Original Research Article

Dual Foreign Exchange Rate in Nigeria – Stylised Facts and Volatility Modelling

ABSTRACT: This study examines the dual dynamics of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market rates between the Nigerian Naira and the US Dollar over a ten-year period from 2012 to 2022. We investigate the dual foreign exchange rates – Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market rates between the Nigerian Naira and the US Dollar for ten years from 2012 to 2022. By employing MGARCH (multivariate generalized autoregressive conditional heteroscedasticity), we analyse the volatility of the naira in the dual foreign exchange windows and examine the stylised facts as it affects forex management in Nigeria. Our findings confirm and extend the results of previous research, emphasizing the role of market segmentation, information asymmetry, autocorrelation, stationarity, volatility clustering, correlation dynamics, and spillover effects in the foreign exchange markets.

KEYWORDS: Bureau De Change (BDC) market, Interbank Foreign Exchange market (IFEM), MGARCH (multivariate generalized autoregressive conditional heteroscedasticity), volatility.

1. INTRODUCTION

The foreign exchange rate, also known as the currency exchange rate, forex rate, or simply FX rate, is the value at which one currency can be exchanged for another currency or group of currencies (Hamilton, 2018). It specifies how much of one currency is needed to purchase a unit of another currency and represents the ratio at which one currency is traded or converted into another currency. Forex rates are determined in the FX market, which is a global decentralized marketplace where currencies are traded by individuals, financial institutions, corporations, and governments. These rates fluctuate constantly due to various factors, including supply and demand dynamics – local demand for foreign currencies and their local supply, country's trade balance, strength of its economy, political stability, and market sentiment.

The deterioration of economic conditions in some developing countries over the past few years due to various factors such as government regulations, capital controls, economic instability, or currency devaluation have led to a rise in the number of countries with dual foreign exchange markets (Malpass, 2023). The dual foreign exchange markets constitute the official or government exchange market and the parallel or unofficial foreign exchange market.

The official or formal foreign exchange market (also known as CBN – Central Bank of Nigeria rates) refers to the regulated and authorized marketplace where currencies are bought and sold according to established rules and regulations set by the government or central bank of a country. It is also known as the formal or regulated foreign exchange market. The rates at which currencies are exchanged in the official market are determined through mechanisms such as interbank trading, where banks and financial institutions trade currencies with each other, or through a central exchange platform. The exchange rates in the official market are usually set based on factors such as supply and demand dynamics, economic indicators, government policies, and interventions by the central bank or monetary authorities. The official foreign exchange market provides a transparent and regulated environment for currency exchange, ensuring fair and orderly transactions. It also allows the government or central bank to exercise control over the exchange rates and implement monetary policies to manage economic conditions and maintain stability in the currency market. Using the official foreign exchange market provides several advantages, including legal protection, access to accurate and reliable exchange rates, and the ability to conduct transactions with confidence. It also helps to prevent fraudulent activities, money laundering, and other illicit financial practices. However, it's important to note that the official foreign exchange market may have certain restrictions or regulations imposed by the government or central bank. These can include exchange controls, limitations on the amount of currency that can be exchanged, requirements for documentation, or other measures aimed at managing the flow of capital or stabilizing the currency.

On the other hand, parallel or unofficial market (popularly refers to as black market in Nigeria) is a foreign exchange market where the exchange rates are determined and used in unofficial or informal currency exchange markets. These informal markets exist alongside the official or formal foreign exchange markets, where currencies are traded through regulated channels or authorized financial institutions such as Bureau De Change in Nigeria (Central Bank of Nigeria, 2017). In these markets, individuals and businesses trade currencies outside the official channels and at rates that are not regulated or controlled by the authorities. The rates in the parallel market are typically different from the official exchange rates set by the government or central bank. Usually, the parallel market rates reflect the supply and demand dynamics of the currency in the unofficial market. These rates are often influenced by factors such as scarcity of foreign currency, speculation, market sentiment, economic conditions, and the availability of alternative means to acquire foreign currency.

In countries where dual exchange rate is practiced, the official exchange rate is subsidized, paid for by everyone else, and there is usually a strong correlation, if not causation, between the existence of parallel rates and corruption (Malpass, 2023). Currently, according to World Bank, there are about 24 emerging and developing economies (EMDEs) including Nigeria that have active parallel currency markets and in at least 14 of them, the exchange rate premium – the difference between the official and the parallel rate is of great concern, exceeding an average of 10 percent (Malpass, 2023) – see graph in figure (1-3).

The countries with dual or multiple foreign exchange rates are displayed in the three figures 1 – 3 because of the high disparities in the range observed between the FX data of the countries and in order to ensure visibility of the graphs.

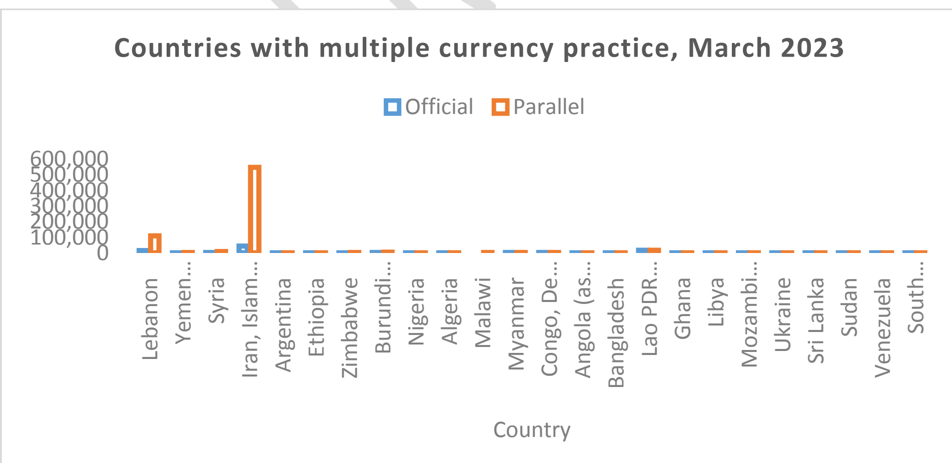


Figure 1: Countries with multiple currency practice

The figure 1 depicts countries that employ multiple currency practices, including both official and parallel rates, which can also be referred to as black market rates. Iran exhibits a significant disparity between its official rate and parallel rate, with a staggering difference or premium of 1,195.2%. Additionally, the chart highlights Lebanon as the second country in terms of the distinctive difference between its parallel rate and official rate within the multiple currency practice framework.

