Cryptocurrency Price Fluctuations and Exchange Rate Volatility in Nigeria: A BEKK-MGARCH Approach

Bala Timothy Sule, Ishaku Rimamtanung Nyiputen (PhD)

Department of Economics, Federal University Wukari, Taraba State, Nigeria

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ABSTRACT

This paper looks at how the prices of Bitcoin and Ethereum move up and down, and how that shakes the naira exchange rate in Nigeria. Many Nigerians now buy and sell Bitcoin and Ethereum every day, and this may be pushing the exchange rate around too. The paper uses monthly data from January 2018 to December 2025, which gives 95 points to work with. Before running the main test, the study checked if the data had a unit root using the Augmented Dickey-Fuller test, and also checked for ARCH effects. The main tool used is the Diagonal BEKK Multivariate GARCH (BEKK-MGARCH) model, built on the work of Baba, Engle, Kraft, and Kroner (1990) and Engle and Kroner (1995). This tool is good because it can show how the shaking (volatility) in Bitcoin and Ethereum prices spills over into the shaking of the exchange rate. The results show that past shocks in the exchange rate and in Bitcoin and Ethereum prices both feed strongly into how much the exchange rate shakes today. The ARCH term for the exchange rate is 1.062 in the Bitcoin system and 0.905 in the Ethereum system, and both are significant at 1 percent. The GARCH term for the exchange rate is only significant in the Bitcoin system (0.572), while Bitcoin's and Ethereum's own volatility is very sticky, with GARCH terms of 0.639 and 0.751. The paper finds that the way Bitcoin and the naira move together changed direction over time, from a small negative link before 2022 to a strong positive link from 2022 onward, right after the exchange rate reforms. The paper says the Central Bank of Nigeria should watch cryptocurrency trading more closely and should build a way to track digital asset flows so it can guard the naira exchange rate better.

Keywords: Cryptocurrency, Bitcoin, Ethereum, Exchange Rate, Volatility, BEKK-GARCH, Nigeria

INTRODUCTION

Money and how it moves around the world has changed a lot in the last twenty years. New computer tools have brought new kinds of money that were never seen before. One of the biggest of these new things is cryptocurrency, a kind of digital money that no central bank owns or controls (Udoh, Akpan, & Bagudo, 2025). Bitcoin came out in 2008, made by a person or group hiding under the name Satoshi Nakamoto, and Ethereum followed in 2015. Both of these started as small computer projects but have now grown into assets worth trillions of dollars around the world (Gbadebo, 2024). At the same time, every country still needs monetary policy, which is the set of tools a central bank uses to control money supply, interest rates, prices, and the exchange rate, to keep its economy steady. When these two things meet, a new question comes up: does the up-and-down price of Bitcoin and Ethereum shake the tools that central banks use to run monetary policy?

Around the world, more and more people are holding and trading Bitcoin and Ethereum, and this raises worry for central banks, including the Central Bank of Nigeria (CBN). If people can freely move their money from naira into Bitcoin whenever they like, the CBN may find it harder to manage the exchange rate the way it used to (Gbadebo, 2024). This worry is not just for Nigeria. Many governments across the world are asking the same question, because digital money moves fast, crosses borders easily, and does not answer to any single central bank.

In Nigeria, this issue is even bigger. The country runs a managed exchange rate system and has struggled for years with a falling naira, high prices, and weak monetary tools (Udoh, Akpan, & Bagudo, 2025). At the same time, Nigeria is one of the biggest places in the world for peer-to-peer Bitcoin trading. This did not stop even after the CBN placed a rule in 2021 that told banks not to help people trade cryptocurrency (Ngong, 2024). Many Nigerians turned to Bitcoin and Ethereum because they trust the naira less than before, thanks to years of the currency losing value and prices climbing higher than the CBN wants.

When the price of Bitcoin or Ethereum jumps up fast, Nigerian buyers need US dollars to buy these coins on foreign exchanges. This pushes up the demand for dollars and puts pressure on the naira to fall (Udoh, Akpan, & Bagudo, 2025). Some Nigerian studies have already looked into small pieces of this puzzle. For example, Udoh, Akpan, and Bagudo (2025) found that Bitcoin prices had a real effect on how much the exchange rate shakes in Nigeria, but they used a plain Vector Autoregression (VAR) tool that cannot show how the shaking itself changes over time. Gbadebo (2024) found that when Bitcoin trading goes up, it pulls money away from treasury bills, but this study did not look at the shaking side of things at all. Other studies, like Umoru, Igbinovia, Ekeoba, Asemota, and Mohammad (2025), used a single-variable EGARCH tool, which can only track one series' shaking at a time and cannot show how two markets' shaking move together.

This gap is the reason for this paper. Even though Bitcoin and Ethereum trading is heavy in Nigeria, and even though the naira exchange rate keeps shaking, no known Nigerian study has used a tool built to catch how the shaking of two markets, cryptocurrency prices and the exchange rate, move together at the same time. Ordinary tools like OLS, plain VAR, or single-series EGARCH miss this joint shaking pattern. The problem is not just that Bitcoin and the naira might be linked; the real puzzle is whether shocks that hit Bitcoin and Ethereum prices carry over into how wildly the naira exchange rate shakes from month to month, and whether this carry-over effect has grown stronger as Nigeria has changed its exchange rate rules in recent years.

This matters a great deal in practice. If the shaking in Bitcoin and Ethereum prices really does spill into the naira exchange rate, then the CBN cannot just watch oil prices, interest rates, and government spending anymore; it also has to watch what is happening in the cryptocurrency market. If this spillover is ignored, the CBN may set exchange rate policy using an incomplete picture, which could mean slower responses to naira pressure, weaker trust in the currency, and a harder time protecting ordinary Nigerians from sudden price shocks that trace back to a market the CBN does not directly control.

