25920	13.50495	13.34983
1	-139.0584	234.4428	0.000186	8.421323	10.14156*	9.055695
2	-93.12401	64.09455	0.000130	7.959256	11.15399	9.137376
3	-29.95389	70.51548*	4.82e-05*	6.695530*	11.36476	8.417397*

Source: Author’s Computation, (2021)

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From the result, Likelihood Ratio (LR), Final Prediction Error (FPE), Schwarz Criterion (SC), Akaike Information Criterion (AIC), and Hannan-Quinn Criterion (HQ) takes 3, 3, 3, 1, and 3 lag respectively, which implies that the lag length to be employed for VAR is 3, being selected by LR, FPE, AIC and HQ.

Result of Johansen Cointegration Test

The Johansen Cointegration Test will help to determine whether a long-run relationship exists among the variables. This is possible due to the fact that the unit root test revealed that variables are integrated of order one, i.e., 1(1).

Table IV: Cointegration Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.672931	144.7706	95.75366	0.0000
At most 1 *	0.588448	97.83207	69.81889	0.0001
At most 2 *	0.495732	60.54362	47.85613	0.0021
At most 3 *	0.355408	31.78846	29.79707	0.0291
At most 4	0.228888	13.34465	15.49471	0.1028
At most 5	0.056169	2.427939	3.841466	0.1192

Sources: Authors' Computation, 2021

Table IV shows the existence of a long-run relationship (cointegration) among bitcoin (BTC), ethereum (ETH), ripple (XRP), litecoin (LTC), binance coin (BNB) and exchange rate (EXR). Evidence of this was seen in the Trace test that indicates 4 cointegrating equations at the 0.05 level.

Appendix I reveals that BTC and XRP have a positive relationship with EXR on the long run while EXR is negatively related to ETH, LTC and BNB in the long run. BTC has the coefficient of 12.15253 meaning that EXR will rise in the long run by 12.15253% if BTC rise by a unit. The coefficient of XRP is 44.01812 meaning that a unit increase in XRP will cause to 44.01812% increase in EXR. ETH is with a coefficient of -16.01041, implying that a unit increase in ETH will bring about a 16.01041% decrease in EXR. Similarly, LTC has a coefficient of -8.162699%, meaning that a unit rise in LTC will cause a 8.162699% decrease in EXR. The coefficient of BNB is -0.029879; this implies that a unit increase in BNB will bring about a 0.029879% decrease in EXR.

Post estimation test result in Appendix II by Breusch- Godfrey serial correlation test shows that there is no serial correlation, meaning that the model is appropriate for adoption of VAR. Heteroskedasticity test in Appendix III revealed that observed R-squared has a P-value of 79% which is more than 5%, meaning that there is no heteroskedasticity problem in the model.

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Vector Autoregressive Result

It has been evidenced that the variables are cointegrated in Table 4; therefore, the vector error correction model will be used in VAR analysis.

Table V: Vector Error Correction Mechanism

Variables	Coefficient	Std. Error	t-Statistic	Prob.
ECM(-1)	-0.058615	0.292773	-0.200206	0.8432
D(EXR(-1))	-0.222927	0.292116	-0.763144	0.4535
D(BTC(-1))	3.550134	8.805599	0.403168	0.6907
D(ETH(-1))	-1.714126	11.60393	-0.147719	0.8839
D(XRP(-1))	4.048591	9.524561	0.425069	0.6749
D(LTC(-1))	2.448345	9.833204	0.248988	0.8057
D(BNB(-1))	-3.243455	6.946915	-0.466891	0.6452
C	0.956129	1.940616	0.492693	0.6271

R^2 = 0.814427, F-stat. = 5.081681, Probability of F-stat. = 0.000211

Sources: Authors' Computation (2021)

The ECM is the speed of adjustment at which the dependent variable adjusts to changes in the independent variables usually negatively significant at 1% level. It is expected theoretically that the coefficient of ECM be negative. The coefficient value of -0.058615 shows that about 6% of the short-run disequilibrium are being corrected and integrated into the long-run equilibrium relationship. Consequently, the present value of EXR adjusts slightly to changes in cryptocurrency. In addition, provided that all independent variables are held constant, EXR will increase by 0.956129% in the long run. BTC has the coefficient of 3.550134, implying a positive relationship between BTC and EXR on the long run. A unit rise in BTC will bring about a rise in EXR by 3.550134%. The coefficient of ETH is -1.714126 showing that ETH and EXR are negatively related. EXR will decrease in the long run by 1.714126% if there is a unit increase in ETH. XRP has a positive relationship with EXR;a unit increase in XRP increases EXR by 4.048591%. LTC has a coefficient of 2.448345; this signifies a positive relationship between LTC and EXR in the long run. A unit increase in LTC will increase EXR by 2.448345%. The coefficient of BNB is -3.243455%; this shows the existence of a negative relationship between BNB and EXR in the long run. EXR will decrease in the long run by 3.243455% if BNB increases by a unit.