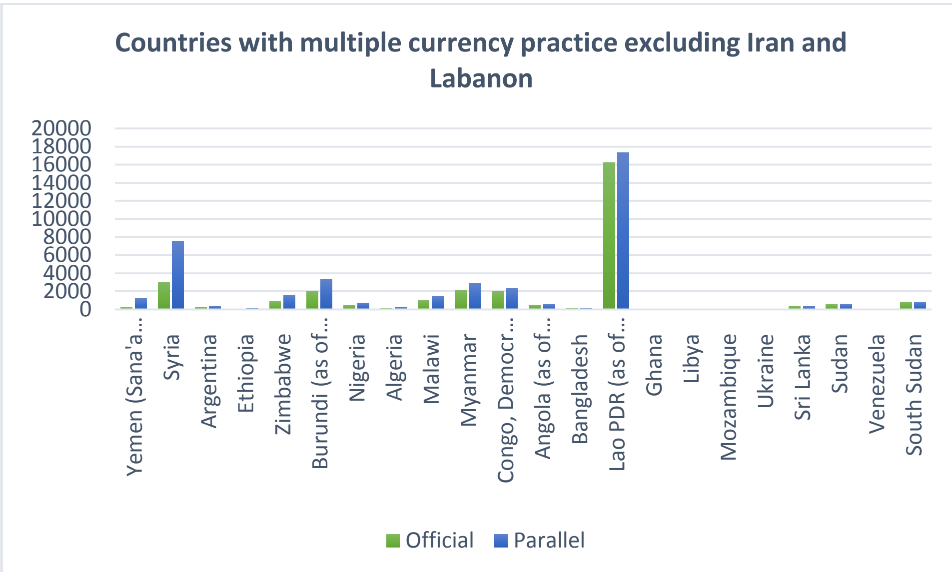


Figure 2: Countries with multiple currency practice excluding Iran and Lebanon

In Figure 2, countries practicing multiple foreign exchange regimes, excluding Iran and Lebanon, are presented to examine the relationship between the official rate and parallel rate in their respective currencies. The graph reveals that Syria's parallel rate surpasses its official rate, indicating a higher value in the parallel market. On the other hand, other countries, such as Lao PDR, exhibit minimal premium between their official rates and parallel rates, suggesting a relatively stable relationship between the two rates in their currencies.

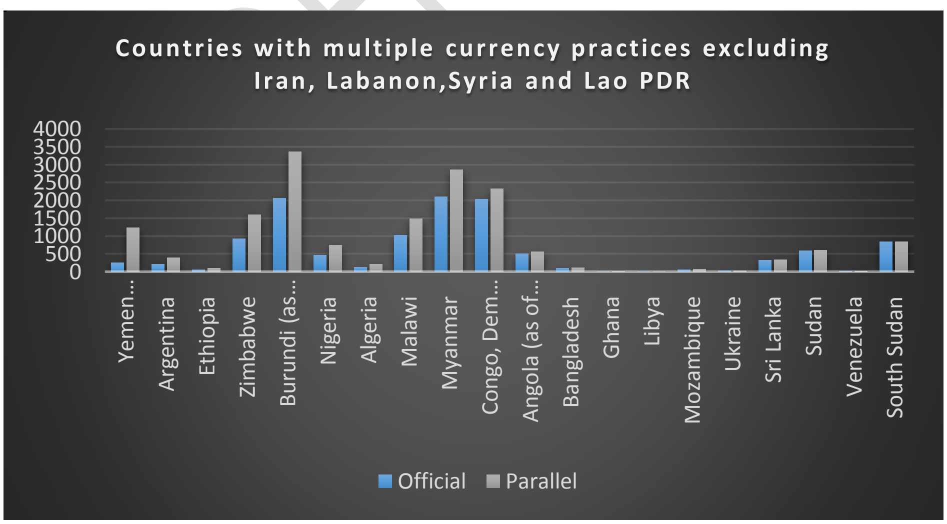


Figure 3: Countries with multiple currency practice excluding Iran, Lebanon, Syria and Lao PDR

Figure 3 provides insights into the multiple currency practices of various countries, excluding certain outliers. The graph clearly illustrates a substantial disparity between the official currency rate and the parallel rate in countries like Burundi, Yemen, Myanmar, Zimbabwe, and Congo. These countries exhibit significant gaps between the two exchange rates. Although Nigeria's gap between the official and parallel rate may be relatively low considering the countries under consideration in the figure, yet a premium of 67.1% is significant enough to warrant this study as we shall uncover subsequently.

Furthermore, the chart highlights that countries such as Congo, Democratic Rep., Angola, Bangladesh, Lao PDR, Ghana, Libya, Mozambique, Ukraine, Sri Lanka, Sudan, Venezuela, and South Sudan exhibit minimal premium of less than 15% between their official rates and parallel rates. These countries demonstrate a relatively stable relationship between the two exchange rates, indicating less volatility in their multiple currency practices. In some countries, various governments have embarked on a unification process to converge the official and the parallel FX rates to a single window, but the speed of adjustment can be a balancing act due to vested interests that may give up the subsidy, and the fear of the free fall of the local currency.

Dual exchange rates may exist as a result of various official exchange rates for different imports in an effort to subsidize key imports; they may be associated with fixed (or tightly managed) exchange rate regimes where the official exchange rate deviates from the market exchange rates – in either case, an exchange rate premium exists (Marcello, Geiger, Carey, & Nguyen, 2021). A premium is the returns or the subsidy on the official FX rates as a result of the differentials between the two exchange rates that drive the non-official supply and demand for foreign currency. This premium is a symptom of the inconsistency of fiscal and monetary policies and provoke distortions by manipulating relative prices in the economy and open opportunities for rent-seeking behaviour for those who have access to preferential rates. Although multiple exchange rates have been abandoned by several countries in recent years, they have been maintained by many others, including Nigeria, Lebanon, Yemen, Syria, Iran, Argentina, Ethiopia, Zimbabwe, Burundi, Algeria, Malawi, Myanmar, Democratic Rep. of Congo, Angola, Bangladesh, Lao PDR, Ghana, Libya, Mozambique, Ukraine, Sri Lanka, Sudan, Venezuela, and South Sudan (Malpass, 2023). Dual exchange rates elimination would therefore lead to a more efficient application of market-driven relative prices to allocate resources in the economy. Impacts of the practice of multiple exchange rates in an economy include lack of transparency and predictability, market distortions, arbitrage opportunities, inequality and corruption, economic inefficiency, reduced foreign investment, and increased fiscal burden (World Bank Group, 2020).