Earlier Nigerian studies leave a clear empirical gap. Udoh, Akpan, and Bagudo (2025) looked only at Bitcoin, leaving out Ethereum, and used a VAR tool that does not model shaking directly. Umoru, Igbinovia, Ekeoba, Asemota, and Mohammad (2025) used EGARCH, which only handles one series at a time and misses the joint covariance between cryptocurrency and the exchange rate. Udofia, Okijie, and Effiong (2025) used OLS and a Vector Error Correction Model, which can catch long-run co-movement but not time-varying volatility spillovers. No Nigerian study so far has combined both Bitcoin and Ethereum together with the exchange rate inside one Diagonal BEKK-MGARCH system, which is the tool built exactly for catching this kind of joint shaking pattern (Baba, Engle, Kraft, & Kroner, 1990; Engle & Kroner, 1995).

This paper fills that gap and, in doing so, adds two things of value. First, it gives the CBN and other Nigerian policy bodies a clearer, more direct picture of how much of the naira's shaking traces back to cryptocurrency markets, which past single-variable tools could not show. Second, it adds to the wider research world by showing, with real Nigerian numbers, how the BEKK-MGARCH tool performs when it is pointed at a developing country's currency instead of the rich-country currencies most past BEKK studies have used (Katsiampa, 2018; 2019). The specific objective of this paper is to examine the effect of Bitcoin price and Ethereum price fluctuations on the exchange rate in Nigeria, covering the period 2018M1 to 2025M12.

LITERATURE REVIEW

Conceptual Review

Monetary policy means the steps a central bank takes to control money, credit, and interest rates so it can reach certain goals for the whole economy. Mishkin (2004) said monetary policy is about managing money supply and interest rates to reach price steadiness and keep as many people working as possible. Bernanke and Blinder (1992) said monetary policy is really about the central bank controlling short-term interest rates to guide spending and output in the economy. In Nigeria, the CBN uses tools such as the Monetary Policy Rate (MPR) and manages the exchange rate to try to reach these same goals (Adesoye, Maku, & Atanda, 2012).

The exchange rate is the price of one country's money measured against another country's money. It links what happens inside Nigeria to what happens in the wider world. Dornbusch (1976) showed that when a country prints more money, its exchange rate can fall further than it should before slowly coming back to where it belongs. This idea shows that the exchange rate acts like a price that reacts fast to what people expect will happen with money in the future. In Nigeria, the naira/dollar rate set by the CBN is the main rate this paper studies, because it is the rate the CBN itself watches and steps in to protect (Aliyu, 2009; Mordi, 2006).

Cryptocurrency is digital money that uses computer codes to keep transactions safe, and it runs on networks that no single company or government controls. The first working idea for this kind of money came from Nakamoto (2008), who wrote the paper that gave the world Bitcoin. Böhme, Christin, Edelman, and Moore (2015) called Bitcoin a spread-out digital currency where many computers check and record every transaction on a public list called the blockchain. Bitcoin is the oldest and biggest cryptocurrency by size, while Ethereum, started by Vitalik Buterin in 2015, is a computer platform that lets people build other programs on top of it, called smart contracts (Ante, 2021).

This paper chooses to talk about cryptocurrency 'fluctuations' rather than 'volatility.' Volatility is a number, usually worked out from a GARCH-type model, that shows how spread out the ups and downs in price are. Fluctuations is a bigger and looser word: it simply means the price of Bitcoin or Ethereum going up and down, whether that is caused by mood in the market, government announcements, or plain guessing by traders (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Corbet, Lucey, Urquhart, & Yarovaya, 2019). The research question and the objective of this paper are framed around fluctuations, but the actual number that is estimated inside the BEKK-MGARCH model in the results section is volatility, since that is the exact statistic the model produces.

Bringing these ideas together, this paper sees cryptocurrency price shaking as something that can spill over into the naira exchange rate through a volatility spillover channel: when Bitcoin or Ethereum prices swing hard, Nigerians rush to buy or sell dollars to take part in the crypto market, and this rush feeds directly into how much the naira exchange rate shakes. This channel is the one that the BEKK-MGARCH model is built to pick up, and it forms the base of the whole study.

THEORETICAL FRAMEWORK

This paper leans on the Interest Rate Parity (IRP) theory, first worked out by Keynes (1923), and later split by other writers into Covered Interest Rate Parity and Uncovered Interest Rate Parity. In simple words, IRP says that if there were no cost or risk to moving money between two countries, the gap between two countries' interest rates should match how much people expect the exchange rate to change. When Nigerians see Bitcoin or Ethereum giving returns far bigger than naira savings accounts or treasury bills, money starts to leave naira assets and move into digital coins. To buy those coins, people need dollars, so demand for dollars goes up and the naira comes under pressure to fall. Frenkel (1976) tested this parity idea using real currency data and found small gaps that mostly matched normal transaction costs, while the Fama (1984) puzzle later showed that in the short run, interest rate gaps often point the wrong way compared to what IRP predicts.

IRP fits this paper well because it gives a clear reason to expect that Bitcoin and Ethereum price shocks would carry over into exchange rate shaking: sharp jumps in crypto prices change how attractive naira assets look compared to digital coins, which pushes demand for foreign currency and feeds pressure into the exchange rate. This paper also draws lightly on the Monetary Policy Transmission Mechanism idea (Bernanke & Gertler, 1995; Mishkin, 1995), which lists the exchange rate as one of the main paths through which outside shocks reach a country's monetary system. Cryptocurrency-driven demand for dollars fits neatly inside this exchange rate channel, giving a second reason to expect the spillover this paper tests for.