Impulse Response Result

Impulse response helps to trace the effects of a shock to one endogenous variable on to the remaining variables in VAR.

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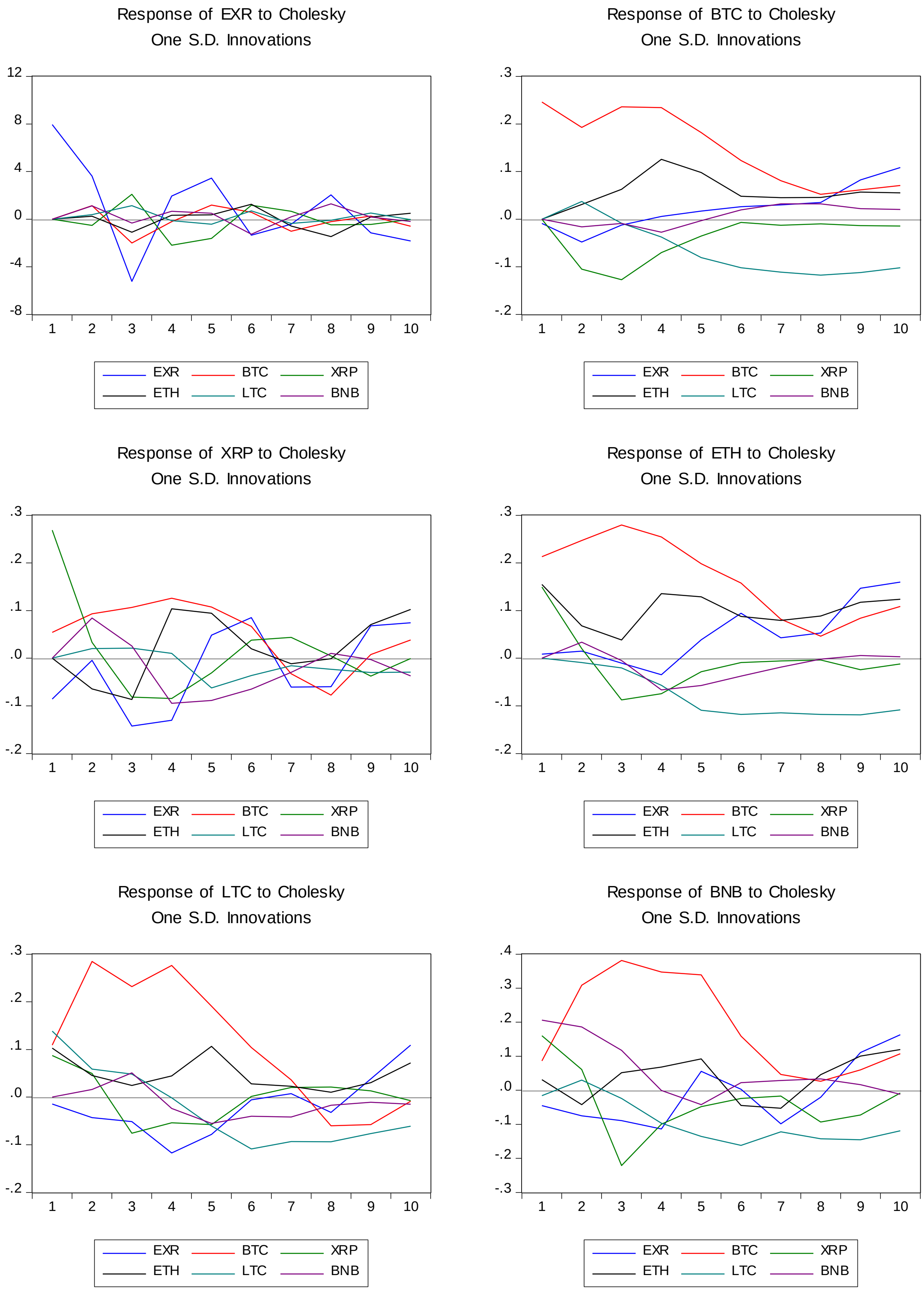

Fig. I Impulse Response

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In Figure I, different curves reflect different variables' response to shocks.