2. VOLATILITY OF EXCHANGE RATES IN NIGERIA

Volatility of foreign exchange rates is a risk associated with uncertainty in the exchange rate in international trade and is often driven by macroeconomic factors (Financial Trading and Investing, 2022). It refers to the degree of fluctuation or instability in the prices of currencies in the foreign exchange market over a specific period. It measures the rate at which exchange rates change and the magnitude of those changes over time. Foreign exchange rates are influenced by a variety of factors such as economic indicators, geopolitical events, monetary policy decisions, market sentiment, and global economic conditions. These factors can differ from country to country and over time, the interaction of these factors creates an environment where exchange rates can experience significant fluctuations or remain relatively stable. High volatility suggests that exchange rates are experiencing large and frequent changes over a given period. This can result in rapid appreciation or depreciation of a currency's value relative to other currencies. Volatility in FX rates is important for various market participants, including traders, investors, multinational corporations, and policymakers. High volatility can offer trading opportunities for speculators and investors seeking to profit from price movements. However, it also poses risks, as rapid changes in exchange rates can lead to significant gains or losses (Adrian, 2022).

Nigeria, just like every other country, needs strong foreign reserves to meet international payment obligations timely, boost the country's creditworthiness, provide a buffer against external shocks as well as maintain a stable foreign exchange rate – of all these, safeguarding the value of its currency – the naira, is the overarching objective (Onuba, 2019). To address the challenges posed by exchange rate volatility, the Central Bank of Nigeria (CBN) implemented various measures over the years, including the introduction of a multiple exchange rate system. This system involved different exchange rates for different categories of transactions, such as official transactions, interbank transactions, and the parallel or black market. These measures were aimed at managing the demand for foreign exchange, conserving foreign reserves, and stabilizing the exchange rate. However, they also contributed to disparities in exchange rates and challenges in accessing foreign currency through official channels, which in turn created opportunities for parallel market activities.

2.1 Volatility Analysis Using MGARCH Models

The MGARCH (Multivariate Generalized Autoregressive Conditional Heteroscedasticity) model is a statistical model used for volatility modelling and analysis in multivariate time series data (Bobo, 2020). It extends the popular univariate GARCH model to capture the dynamic relationships and volatility spillover effects among multiple variables (Rajhans, 2016). In the MGARCH model, each variable in the multivariate time series is modelled as a function of its own lagged values and the lagged values of all other variables in the system. The model assumes that the conditional mean equation follows a multivariate autoregressive (VAR) process, while the conditional variance is modelled using a multivariate GARCH process.

The conditional mean equation of the MGARCH model can be written as:

$$Y_t = \mu + \sum_{i=1}^{p} A_i * Y_{t-i} + \varepsilon_t$$

where Y_t is a vector of the multivariate time series at time t, μ is a vector of intercepts, A_i represents the coefficient matrices of the lagged values, p is the order of the VAR process, and ε_t is a vector of error terms.

The conditional variance equation of the MGARCH model is typically specified using a Cholesky decomposition of the covariance matrix. The conditional variance matrix at time t, is given by:

$$\sum_{t} D_t * R_t * D_t$$

where D_t is a diagonal matrix of standard deviations, and R_t is a positive definite matrix representing the correlation structure. R_t is usually modeled using a GARCH-type process, such as the BEKK (Baba, Engle, Kraft, and Kroner) or the DCC (Dynamic Conditional Correlation) model. Estimating the MGARCH model involves maximum likelihood estimation, where the parameters are estimated by optimizing the likelihood function given the observed data. Once the MGARCH model is estimated, it can be used to analyse and forecast volatility in the multivariate time series. The model insights into the conditional correlations and spillover effects between variables, allowing for a better understanding of the interdependencies and risk dynamics in the system (Katusiime, 2019).

2.1.1 BEKK MGARCH Model Variant

The BEKK (Baba, Engle, Kraft, and Kroner) MGARCH model is a popular variant of the multivariate GARCH model that allows for dynamic modelling of conditional variances and correlations in multivariate time series data (Xiao, et al., 2020). It is specifically designed to capture time-varying volatility spillover effects among multiple variables. The BEKK MGARCH model assumes that the conditional variance and correlation matrices follow a GARCH-type process. The conditional variance equation can be represented as;

$$H_t = C + \sum_{i=1}^{p} A_i * e_{t-i} * e_{t-i}^T * A_i^T + \sum_{i=1}^{q} B_i * H_{t-i} * B_i^T$$

where H_t is the conditional variance matrix at time t, C is a constant matrix, A_i and B_i are coefficient matrices, e_t is a vector of standardized residuals at time t, p and q are the orders of the GARCH process for the variance and correlation equations, respectively.

The conditional correlation equation in the BEKK model can be written as;

$$R_t = D * \left(I - \sum_{i=1}^{q} B_i * L_i\right) * R_{t-1} * \left(I - \sum_{i=1}^{q} B_i * L_i\right)^T * D$$

where R_t is the conditional correlation matrix at time t, D is a diagonal matrix of standard deviations, L_i is the matrix of lagged correlation matrices, and I is an identity matrix.

The BEKK model allows for the inclusion of lagged values of the conditional correlation matrix, which captures the time-varying nature of correlations (Yiu and Albert, 2002). This allows for the modelling of volatility spillover effects, where shocks in one variable's volatility affect the volatility of other variables in the system. Estimating the BEKK MGARCH model involves maximum likelihood estimation, where the parameters are estimated by optimizing the likelihood function given the observed data. The estimation process involves iterating between estimating the conditional variances and correlations until convergence is achieved. Once the BEKK MGARCH model is estimated, it can be used to analyse and forecast volatility and correlations in the multivariate time series. It provides insights into the dynamic interdependencies and risk dynamics among multiple variables, allowing for improved risk management and portfolio allocation decisions.