Empirical Review and Gap in Literature

A large body of work outside Nigeria has already used GARCH-family tools to study cryptocurrency price shaking. Bollerslev (1986) built the original GARCH model, stretching the earlier ARCH idea of Engle so that past shocks and past shaking both feed into today's shaking. Nelson (1991) then built the EGARCH model to catch the fact that bad news can shake a market harder than good news of the same size. Chu, Chan, Nadarajah, and Osterrieder (2017) tested several GARCH-family tools on Bitcoin and found that GARCH-type tools fit the data well and picked up strong shaking clustering. Yao, Zhou, and Zhu (2025) tested ARCH, GARCH, ARCH-M, EGARCH, and PARCH tools on daily Bitcoin prices from 2022 to 2023 and found that the plain GARCH tool beat basic ARCH, while EGARCH and PARCH fit even better because they catch uneven responses to good and bad news; however, this study looked only at Bitcoin's own shaking and did not stretch out to any macro or financial market spillover.

Moving to two-series (multivariate) tools, Katsiampa (2018) used a two-way Diagonal BEKK model on Bitcoin and Ether and found that the two coins' shaking and the way they move together both respond to big news events, and that Ether can work as a decent hedge against Bitcoin. Katsiampa (2019) stretched this to five coins, Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen, using an uneven Diagonal BEKK tool, and found that both past shocks and past shaking feed strongly into today's shaking for all five coins, with uneven effects showing up for Bitcoin, Ether, Ripple, and Litecoin. Klein, Thu, and Walther (2018) used a BEKK-GARCH tool to compare Bitcoin and gold and found that, unlike gold, Bitcoin does not act as a safe place to hide money when markets fall; instead it moves along with falling markets. Conrad, Custovic, and Ghysels (2018) used the GARCH-MIDAS tool to split Bitcoin's shaking into a long-run piece and a short-run piece, and found that stock market shaking and worldwide economic activity both feed into Bitcoin's long-run shaking.

On the direct link between cryptocurrency and exchange rates, Dumitrescu et al. (2023) used quantile regression on nine European currencies and found that Bitcoin price jumps went with currency strengthening in normal times, but this flipped during the COVID-19 period. Sidorov (2024) studied how Bitcoin, Ethereum, Ripple, and Dogecoin react to news and rule announcements and found that Dogecoin reacted the hardest and longest, while Bitcoin and Ethereum settled faster; but this study did not build any direct exchange rate model. Aliu, Asllani, and Hašková (2024) used VAR, SVAR, and wavelet tools on weekly data and found a strong two-way link between Bitcoin and gold, while the link with the US dollar index was mixed across the different tools used, showing that Bitcoin's tie to the dollar is not steady.

Turning to Nigeria and nearby developing countries, Udoh, Akpan, and Bagudo (2025) is the closest match to this paper. They used quarterly Nigerian data from 2015Q1 to 2022Q4 and a plain VAR tool, and found that Bitcoin prices had a real, measurable effect on Nigeria's exchange rate shaking, giving good policy-level proof for a developing country; however, because a plain VAR tool does not model shaking directly, they could not show how the shaking itself moves and cannot separate out Ethereum's own effect since Ethereum was left out of their study. Gbadebo (2024) used an ARDL transfer tool and found that rising Bitcoin prices and trading pulled money and activity away from Nigeria's treasury bill market, giving strong proof of a substitution effect, but this paper stayed away from the foreign exchange market and shaking altogether. Umoru, Igbinovia, Ekeoba, Asemota, and Mohammad (2025) used daily data across richer economies and an EGARCH plus ARMA-FIGARCH combination and found that Bitcoin returns react strongly to exchange rate moves with real feedback effects, but their sample sat inside OECD countries, so it is hard to say the same result would hold for a country like Nigeria. Udofia, Okijie, and Effiong (2025) used Nigerian monthly data from 2018 to 2025 with OLS and a Vector Error Correction Model and found that more crypto trading pushed the naira toward depreciation, and that exchange rate shocks fed back into crypto trading too; yet because they measured crypto activity using transaction volumes rather than prices, and because their tool does not track time-varying shaking, they could not show whether price-driven volatility spillover, the exact channel this paper studies, is present.

Pulling these findings together, three patterns and three matching gaps come out clearly. First, the strongest proof that Bitcoin affects the Nigerian exchange rate (Udoh, Akpan, & Bagudo, 2025) rests on a plain VAR tool, which is an evidence gap because it cannot show whether the link works through shaking (volatility) or simply through the average level of prices. Second, the tools used inside Nigeria so far, VAR, EGARCH, OLS, and VECM, are each built to answer only one piece of the puzzle and none of them is built to catch the joint, time-varying shaking between two markets at once; this is a methodology gap, since only a Diagonal BEKK-MGARCH tool, built by Baba, Engle, Kraft, and Kroner (1990) and refined by Engle and Kroner (1995), is designed to estimate the full shaking-and-covariance picture between cryptocurrency prices and the exchange rate together. Third, no Nigerian study has placed both Bitcoin and Ethereum side by side inside the same volatility model, even though outside evidence shows Ethereum behaves differently from Bitcoin because it is tied more closely to financial technology use rather than pure store-of-value demand (Corbet, Lucey, & Yarovaya, 2018); this is a knowledge gap, because policymakers cannot yet tell whether naira exchange rate shaking traces mainly to Bitcoin, mainly to Ethereum, or to both together. This paper is built to close all three gaps by fitting a Diagonal BEKK-MGARCH model separately to the exchange rate paired with Bitcoin and the exchange rate paired with Ethereum, using nearly eight years of monthly Nigerian data running from January 2018 to December 2025.