The first graph shows the response of EXR to the shocks coming from BTC, ETH, XRP, LTC and BNB. BTC was positive between period 0 and 1 but became negative at period 3 and later fluctuated between positive and negative trends. ETH was positive at the beginning but became negative at period 3 and later moved between positive and negative trends. XRP fluctuated between positive and negative trends. LTC was positive at the first quarter, negative at periods 4 and 5 and then moved between positive and negative trends. BNB fluctuated between positive and negative trends throughout the periods.

The second figure presents the response BTC to shocks coming from other variables. EXR was negative in the first quarter, became positive at period 4 and remained positive throughout the period. ETH was positive throughout whereas XRP and LTC were negative throughout the periods. BNB was negative from period 1 to 5 and then became positive for the remaining periods

The response of XRP to the shocks coming from other variables is presented in the third figure. EXR was negative in periods 1 to 4 and moved between positive and negative trends. BTC was positive in periods 1 to 6, became negative in 7 and 8 and then remained positive. ETH fluctuated between positive and negative trends. LTC was positive in periods 1 and 2 but remained negative throughout the periods. BNB fluctuated between positive and negative trends.

The fourth figure shows the response of ETH to shocks of other variables. EXR was positive in periods 1 and 2, negative in 3 and 4 and then remained positive. BTC responded positively to the shocks in all the periods. XRP and LTC were positive initially, then remained negative throughout the periods; BNB was positive in the early and later periods but negative in-between the periods.

The response of LTC to shocks of other variables could be seen in the fifth figure. EXR was negative between periods 1 and 6, negative in 7 and then remained positive in the rest of the periods. BTC was positive in the first seven periods then negative in the rest of the periods. XRP fluctuated between positive and negative trends. ETH responded positively all through the periods. LTC and BNB were positive between 1 and 4 and then became negative.

The last figure shows the response of BNB to shocks coming from other variables. EXR fluctuated between negative and positive trends, BTC was positive all through, and LTC responded negatively throughout the periods. XRP was initially positive but rebounded to negative trend; ETH fluctuated between positive and negative trends.

It can therefore be seen that recently EXR responded negatively to shocks coming from BTC, XRP, LTC and BNB but had a positive response to ETH.

Variance Decomposition Result

Variance decomposition shows the amount of the forecast error variance of individual variables described by exogenous shocks to the remaining variables. This is done by providing information about the relative importance of each random innovation affecting the variables in the VAR.

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Table VI: Variance Decomposition of Exchange Rate to Cryptocurrency

Variance Decomposition of EXR:							
Period	S.E.	logEXR	logBTC	logETH	logXRP	logLTC	logBNB
1	7.939638	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	8.898605	96.17968	1.633855	0.041271	0.377600	0.175546	1.592044
3	10.83706	88.07461	4.539413	0.399856	4.615205	1.205397	1.165516
4	11.25123	84.66381	4.247517	1.681250	6.845990	1.129187	1.432243
5	11.96150	83.23416	4.751508	2.003738	7.441353	1.126217	1.443029
6	12.25668	80.46850	4.754904	3.861298	7.087729	1.402180	2.425386
7	12.34416	79.45181	5.355270	3.808223	7.502491	1.464766	2.417439
8	12.67315	77.97961	5.106537	4.791881	7.400217	1.395518	3.326232
9	12.74711	77.87445	5.090296	4.755678	7.428889	1.541246	3.309443
10	12.90344	78.02517	5.182129	4.709549	7.326679	1.505190	3.251285

Source: Author's Computation (2021)

The result from Table VI shows the variance decomposition of exchange rate to cryptocurrency. In the short run (period 3), Apart from its own shock, XRP and BTC showed higher variation of 4.62% and 4.53% to exchange rate (EXR) followed by LTC, BNB and ETH which accounted for 1.21%, 1.17% and 0.4% respectively to EXR. In the long run (period 10), XRP accounted for a higher variation of 7.33% to EXR, followed by BTC with 5.18%, ETH with 4.71%, BNB with 3.25% and LTC with 1.51% respectively. This shows that Ripple, followed by Bitcoin, shows higher variations to exchange rate in both the short and long runs. This implies that Ripple and Bitcoin have more impact on exchange rate.