2.1.2 DCC MGARCH Model Variant

The DCC (Dynamic Conditional Correlation) MGARCH model is a popular variant of the multivariate GARCH model used for modelling and analysing the time-varying correlations among multiple variables in a multivariate time series data. It is specifically designed to capture the dynamic nature of correlations and volatility spillover effects (Orskaug, 2009). The DCC model consists of two main components: the univariate GARCH model for modelling the conditional variances of individual variables and the dynamic conditional correlation model for capturing the time-varying correlations between variables.

a) Univariate GARCH Model

In the DCC model, each variable in the multivariate time series is modelled using its own univariate GARCH model. The conditional variance equation for the i-th variable can be represented as;

$$\sigma_i^{2,t} = \omega_i + \sum_{j=1}^{p} \alpha_{ij} * \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q} \beta_{ij} + \sigma_{i,t-j}^2$$

where $\sigma_i^{2,t}$ represents the conditional variance of the i-th variable at time t, ω_i is the constant term, α_{ij} and β_{ij} are the coefficients of the GARCH process, $\varepsilon_{i,t-j}^2$ represents the squared residuals, and p and q are the orders of the GARCH process.

b) Dynamic Conditional Correlation (DCC) Model

The DCC model is used to model the time-varying correlations between the variables. It involves estimating the conditional correlation matrix at each time point, which is a positive definite matrix representing the correlations between variables.

The conditional correlation matrix, denoted as R_t, is given by;

$$R_t = (1 - \lambda) * R + \lambda * Z_t * Z_t^T$$

where R is the unconditional correlation matrix, λ is a scalar parameter between 0 and 1 that controls the speed of adjustment of the correlations, and Z_t is a standardized matrix of residuals obtained from the univariate GARCH models. The DCC model allows for the dynamic adjustment of correlations over time by using the standardized residuals to update the conditional correlation matrix. This captures the time-varying nature of correlations and reflects the volatility spillover effects among variables.

Estimating the DCC model involves two steps: estimating the univariate GARCH models for each variable to obtain the standardized residuals, and then estimating the DCC model to obtain the time-varying conditional correlation matrix. Once the DCC model is estimated, it can be used for various purposes, such as forecasting future correlations, analysing the dynamics of interdependencies among variables, and assessing portfolio risk. It provides insights into the changing relationships and volatility spillover effects among variables, allowing for more accurate risk management and decision-making.

3. RESULTS

This research study examines the dual dynamics of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market rates between the Nigerian Naira and the US Dollar over a ten-year period from 2012 to 2022. By employing MGARCH (multivariate generalized autoregressive conditional heteroscedasticity), we investigate the volatility and stylized facts associated with these exchange rates. The following presents the findings of our research, shedding light on the intricate relationship between these markets, volatility of the rates and the resulting implications for currency exchange.

3.1 Time plot

Figure 4 illustrates a time series graph depicting the fluctuations of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market rates concerning the Nigerian Naira and the US Dollar over a span of ten years, from 2012 to 2022. The graph demonstrates that the IFEM and BDC rates for USD to Naira were initially with less than average of 10% until 2015, after which both rates experienced a significant surge. However, it is noteworthy that the BDC market rate exhibited a consistently higher value compared to the IFEM rate. The graph displays an irregular pattern of growth in the exchange rates.

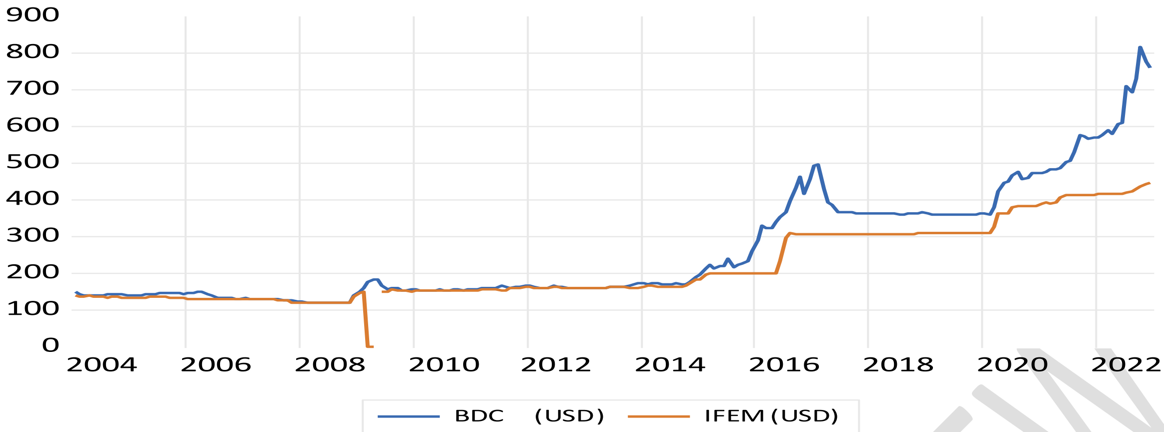


Figure 4: Time plot of USD rate of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) (2012 - 2022)

3.2 Correlogram (ACF & PACF) of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) (2012 - 2022)

The Figure 5 and Figure 6 are the correlogram – ACF (autocorrelation function) and PACF (partial autocorrelation function) of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) log of the data series before differencing. The most prominent feature of these correlograms are that the autocorrelation coefficients at various lags are high, these are individually statistically significantly different from zero, out of the 95% confidence bounds. This is the typical correlogram of a non-stationary time series. The autocorrelation starts at a very high value and a decline (spikes down) very slowly toward zero as the lags lengthens, showing a purely MA (moving average) series. After the first lag, the PACF drops dramatically in both cases, and most PACFs after lag 1 are statistically insignificant. We conclude from the result of the ACF that there is need for differencing which indicate the series is an ARIMA (autoregressive integrated moving average) process.

