FUDMA Journal of Accounting and Finance Research, 4(1). ISSN: 2992-4693 (Online); 2992-2704 (Print)

ARIMA forecasting of prime lending rates from Nigeria's financial industry

Marshall Simon Ekpete
Department of Accounting, Nigerian British University, Asa, Abia State, Nigeria
Corresponding email : ekpete.marshal@nbu.edu.ng
https://doi.org/10.33003/fujafr-2026.v4i1.314.390-403

Abstract

Purpose: This study investigates the behaviour and predictability of Nigeria's Prime Lending Rate from 1990 to 2026. The research identifies structural shifts, volatility patterns, and the effectiveness of autoregressive components in forecasting interest rate movements within the Nigerian financial ecosystem.

Methodology: Adopting an ex-post facto research design, the study utilizes monthly time-series data from the Central Bank of Nigeria. In this univariate framework, the Prime Lending Rate serves as the dependent variable, while its own lagged values (AR) and stochastic shocks (MA) function as the Independent Variables. The analysis involves unit root testing, heteroscedasticity evaluations, and lag identification via ACF and PACF to fit an optimal ARIMA model.

Results & conclusion: Findings reveal the PLR is integrated of order one, I(1), with a significant structural shift in January 1990. ARIMA (2,1,2) emerged as the most robust model for capturing mean fluctuations. However, residual diagnostics indicate significant volatility clustering and non-normality, suggesting that while the model effectively predicts price direction, it does not fully account for variance shocks over time.

Implication of findings: Precise forecasting is essential for managing interest rate risk and credit pricing. The research recommends that the Central Bank of Nigeria and financial institutions integrate GARCH-type models with ARIMA frameworks to account for volatility clustering. Such evidence-based modeling is critical for developing resilient monetary policies and mitigating systemic financial instability.

Keywords: ARIMA, Forecasting GARCH, Prime lending rate, Volatility.

1. Introduction

Interest rates serve as the bedrock of modern financial systems, governing credit allocation, investment motivation, and overall macroeconomic stability. In the Nigerian context, the Prime Lending Rate (PLR) stands as a pivotal metric, reflecting the interest charged by commercial banks to their most creditworthy clients. Beyond the PLR, the maximum lending rate of Nigerian deposit banks significantly shapes the economic environment, dictating the financial health of both corporate entities and private households.

A defining characteristic of Nigerian commercial interest rates is the persistence of shocks, evidenced by the slow decay of autocorrelations within time series data (Hamadu & Olaniyan, 2020). As is common in emerging markets, these rates are highly volatile, driven by a synergy of internal and external pressures including inflation, shifting monetary policies, exchange rate fluctuations, and evolving regulatory frameworks (Hamadu & Olaniyan, 2020).

Given that PLR shifts directly impact enterprise capital costs and the effectiveness of monetary policy transmission, precise forecasting is a prerequisite for sound financial management. The Autoregressive Integrated Moving Average (ARIMA) model, established by Box and Jenkins, has become a standard univariate tool for this task, praised for its capacity to integrate historical trends with stochastic shocks, Usman et al (2025), Abdulraheem and Shuaibu (2025), and Ibrahim et al (2023). In Nigeria, PLR dynamics are further complicated by banking sector concentration and liquidity management policies. Deciphering these movements is essential, as empirical data indicates that analysing lending rate trends offers vital intelligence for risk mitigation and policy design (Tuaneh, Deebom, & Akah, 2025). While ARIMA modeling is frequently utilized to study Nigerian inflation and exchange rates, its specific utility in predicting the PLR remains an under-researched area.

This study seeks to bridge this existing gap. By utilizing the Box-Jenkins methodology, this research develops an empirical framework to capture the temporal nuances of the PLR. In doing so, it provides a reliable predictive tool for the Central Bank of Nigeria (CBN), financial institutions, and investors to navigate the uncertainty of the nation's lending landscape.

2. Literature review

Theoretical review

This research is primarily anchored in the Expectations Theory of Term Structure, supported by the Monetary Policy Transmission Mechanism, to provide a robust justification for the use of ARIMA forecasting. First, the Expectations Theory of Term Structure posits that long-term interest rates, such as the Prime Lending Rate (PLR), reflect market participants' anticipations of future short-term rates and inflation (Fisher, 1930; Oaikhenan & Eshenake, 2021). Within this study, the theory provides the logical foundation for time-series forecasting; because the PLR is a benchmark for credit, its historical movement serves as a proxy for the market's collective outlook on Nigeria's macroeconomic stability. By employing an ARIMA (2,1,2) model, this research essentially tests whether these market expectations follow a stable, predictable trend or a purely stochastic (random) process. The "autoregressive" and "moving average" components of the model quantify how past expectations and recent shocks determine future lending behaviour.