METHODOLOGY

Introduction

This section explains how the study was carried out. It lays out where the data came from, what the variables mean, how the model is built, and what tools and checks were used to make sure the results can be trusted. The study followed a numbers-based (quantitative) design using secondary time series data collected on a monthly basis. Because the goal of this paper is narrowed to the exchange rate objective alone, only the Diagonal BEKK-MGARCH tool is described and used here, dropping the wider SVAR and Granger causality tools that a fuller study of monetary policy might otherwise carry.

Data Sources and Variables

The study used monthly time series data running from January 2018 to December 2025, giving 95 usable observations after adjustments. This start date was picked because it is around this time that Bitcoin and Ethereum began to catch real, wide attention among Nigerian traders. The official naira/US dollar exchange rate was taken from the Central Bank of Nigeria Statistical Bulletin, with checks against International Monetary Fund figures. Bitcoin and Ethereum monthly closing prices, both measured in US dollars, were taken from Yahoo Finance. All three series were turned into natural logarithms, and then into first differences (returns), before being fed into the shaking (GARCH) model, since GARCH tools need a settled (stationary) series to work properly.

Table 1 Definition, Measurement, and Sources of Variables

Variable	Definition	Measurement	Source
Official Exchange Rate (OEX)	Naira price of one US dollar	Naira per US dollar, monthly average	CBN Statistical Bulletin; IMF
Bitcoin Price (BIT)	Price of Bitcoin used to track crypto market activity	Monthly average closing price in US dollars	Yahoo Finance
Ethereum Price (ETH)	Price of Ethereum used to track crypto market activity	Monthly average closing price in US dollars	Yahoo Finance

Note. Prepared by the author (2026).

Model Specification

Following the approach used by Ajayi, Oloyede, and Oluwaleye (2022) and Safiyanu et al. (2022), the exchange rate is written as a function of Bitcoin and Ethereum prices in natural log form:

$lnRER_t = f(lnbtc_t, lnethr_t)$ .... (3.1)

where OEX is the official exchange rate at time t, BIT is Bitcoin price at time t, and ETH is Ethereum price at time t. The return series for each variable was built as the first difference of the log price:

$r_t = lnP_t - lnP_{t-1}$................*(2)*

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where r_t is the return at time t, and lnP_t and lnP_(t-1) are the natural log prices at time t and t-1. This return formula is simply the first difference of prices (Darne & Charles, 2019). The conditional mean equation for the two-series (bivariate) return vector is written as:

$$r_t = \mu + \varepsilon_t \quad (3)$$

where r_t is the vector of returns, μ is a vector of mean parameters, and ε_t is a vector of leftover errors with a shaking (covariance) matrix H_t, given everything known up to time t-1.

The study followed Kroner and Ng (1998) and used the Asymmetric Diagonal BEKK model, which is a special, lighter version of the full BEKK model built by Baba, Engle, Kraft, and Kroner (1990) and Engle and Kroner (1995). This special version needs fewer numbers to be worked out than the full BEKK model, while still keeping the shaking matrix positive and workable, and it lets the model tell apart the effect of a bad-news shock from the effect of a good-news shock of the same size (Glosten, Jagannathan, & Runkle, 1993; Terrell & Fomby, 2006). The shaking (covariance) matrix is written as:

The conditional covariance matrix of the asymmetric Diagonal BEKK model is given as;

$$H_t = W'W + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + D'n_{t-1}n'_{t-1}D + B'H_{t-1}B \quad (3.4)$$

where W, A, B, and D are matrices of parameters with appropriate dimensions, with W being an upper triangular matrix, while the diagonal elements of, H_t, $h_{ii,t,}$ $i = 1, \ldots 5$,

denote the conditional variances, and the off-diagonal elements of H_t, $h_{ii,t,}$ $i \neq j, i, = 1, \ldots 5$,

represent the corresponding conditional covariances, whereas $n_t = (n_{1,t,}\ n_{2,t,}\ n_{3,t,})'$ and $n_{i,t,} = \min\{\varepsilon_{i,t}\ ,0\}$, i = 1,…3,. The elements of matrix A measure the effects of past squared errors (news) in current conditional variances, while the elements of matrix B show how past conditional variances affect the current levels of volatility (Begiazi & Katsiampa, 2019). On the other hand, the elements of matrix D capture the asymmetric effects of negative and positive shocks.

The conditional variance of cryptocurrency i, $h_{i,t,}$ i =1,…3 is given as follows;

$$h_{i,t} = \tilde{w}_{ii} + \alpha^2_{ii}\varepsilon^2_{i,t-1} + d^2_{i,i}\, n^2_{i,t-1} + \beta^2_{i,i}\, h_{i,t-1} \quad (3.5)$$

while the conditional covariance between any two cryptocurrencies i and j, h_{ijt}, i, j = 1, … ,3, $i \neq j$, can be expressed as

$$h_{ijt} = \tilde{w}_{ij} + a_{ii}a_{jj}\varepsilon_{it-1}\varepsilon_{jt-1} + d_{ii}d_{jj}n_{it-1}n_{jt-1} + \beta_{ii}\beta_{jj}h_{it-1,} \quad (3.6)$$

where $\tilde{w}_{ij}$ is the ijth element of $W'W$. It can be noticed from the above equations that the current volatility of cryptocurrency i is a function of its own lagged value and own lagged squared shocks and reacts to negative shocks, η_{it}, as determined by the estimated asymmetry parameter, d_{ii}, while the current conditional covariance of cryptocurrencies i and j is a function of its own lagged covariance as well as of cross-products of the corresponding shocks and captures asymmetric effects of negative and positive shocks accordingly. Consequently, the asymmetric Diagonal BEKK model can not only investigate volatility dynamics between cryptocurrencies but can also capture asymmetric responses of negative and positive shocks to their conditional volatility and covariances, which is the primary objective of this study.