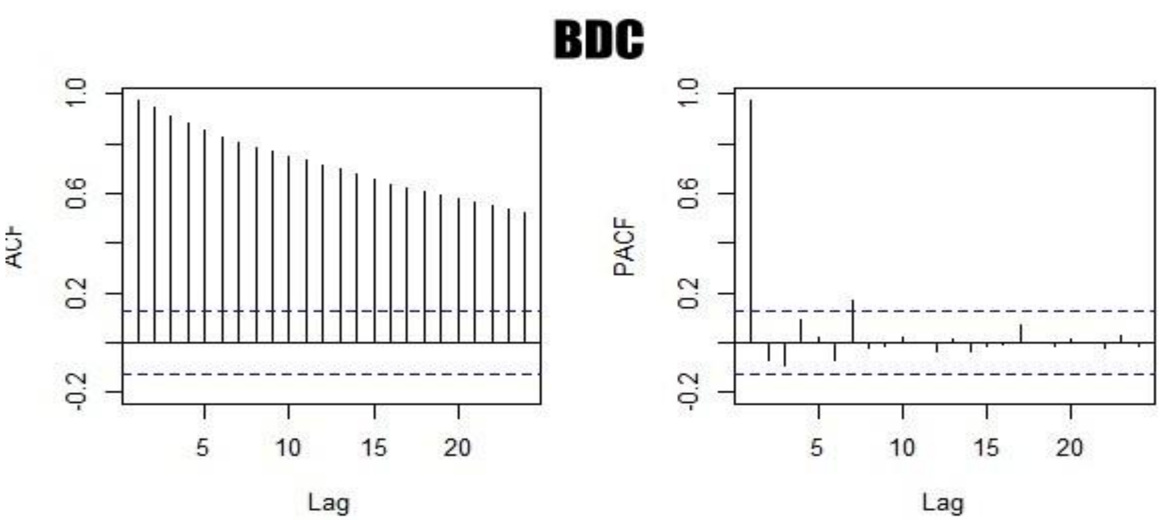


Figure 5: The ACF and PACF of Bureau De Change (BDC) exchange market

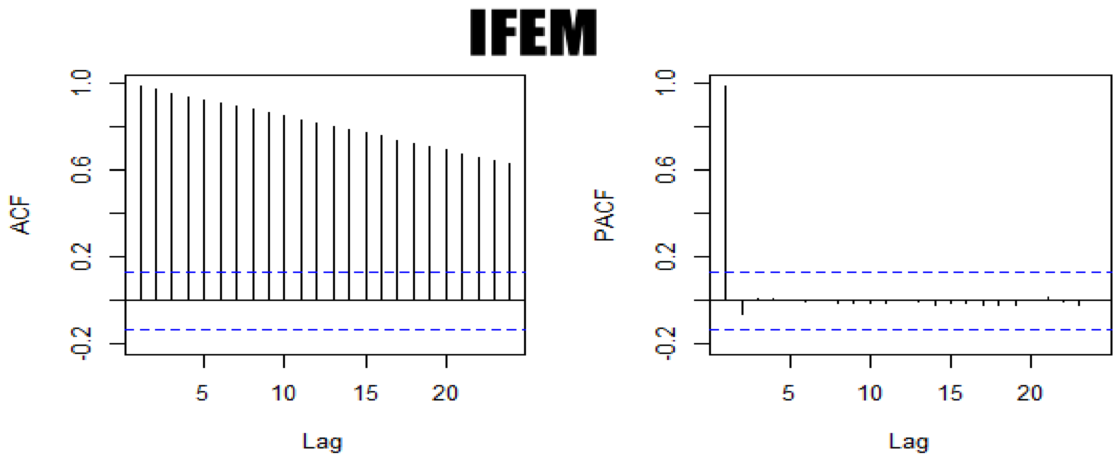


Figure 6: The ACF and PACF of Interbank Foreign Exchange Market (IFEM)

3.2.1 Autocorrelation

<u>Hypothesis</u>

H_0: No autocorrelation

H_1: Autocorrelation

Level of significant: $\alpha = 0.05$

<u>Test statistics</u>

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: No residual autocorrelations up to lag h
Date: 05/15/23 Time: 10:59
Sample: 2004M01 2022M12
Included observations: 225

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	6.614198	---	6.643725	---	---
2	9.520167	0.0493	9.575757	0.0482	4
3	19.53734	0.0122	19.72830	0.0114	8
4	20.35444	0.0607	20.56019	0.0572	12

*Test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

Decision Rule: Reject Ho if Portmanteau Test statistic is less than the test critical values at 5% level of significant or if the prob. value is less than 0.05.

Decision: Since, the Portmanteau Test Statistic is less than the test critical value at 5% level of significant, we reject Ho, which means; there is presence of autocorrelation in the data at 5% level of significant.

Conclusion: With this, we say that the data is autocorrelated at 5% level of significant

3.3 Stationarity Test by Unit Root Method

Unit root tests help determine whether a time series is stationary or non-stationary. They examine whether the series possesses a unit root, which implies non-stationarity. If a unit root is detected, it suggests that the time series has a stochastic trend and lacks a stable mean or variance.

3.3.1 Unit Root Test

The Augment Dickey Fuller (ADF) test was conducted. The results of the test as given below shows the presence of a unit root which indicates non stationarity, since the tests statistics are greater than the p/critical values at some levels. Since the time series is not stationary, we have to make it stationary before we can apply the Box-Jenkins methodology. This can be done by differencing the series once.

Hypothesis

H_0: The data has a unit root
H_1: The data has no unit root
Level of significant: $\alpha = 0.05$

Test statistics

Augmented Dickey-Fuller Test:

data: BDC
Dickey-Fuller = -0.18587, Lag order = 6, p-value = 0.99
alternative hypothesis: stationary

Augmented Dickey-Fuller Test:

data: IFEM
Dickey-Fuller = -1.4826, Lag order = 6, p-value = 0.7933
alternative hypothesis: stationary

Decision Rule: If the Augmented Dickey-Fuller test statistic is greater than or equal to the critical value at the 5% significance level or if the p-value is greater than 0.05, we fail to reject the null hypothesis (Ho).

Decision: Since the Augmented Dickey-Fuller test statistic is not greater than the critical value at the 5% significance level, we fail to reject the null hypothesis. Thus, the data indicates the presence of a unit root at the 5% significance level.

Conclusion: Based on these results, we can conclude that the data is non-stationary at the 5% significance level in both markets.

Figure 7 displays a time plot illustrating the first difference of the data series. Upon a visual examination of the plot, it is evident that the series maintains a consistent mean and variance over time. However, the absence of any visible patterns or trends in the plot suggests that the data does not exhibit stationary behaviour. Additionally, the plot highlights the presence of volatility, indicating fluctuations and irregularities in the series. These observations emphasize the dynamic and unpredictable nature of the data.