Table VII: Variance Decomposition of Each Variable to Exchange Rate

Period	Variance Decomposition of logBTC:	Variance Decomposition of logETH:	Variance Decomposition of logXRP:	Variance Decomposition of logLTC:	Variance Decomposition of logBNB:
1	0.130784	0.082201	8.957064	0.424773	2.555163
2	2.087453	0.184114	7.130411	1.456523	3.452743
3	1.332790	0.162004	18.34463	2.247907	3.528954
4	0.957921	0.464480	21.16778	6.067240	4.765609
5	0.897401	0.743507	19.06307	6.674135	4.233395
6	1.021856	2.539533	20.44001	6.256953	3.945845
7	1.201318	2.764479	21.19123	6.073532	4.961605
8	1.454047	3.156077	21.69164	6.114287	4.820310
9	2.985600	6.516959	22.38088	6.283716	5.892994
10	5.404025	9.789456	22.73714	8.624574	8.190611

Source: Author's Computation (2021)

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Table VII shows the reaction of each variable to the exchange rate. In the short run period 3, XRP had the highest percentage (18.3%) variation in EXR decision. This was followed by BNB that accounted for 3.53% variation in exchange rate decision during the study period. Also, LTC accounted for 2.25% variation in exchange rate decision while BTC and ETH were equally responsible for a 1.3% and 0.2% variation in exchange rate decision respectively. In the long run period 10, XRP accounted for 22.7% variations, ETH had 9.8% variations and 8.62 had 8.62% variations in exchange rate in the long run. BNB and BTC accounted for 8.2% and 5.4% variations respectively to exchange rate decisions in Nigeria. Arising from above, XRP had the highest variation in exchange rate in both short and long periods. This implies that XRP has more influence on EXR.

CONCLUSION

Evidently, cryptocurrency network has truly helped in revolutionizing global business transactions, with some exceptions in the area of money laundry, terrorist financing and so on. This study investigated the relationship between cryptocurrency shocks and exchange rate behaviour in Nigeria from August 2017 to June 2021. The result from the cointegration test showed that a long run relationship exists among the variables. The Breusch–Godffrey serial correlation test and heteroskedasticity test showed that there is no serial correlation and heteroskedasticity problems in the model. Error correction model revealed that about 6% of the short-run disequilibrium are being corrected and integrated into the long-run equilibrium relationship. This implies that the present value of the exchange rate adjusts slightly to changes in cryptocurrency. Also, Bitcoin, Ripple and Litecoin have a positive influence on exchange rate while Ethereum and Binance coin have a negative impact on exchange rate. The impulse response result showed that the exchange rate responds positively and negatively to shocks coming from cryptocurrency over the years. However, the exchange rate recently responded negatively to shocks coming from BTC, XRP, LTC and BNB but had a positive response to shocks coming from ETH.

Similarly, the Variance Decomposition result showed that Ripple, followed by Bitcoin, has the highest variations to exchange rate in the short and long runs. This implies that the highest shock comes from Ripple followed by bitcoin. From the findings of this study, it is suggested that monetary authorities in Nigeria should be abreast the happenings in the cryptocurrency world and make policy decisions on how best to reduce the prevailing high exchange rate in Nigeria by ensuring the integration of crypto transactions in their systems.

Future research work in cryptocurrency and exchange rate should add more cryptocurrencies and elongate the study period.

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APPENDIX I

Normalized Co-integration and Diagnostic Result

Vector Error Correction Estimates
Date: 07/20/21 Time: 14:53
Sample (adjusted): 2018M01 2021M06
Included observations: 42 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
EXR(-1)	1.000000
BTC(-1)	12.15253
	(6.02681)
	[2.01641]
ETH(-1)	-16.01041
	(3.97395)
	[-4.02884]
XRP(-1)	44.01812
	(7.70917)
	[5.70984]
LTC(-1)	-8.162699
	(5.16762)
	[-1.57958]
BNB(-1)	-0.029879
	(2.16104)
	[-0.01383]
C	-230.8004

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APPENDIX II

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.319074	Prob. F(2,27)	0.7295
Obs*R-squared	0.992845	Prob. Chi-Square(2)	0.6087

APPENDIX III

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.577098	Prob. F(18,24)	0.8825
Obs*R-squared	12.98932	Prob. Chi-Square(18)	0.7922
Scaled explained SS	12.49824	Prob. Chi-Square(18)	0.8205

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