The model was picked over the full BEKK, the VECH model, and the Dynamic Conditional Correlation (DCC-GARCH) model of Engle (2002) for three reasons. First, cryptocurrency prices and exchange rates are both known to shake in clusters, quiet spells followed by wild spells, which is exactly what GARCH-type tools are built to catch. Second, Engle and Kroner (1995) showed that the BEKK way of writing the model always keeps the shaking matrix positive, something the VECH model cannot promise. Third, the steadiness and normal spread of the numbers worked out under DCC-GARCH have not yet been fully proven (Caporin & McAleer, 2012;

2013), while BEKK does not have this weak point. Because the numbers were worked out under a Student's-t error spread, which fits cryptocurrency data better than a normal spread (Katsiampa, 2018), the numbers were solved using the maximum likelihood method, run through the Broyden-Fletcher-Goldfarb-Shanno (BFGS) search method.

Estimation Techniques

Pre-Estimation Tests

Before fitting the BEKK-MGARCH model, three checks were carried out. First, descriptive statistics (mean, highest, lowest, spread, skew, and peak) were worked out for all three series to see their basic shape. Second, the Augmented Dickey-Fuller (ADF) unit root test was run on each series to check whether it needed to be turned into returns before it could be used, since a GARCH tool cannot give trustworthy shaking numbers on a series that keeps wandering without settling down. Third, Engle's ARCH-LM test and the Ljung-Box Q-statistic were run on the return series to check for ARCH effects (shaking clustering) and leftover patterning; both tests needed to reject the idea of 'no shaking clustering' before a GARCH-type tool could be justified over a plain constant-shaking tool.

Techniques of Data Analysis

After the pre-checks, the returns of the exchange rate were paired separately with Bitcoin returns and with Ethereum returns, giving two separate two-series systems: OEX-BIT and OEX-ETH. Each system was fitted using the Asymmetric Diagonal BEKK-MGARCH model described above, and the mean and shaking equations were worked out together (at the same time) rather than in separate steps, following Katsiampa (2018).

Post-Estimation Tests

After the model was fitted, two checks were run to see if the model was good enough. The Portmanteau Q-statistic checked whether any leftover patterning remained in the model's errors, and the joint Jarque-Bera test checked whether the errors followed a normal spread. Non-normal errors are common and expected in GARCH-type models fitted to financial data, and this does not spoil the parameter numbers because the maximum likelihood method used here (quasi-maximum likelihood) still gives trustworthy numbers even when the errors are not perfectly normal.

Data Analysis and Interpretation

Introduction

This section shows and explains the results. It starts with a plain look at the data (descriptive statistics), then checks how the three variables move together (correlation), then checks whether the data has a unit root, before moving to the main BEKK-MGARCH results for the two systems, OEX-BIT and OEX-ETH, and finishing with the checks done after fitting the model.

Preliminary Analysis

Descriptive Statistics

Table 2 shows the basic shape of the data used in this study, based on 95 monthly points.

Table 2 Descriptive Statistics

Statistic	BIT (US$)	ETH (US$)	OEX (N/$)
Mean	26,473.89	1,482.47	673.88
Maximum	61,318.96	4,631.48	1,825.00

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Statistic	BIT (US$)	ETH (US$)	OEX (N/$)
Minimum	3,457.79	107.06	305.25
Std. Dev.	15,810.41	1,055.12	527.03
Skewness	0.053	0.354	1.048
Kurtosis	1.781	2.703	2.244
Observations	95	95	95

Note. Author's computation using EViews 12 (2026).

Table 2 shows that Bitcoin's price jumped around a lot: its spread (standard deviation) of US$15,810.41 is more than half its own mean, showing that the price moved by huge amounts from month to month. Ethereum followed the same pattern, moving from as low as US$107.06 to as high as US$4,631.48. The official exchange rate had a mean of N673.88 per dollar, but its skewness of 1.048, the highest of the three, shows that most of the values sat lower while a small number of very high values (from the naira's sharp fall in 2023 and 2024) pulled the mean upward. This shows straight away why a plain, constant-shaking model would not be right for this data, since all three series show signs of wide and uneven swings rather than steady, settled movement.

Correlation Analysis

Table 3 Correlation Matrix

Variable	LOGBIT	LOGETH	LOGOEX
LOGBIT	1.000		
LOGETH	0.950*	1.000	
LOGOEX	0.608*	0.573*	1.000

Note. * indicates significance at the 5% level. Author's computation using EViews 12 (2026).

Table 3 shows that Bitcoin and Ethereum move almost perfectly together, with a correlation of 0.950, confirming that both coins react to the same worldwide crypto market mood. Both coins also carry a fair, positive link with the exchange rate, 0.608 for Bitcoin and 0.573 for Ethereum, hinting that months when crypto prices rose were also months when the naira tended to weaken. This plain correlation number, however, cannot show whether this link comes from shared shaking (volatility spillover) or just from both series drifting upward together over time; that question is answered properly only once the BEKK-MGARCH model is fitted in Section 4.3.

Unit Root Test

The Augmented Dickey-Fuller (ADF) test was run on each series in level form and after first differencing. Table 4 shows the results, using a maximum lag of 11 chosen by the Schwarz Information Criterion.