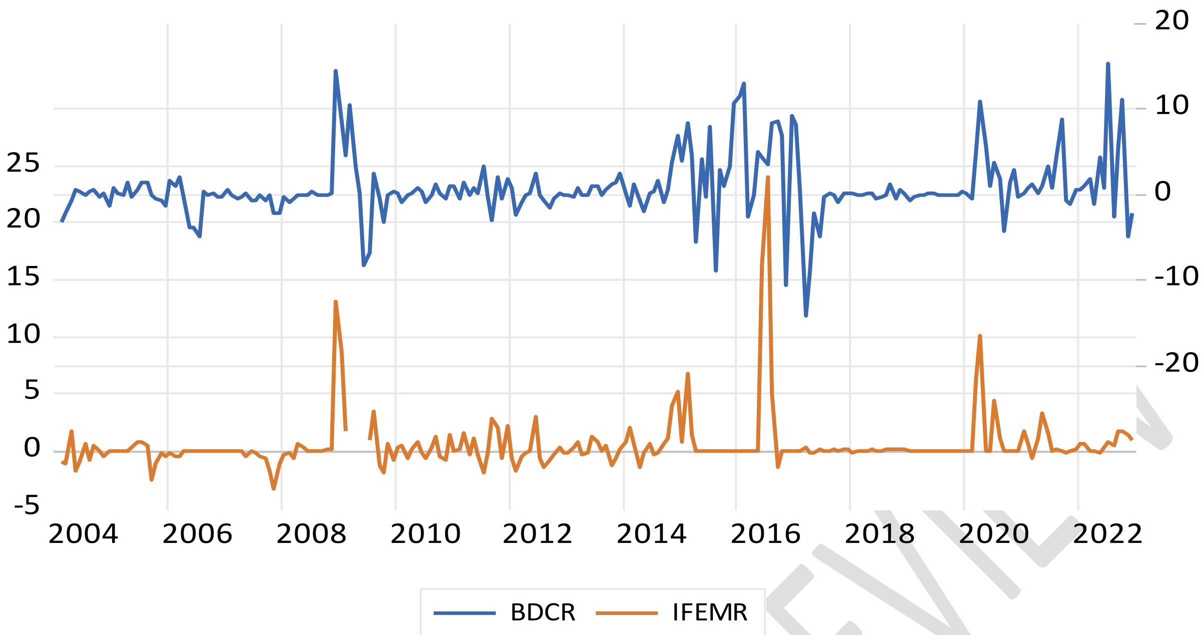
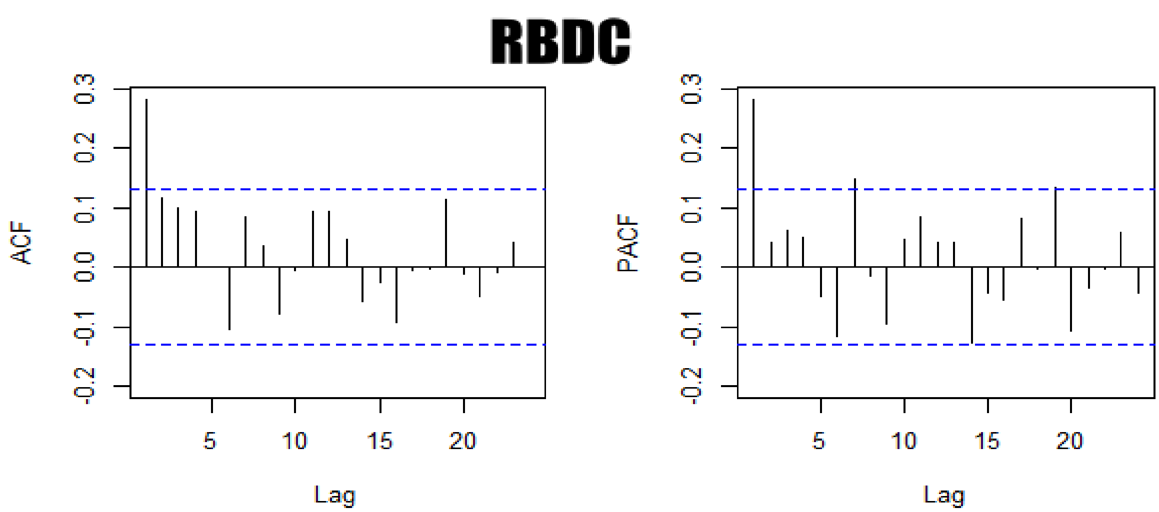


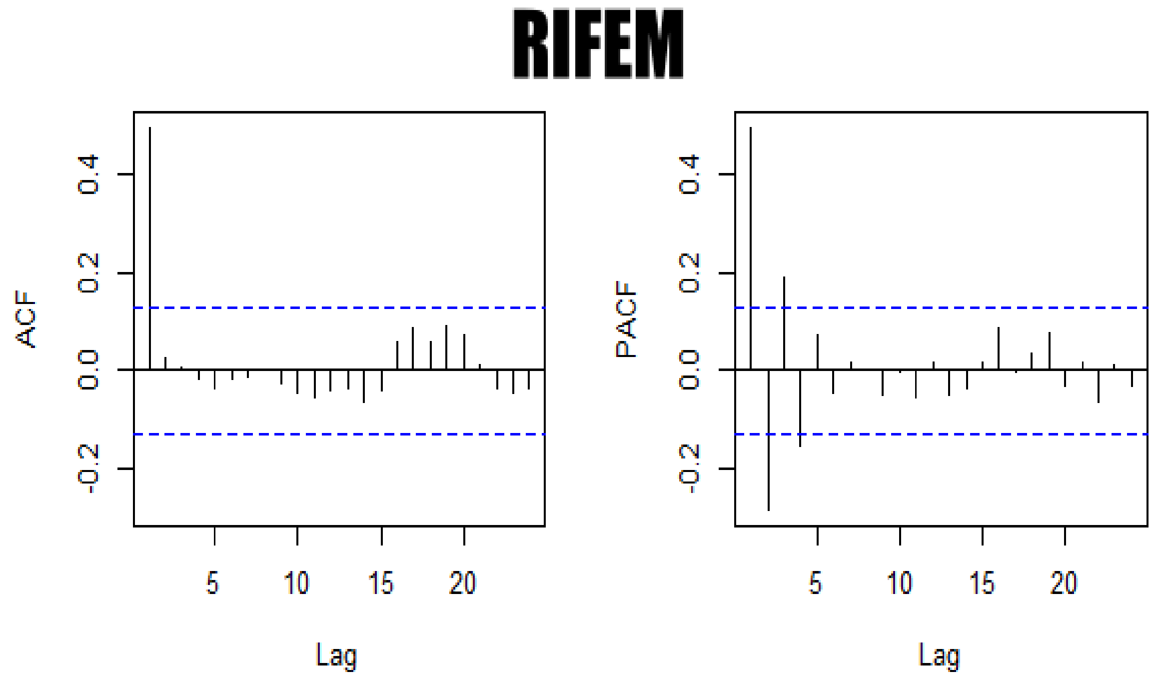
Figure 7: Time plot after first difference of Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) (2012 - 2022)

The correlogram after differencing are shown in figure 8 and figure 9: The ACFs at lag 1 in both cases seem statistically different from zero (at the 95% confidence limit, the lags are asymptotic and so can be considered approximate), but at all other lags, they are not statistically different from zero. We therefore conclude that the data series is now stationary. A formal application of the Augmented Dickey-Fuller below may show that this is indeed the case.



Note: RBDC indicate first differencing of Bureau De Change (BRC) market value

Figure 8: ACF and PACF after first differencing of Bureau De Change (BDC) exchange market



Note: RIFEM indicate the first differencing of Interbank Foreign Exchange Market (IFEM) value
Figure 9: ACF and PACF after first differencing of Interbank Foreign Exchange Market (IFEM)

3.3.2 Unit Root After First Differencing

The Augment Dickey Fuller (ADF) test was conducted. The results of the test are given below which shows the entire test statistics of the ADFs are less than the critical regions, we reject the null hypothesis and therefore conclude that there is no unit root or the time series is stationary.

<u>Hypothesis</u>
H_o: The data has a unit root
H_1: The data has no unit root
Level of significant: α = 0.05

<u>Test statistics</u>
Augmented Dickey-Fuller Test:
data: rifem
Dickey-Fuller = -5.4881, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Augmented Dickey-Fuller Test:
data: rbdc
Dickey-Fuller = -4.8911, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Decision Rule: Reject Ho if Augmented Dickey-Fuller Test statistic is less than the test critical values at 5% level of significant or if the prob. Value is less than 0.05.

Decision: Since, the Augmented Dickey-Fuller test statistic in both data are less than the test critical value at 5% level of significant, I reject Ho, which means; the data has no unit root at 5% level of significant.

Conclusion: With this, we say that the data is stationary at 5% level of significant.

3.4 Selection of Right Model for the Data

Table 1 shows the ARIMA model estimate. With the use of **R**, the best fit auto-regression integrated moving average (ARIMA) model was fitted for both market exchange rate. It is indicated that ARIMA(0,1,1) is the best fit for Interbank Foreign Exchange market (IFEM) while ARIMA(1,0,0) is the best fit for Bureau De Change (BDC) market

Table 1: ARIMA model estimates

USD Exchange Rate to Naira	AR(1) (S.E.)	MA(1) (S.E.)
Interbank Foreign Exchange Market (IFEM)	-	0.6834
	-	0.0438
Bureau De Change (BDC) Market	0.2825	-
	0.0637	-

Note: S.E means standard error

<u>ARCH (Autoregressive Conditional Heteroskedasticity) Test Result</u>

<u>Hypothesis</u>

H_o: No ARCH effects
H_1: ARCH effects
Level of significant: α = 0.05

<u>Test statistics</u>

ARCH LM-test; Null hypothesis: no ARCH effects:
data: rbdc
Chi-squared = 44.361, df = 12, p-value = 1.325e-05

ARCH LM-test; Null hypothesis: no ARCH effects:
data: rifem
Chi-squared = 41.137, df = 12, p-value = 4.649e-05

Decision Rule: Reject Ho if ARCH LM-test statistic is less than the test critical values at 5% level of significant or if the prob. Value is less than 0.05.

Decision: Since, the ARCH LM-test statistic in both data are less than the test critical value at 5% level of significant, I reject Ho, which means; the data has ARCH effects at 5% level of significant.

Conclusion: With this, we say that there are presence of ARCH effects in data at 5% level of significant.

Table 2: GARCH model estimates

USD Exchange Rate to Naira	Omega (S.E.)	Alpha (S.E.)	Beta (S.E.)
Interbank Foreign Exchange Market (IFEM)	0.000305	0.201652	0.000000
	0.000024	0.079009	0.131675
Bureau De Change (BDC) Market	0.000162	0.577003	0.421996
	0.000028	0.134440	0.064518

The GARCH model results in table 2 for the USD Exchange Rate to Naira indicate the following for the Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market:

IFEM:

- The estimated Omega value suggests a relatively low long-term average volatility level.
- The estimated Alpha value indicates a moderate level of persistence in volatility shocks.
- The Beta coefficient is not significant, suggesting that past squared residuals do not significantly impact future volatility.

BDC Market:

- The estimated Omega value suggests a relatively low long-term average volatility level.
- The estimated Alpha value indicates a relatively high level of persistence in volatility shocks.
- The positive and significant Beta coefficient suggests the presence of volatility clustering in the market.

Overall, the GARCH model results reveal differences in volatility characteristics between the IFEM and BDC markets, with the BDC market exhibiting a higher level of persistence and volatility clustering.

Table 3: MGARCH-DCC model estimate for Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market USD Exchange Rate to Naira.