Table 4 Augmented Dickey-Fuller Unit Root Test Results

Variable	ADF Stat. (Level)	ADF Stat. (1st Diff.)	5% Crit. Value	Order of Integration
LOGBIT	-0.976	-8.578	-2.893	I(1)
LOGETH	-0.849	-10.468	-2.893	I(1)
LOGOEX	n/a	-10.322	-2.893	I(1)

Note. All p-values at first difference are below 0.05. Author's computation using EViews 12 (2026).

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Table 4 shows that none of the three series is settled (stationary) at level, since all ADF numbers at level sit above the 5 percent line. Once turned into first differences (returns), all three series become settled, with ADF numbers running from -8.578 to -10.468, each easily beating the 5 percent line. Because GARCH-type tools need a settled series to produce trustworthy shaking numbers, this confirms that Bitcoin price, Ethereum price, and the exchange rate all needed to be turned into log returns, exactly as done in Section 3.3, before they were fed into the BEKK-MGARCH model.

BEKK-MGARCH Estimation Results

Before the main model was fitted, the return series for all three variables were tested with Engle's ARCH-LM test and the Ljung-Box Q-statistic. Both tests rejected the idea of 'no shaking clustering' at usual significance lines, showing that all three return series carry the kind of shifting, clustered shaking that the BEKK-MGARCH tool is built to catch, and this justifies using it instead of a constant-shaking alternative.

Results: Exchange Rate and Bitcoin

The mean equation shows that the lagged Bitcoin price (LOGBIT(-1)) has a coefficient of 0.511 and is strongly significant (z = 10.648, p = 0.000), showing that past Bitcoin prices carry real information for guessing today's exchange rate. This matches the idea that when Nigerians chase Bitcoin, the extra demand for dollars needed to buy it feeds into the naira exchange rate.

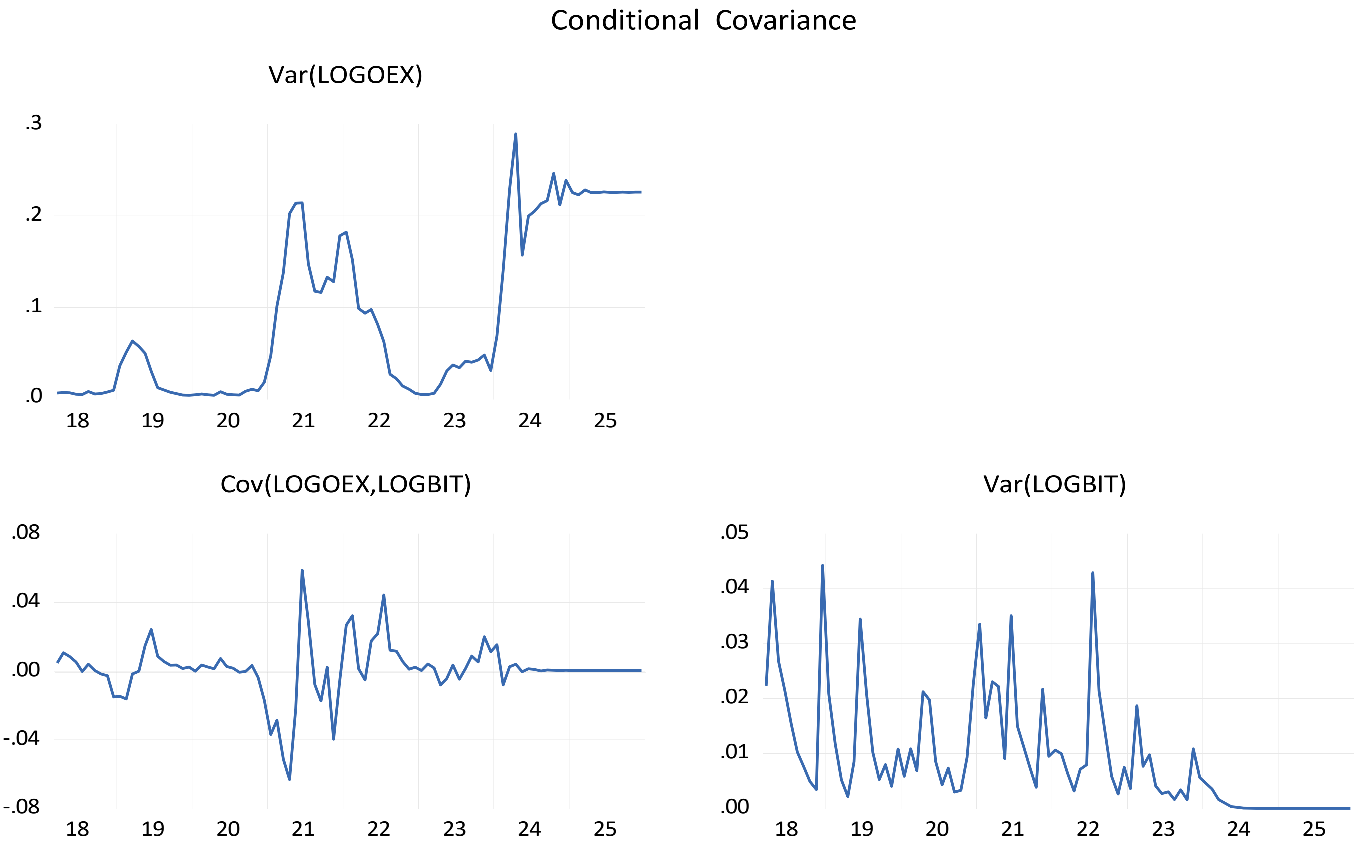

Figure 4.1: Conditional Covariance and Correlation between LOGOEX and LOGBIT

Source: Generated by the Author using E-views version 12.0 (2026)