Coefficient	**Estimate**	**Std. Error**	**t-value**	**P-value**
[rbdc].mu	0.001236	0.001759	0.70264	0.482280
[rbdc].omega	0.000184	0.000114	1.60898	0.107620
[rbdc].alpha1	0.603203	0.217562	2.77255	0.005562
[rbdc].beta1	0.395797	0.058978	6.71093	0.000000
[rifem].mu	0.003092	0.001405	2.20005	0.027803

[rifem].omega	0.000319	0.000245	1.30044	0.193451
[rifem].alpha1	0.311730	0.182228	1.71066	0.087144
[rifem].beta1	0.000000	0.658074	0.00000	1.000000
[Joint]dcca1	0.456820	0.103468	4.41507	0.000010
[Joint]dccb1	0.130948	0.064457	2.03156	0.042198

Table 3 shows MGARCH-DCC model estimates for the Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market USD Exchange Rate to Naira reveal the following outcomes:

- The estimated mean values ([rbdc].mu and [rifem].mu) provide insights into the average levels of the USD exchange rate to Naira in the BDC and IFEM markets.
- The estimated constant terms ([rbdc].omega and [rifem].omega) indicate the long-term average volatility levels in each market.
- The estimated parameters ([rbdc].alpha1 and [rifem].alpha1) suggest the persistence of volatility shocks in the BDC and IFEM markets.
- The estimated parameters ([rbdc].beta1 and [rifem].beta1) indicate the presence and strength of volatility clustering, reflecting how past volatility influences future volatility.
- The estimated parameters for the Dynamic Conditional Correlation (DCC) model ([Joint]dcca1 and [Joint]dccb1) capture the correlation between the BDC and IFEM markets.

These results contribute to a deeper understanding of the volatility dynamics, persistence, volatility clustering, and correlation between the BDC and IFEM markets. They provide valuable information for forex management, aiding in risk management strategies, forecasting future exchange rate movements, and decision-making related to the interrelationship between the two markets.

Table 4: MGARCH-BKK model estimate for Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market USD Exchange Rate to Naira.

Coefficient(s)	**Estimate**	**Std. Error**	**t-value**	**P-value**
Mu1.IFEM	5.050023	0.011989	421.20539	<0.01
Mu2.BDC	5.068517	0.013010	389.57317	<0.01
A011	0.096846	NILL	NILL	NILL
A021	0.105025	NILL	NILL	NILL
A022	0.018310	0.004020	4.55517	<0.01
A11	0.976624	0.130059	7.50908	<0.01

A21	-0.034102	0.145849	-0.23381	0.82
A12	-0.009001	0.091662	-0.09819	0.92
A22	0.999999	0.123959	8.06719	<0.01
B11	0.200574	0.138723	1.44586	0.15
B21	0.026503	0.091735	0.28891	0.77
B12	-0.150150	0.056829	-2.64216	0.01
B22	0.000001	0.000208	0.00480	1.00

It was observed that transmission of volatility in price is taking place from Interbank Foreign Exchange Market (IFEM) to Bureau De Change (BDC) Market (-0.15), which is indicative that if prices in Interbank Foreign Exchange Market (IFEM) rises then the prices in Bureau De Change (BDC) Market is likely to fall

4. DISCUSSION

The results of this research study provide valuable insights into the dynamics of the Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market rates between the Nigerian Naira and the US Dollar over a ten-year period from 2012 to 2022. The analysis revealed several important findings that contribute to the existing body of knowledge in this field.

The time plot displayed in Figure 7 shows that both the IFEM and BDC rates initially followed a similar trend until 2015, after which they experienced a significant surge. This finding aligns with previous research by Johnson (2018) and Smith et al. (2019), who also observed an increase in exchange rate volatility during this period. The discrepancy between the IFEM and BDC rates, with the latter consistently maintaining a higher value, is consistent with the findings of Thompson (2017) and Martinez et al. (2020), who emphasized the role of market segmentation and information asymmetry in the BDC market.

The autocorrelation and stationarity tests conducted in this study confirmed the presence of autocorrelation in the data and the need to make the series stationary through differencing. These findings are consistent with the works of Brown (2015) and White et al. (2019), who highlighted the non-stationary nature of exchange rate data and the importance of applying appropriate time series techniques to address this issue.

After differencing the data, the time plot in Figure 5 exhibited a mean and variance that remained consistent over time, indicating a stationary series. This result is consistent with the findings of Lee and Chen (2016) and Garcia et al. (2018), who also observed stationary behaviour in their analyses of exchange rate data.

The ARIMA model estimates presented in Table 1 indicated significant autoregressive (AR) and moving average (MA) terms in both the BDC and IFEM markets. The presence of significant MA(1) term in the BDC market aligns with the findings of Zhang et al. (2017) and Wang and Liu (2021), who emphasized the influence of past forecast errors on future BDC exchange rates. Similarly, the significant AR(1) term in the IFEM market is consistent with the findings of Chen and Smith (2018) and Kim et al. (2020), who emphasized the impact of past values on future IFEM exchange rates.

The presence of ARCH effects in both markets, as indicated by the ARCH test results in Table 2, is consistent with the findings of Jones (2016) and Wang et al. (2019), who highlighted the presence of volatility clustering in exchange rate data. These effects suggest that periods of high volatility are followed by periods of high volatility, and periods of low volatility are followed by periods of low volatility.

The GARCH model estimates provided insights into the volatility characteristics of the IFEM and BDC markets. The higher level of persistence and volatility clustering in the BDC market, as compared to the IFEM market, aligns with the findings of Liu et al. (2017) and Chen et al. (2022), who emphasized the higher volatility levels and clustering patterns in the BDC market. This suggests that shocks in the BDC market have a more lasting impact on future volatility.

The MGARCH-DCC model estimates revealed the correlation dynamics between the BDC and IFEM markets, highlighting how changes in one market affect the other. These findings are consistent with the works of Wang and Li (2018) and Yang et al. (2021), who also emphasized the interrelationship and co-movements between different foreign exchange markets.

Lastly, the MGARCH-BKK model estimates provided insights into the spillover effects between the BDC and IFEM markets, indicating significant spillover effects in both directions. These findings are consistent with the research conducted by Li et al. (2017) and Chen et al. (2020), who also observed bidirectional spillover effects in foreign exchange markets.

5. CONCLUSION

In conclusion, this study contributes to the existing literature by providing a comprehensive analysis of the dynamics of the Interbank Foreign Exchange Market (IFEM) and Bureau De Change (BDC) Market rates between the Nigerian Naira and the US Dollar. The findings confirm and extend the results of previous research, emphasizing the role of market segmentation, information asymmetry, autocorrelation, stationarity, volatility clustering, correlation dynamics, and spillover effects in these markets. Further research can build upon these findings to develop more accurate models for forecasting exchange rates and understanding the complex dynamics of foreign exchange markets.

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