Table 5 BEKK-MGARCH Estimation Results (LOGOEX and LOGBIT)

Parameter	Coefficient	Std. Error	z-Statistic	Prob.
C(1) – Constant (LOGOEX eq.)	0.4797	0.1929	2.487	0.013
C(2) – LOGBIT(-1) on LOGOEX	0.5109	0.0480	10.648	0.000

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Parameter	Coefficient	Std. Error	z-Statistic	Prob.
C(3) – Constant (LOGBIT eq.)	0.1144	0.0001	2155.300	0.000
C(4) – LOGBIT(-1) on LOGBIT	0.9750	0.0001	6998.500	0.000
A1(1,1) – ARCH term (LOGOEX)	1.0617	0.2275	4.666	0.000
A1(2,2) – ARCH term (LOGBIT)	0.9588	0.1351	7.096	0.000
B1(1,1) – GARCH term (LOGOEX)	0.5724	0.0623	9.189	0.000
B1(2,2) – GARCH term (LOGBIT)	0.6392	0.0429	14.905	0.000
Log Likelihood	229.610			
AIC / SC	-4.651 / -4.354			

Note. Author's computation using EViews 12 (2026).

The ARCH term for the exchange rate, A1(1,1) = 1.062, is strongly significant, meaning that past squared shocks to the exchange rate feed heavily into today's exchange rate shaking. The ARCH term for Bitcoin, A1(2,2) = 0.959, is also strongly significant, confirming that Bitcoin's own past shocks drive its own shaking. Both GARCH terms, B1(1,1) = 0.572 for the exchange rate and B1(2,2) = 0.639 for Bitcoin, are strongly significant too, showing that once a shock hits either market, its shaking effect does not fade quickly but stays around for a while. The shared (conditional) covariance between LOGOEX and LOGBIT moved from close to zero in 2018-2019, to negative in 2020-2021, and then turned firmly positive from 2022 onward, climbing toward 0.22-0.25 by 2024-2025. This shows that the way Bitcoin shocks and naira shocks move together has not stayed the same over time; it flipped direction right around when Nigeria loosened its exchange rate rules.

Results: Exchange Rate and Ethereum

The Ethereum system shows that lagged Ethereum price (LOGETH(-1)) has a positive, strongly significant effect on the exchange rate (coefficient = 0.200, z = 7.638, p = 0.000). The ARCH term for the exchange rate in this system, A1(1,1) = 0.905, is also strongly significant, matching what was found in the Bitcoin system.

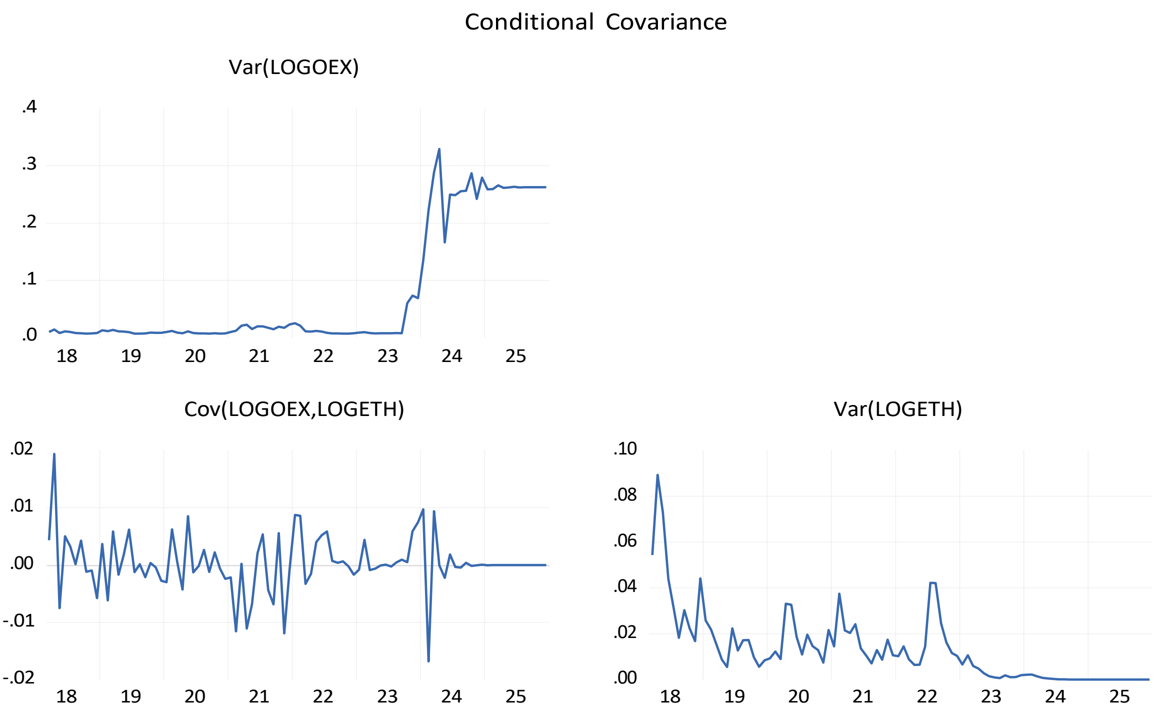

Figure 4.3: Conditional Covariance and Correlation between LOGOEX and LOGETH

Source: Generated by the Author using E-views version 12.0 (2026)

Table 6 BEKK-MGARCH Estimation Results (LOGOEX and LOGETH)

Parameter	Coefficient	Std. Error	z-Statistic	Prob.
C(1) – Constant (LOGOEX eq.)	1.9901	0.0754	26.390	0.000
C(2) – LOGETH(-1) on LOGOEX	0.2004	0.0262	7.638	0.000
C(3) – Constant (LOGETH eq.)	0.0679	0.0029	23.627	0.000
C(4) – LOGETH(-1) on LOGETH	0.9796	0.0016	618.531	0.000
A1(1,1) – ARCH term (LOGOEX)	0.9051	0.2583	3.503	0.000
A1(2,2) – ARCH term (LOGETH)	0.7085	0.0856	8.273	0.000
B1(1,1) – GARCH term (LOGOEX)	-0.2872	0.3401	-0.844	0.399
B1(2,2) – GARCH term (LOGETH)	0.7505	0.0232	32.326	0.000
Log Likelihood	231.769			
AIC / SC	-4.697 / -4.400			

Note. Author's computation using EViews 12 (2026).

The Ethereum ARCH term, A1(2,2) = 0.709, is strongly significant, showing that Ethereum's own past shocks push its own shaking. The GARCH term for Ethereum, B1(2,2) = 0.751, is strongly significant and even a touch stronger than Bitcoin's own GARCH term, showing that Ethereum's shaking is very sticky and does not fade fast. But the GARCH term for the exchange rate inside this pairing, B1(1,1) = -0.287, is not significant (p = 0.399). This is different from the Bitcoin pairing, and it suggests that in the OEX-ETH system, the exchange rate's own shaking memory is mostly swallowed up by the shock coming across from the Ethereum side rather than carrying on its own steam. The shared correlation between LOGOEX and LOGETH swung between roughly -0.31 and +0.54 during 2018-2021, then became more mixed after 2022, before turning strongly negative by late 2025, reaching close to -0.998 at the very end of the sample. This late, strong negative link may point to a kind of flight-to-safety pattern, where Ethereum held its dollar value steady while the naira kept losing ground, so the two moved in opposite directions.

Diagnostic Tests for the BEKK-MGARCH Models

Table 7 Diagnostic Tests for BEKK-MGARCH Models

System / Test	Statistic	Prob.	df	Decision
OEX-BIT: Portmanteau (Lag 1)	90.445	0.000	4	Leftover pattern present
OEX-BIT: Portmanteau (Lag 12)	607.056	0.000	48	Leftover pattern present
OEX-BIT: Joint Jarque-Bera	239.362	0.000	-	Not normal
OEX-ETH: Portmanteau (Lag 1)	87.738	0.000	4	Leftover pattern present
OEX-ETH: Portmanteau (Lag 12)	657.622	0.000	48	Leftover pattern present
OEX-ETH: Joint Jarque-Bera	16.015	0.003	-	Not normal

Note. Portmanteau test null: no leftover autocorrelation up to lag h. Jarque-Bera null: normal spread. Author's computation using EViews 12 (2026).

The checks show leftover patterning in both systems at every lag tested, which is a common finding in GARCH-type models fitted to financial data, since the mean equation alone rarely mops up every bit of the timing pattern in the raw series; what matters most for a shaking (variance) model is whether the ARCH and GARCH terms themselves are doing their job, which the strongly significant coefficients in Tables 5 and 6 already show. The normal-spread checks reject the idea of a normal spread for both systems, with the OEX-ETH system showing a smaller Jarque-Bera number (16.015) than the OEX-BIT system (239.362). Non-normal leftover errors are ordinary in financial GARCH work and do not spoil the numbers already worked out, since the quasi-maximum likelihood method used here still gives steady, trustworthy parameter numbers even when the errors do not sit perfectly on a normal curve.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This paper set out to check whether Bitcoin and Ethereum price shaking spills over into the naira exchange rate in Nigeria, using a Diagonal BEKK-MGARCH model fitted to monthly data running from January 2018 to December 2025. The null hypothesis, that Bitcoin and Ethereum price fluctuations have no significant effect on the exchange rate, is rejected. Both cryptocurrencies show clear, strongly significant volatility spillover into the exchange rate: past shocks and past shaking in the Bitcoin and Ethereum markets both feed into today's exchange rate shaking, and the direction of the shared movement between crypto prices and the naira flipped from mostly negative before 2022 to strongly positive from 2022 onward, right around Nigeria's exchange rate reform period.

This is a real cross-market spillover, where shaking born in the cryptocurrency market travels into a core piece of Nigeria's own monetary system. It shows that keeping the naira exchange rate steady is now tied, at least in part, to what happens in worldwide cryptocurrency markets, a link that plain VAR and single-series EGARCH tools used in earlier Nigerian work could not properly capture. Because the model fitted here is a Diagonal BEKK, it captures how each market's own past shocks and shaking feed into the exchange rate, but it does not estimate every possible cross-market ARCH and GARCH term; a full (non-diagonal) BEKK model is a natural next step for anyone wanting to push this finding further.

Recommendations

Based on the conclusions above, the paper offers the following recommendations.

1. The Central Bank of Nigeria should build a real-time watch system for cryptocurrency trading volumes and prices, most of all during periods when the naira is falling fast, so that exchange rate management decisions can account for pressure coming from the crypto market.

2. The CBN should ask licensed banks and fintech companies to report how much naira liquidity is being turned into Bitcoin and Ethereum, so that a clearer, more complete picture of dollar demand pressure can feed into exchange rate forecasting work.

3. The CBN's research team should build a small cryptocurrency price index made for Nigerian conditions and add it as a side indicator inside its regular exchange rate monitoring work, rather than relying only on oil prices and reserves.

4. The Federal Government, through the Securities and Exchange Commission, should speed up its Virtual Assets Service Providers rules, so that cryptocurrency trading is brought into the open, formal reporting system, which would also make it easier for the CBN to track the very spillover this paper has found.

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