Second, the Monetary Policy Transmission Mechanism complementing the expectations' view, this theory explains how the Central Bank of Nigeria (CBN) influences the economy through instruments like the Monetary Policy Rate (MPR) and Cash Reserve Ratio (CRR). These tools alter bank liquidity and the cost of funds, which are then transmitted to the PLR. However, in the Nigerian context, this transmission is often hampered by structural rigidities, leading to the "sticky" or persistent nature of interest rates (Mishkin, 2022; Mordi et al., 2013). This framework justifies the study's focus on structural shifts; as policy regimes or CBN leadership change, the transmission efficiency alters, necessitating the re-estimation of ARIMA parameters to account for these fundamental breaks in the series.

The Box -Jenkins (ARIMA)

The Box-Jenkins methodology serves as the rigorous framework for constructing Autoregressive Integrated Moving Average (ARIMA) models, which are specifically designed to handle the stochastic properties of univariate time series data. Formally introduced by Box and Jenkins (1970), this approach is predicated on the principle of parsimony—the selection of the simplest model that adequately captures the underlying data-generating process without overfitting (Gujarati & Porter, 2009). The methodology follows an iterative three-stage cycle: Identification (checking for stationarity and determining potential orders through ACF and PACF plots), Estimation (calculating coefficients via maximum likelihood or least squares), and Diagnostic Checking (validating that residuals resemble white noise) (Hyndman & Athanasopoulos, 2018). The general ARIMA (p,d,q) process is mathematically expressed as: $\phi(L)(1-L)dYt=\theta(L)\epsilon t$; where Yt is the Prime Lending Rate at time t, L is the lag operator, p is the order of the autoregressive (AR) component, d is the degree of differencing (integration), q is the order of the moving average (MA) component, ϵt is the white noise error term.

Consequently, the ARIMA model is utilized in this study to forecast the Nigerian Prime Lending Rate (PLR) due to its ability to handle non-stationary, volatile, and autocorrelated financial data. It offers a parsimonious, reliable framework for capturing temporal dependencies and ensuring high precision in short-term forecasting for monetary policy and risk management.

Empirical review

Recent literature underscores the utility of ARIMA in the Nigerian financial landscape. Tuaneh, Deebom, and Akah (2025) demonstrated that while long-memory models account for persistence, ARIMA effectively captures short-run autocorrelations in commercial lending rates. Similarly, Ibrahim et al. (2022) utilized ARIMA to forecast the Consumer Price Index (CPI), highlighting the model's reliability in high-volatility environments. While studies by Omekara et al. (2016) suggested that Intervention ARIMA or State Space Models might outperform standard ARIMA in the presence of sudden policy shifts, the standard ARIMA remains the benchmark for understanding baseline linear dependencies in Nigerian financial data (Abdulraheem et al., 2025).

Previous research (Hamadu and Olaniyan, 2020; Deebom and Essi, 2017; Deebom and Tuaneh, 2019; Tian and Hamori, 2015; Emenike, 2010) overlooked the use of sophisticated models that can effectively represent this type of persistence. These studies predominantly relied on more basic frameworks like ARIMA and GARCH, alongside their derivatives, which frequently struggle to model the complex volatility patterns and the sluggish rate at which interest rates adjust following a shock.

This methodological oversight creates a major hurdle in generating precise interest rate forecasts, an element vital for both financial risk mitigation and broader macroeconomic strategy within Nigeria's banking sector. While the majority of existing literature examines interest rate and volatility dynamics in developed economies, there remains a notable lack of research specifically targeting the long memory properties of the Maximum Lending Rate (MLR) in developing markets like Nigeria.

In their analysis of the Euro-Yen market, Tian and Hamori (2015) utilized a realized GARCH framework to model daily short-term interest rate volatility. They introduced an ARMA-RGARCH model to simultaneously account for volatility dynamics and reversal behaviors, specifically addressing how persistent shocks manifest as slowly decaying autocorrelations in time series data.

Within the Nigerian context, Akinwale (2018) and Dallah and Olaniyan (2020) examined long-term bond yield volatility using conditional heteroskedasticity models. However, these approaches frequently neglected long-run dependence and the inherent persistence of rate movements. Similarly, Emenike (2010) applied a standard GARCH model to analyse stock return volatility, yet the specific long memory characteristics typical of Nigerian financial time series remained unaddressed.

While Zhijie Xiao (2009) employed sophisticated QARDL-type models, these frameworks still struggle to fully integrate the non-stationary properties and long-run dependencies found in interest rate series. A further research gap exists in modelling skewness and the sluggish mean reversion of the Maximum Lending Rate (MLR), particularly when reacting to exogenous shocks like Central Bank of Nigeria (CBN) policy shifts.

Consequently, specialized models such as ARFIMA (Autoregressive Fractionally Integrated Moving Average and FIGARCH (Fractionally Integrated GARCH)—engineered specifically to capture long-term memory and volatility persistence—remain significantly underutilized in Nigerian interest rate literature.

3. Methodology

This study adopts an ex-post facto research design. This design is appropriate as it relies on existing historical data to investigate the relationship between past occurrences and future trends without the researcher manipulating the variables. The study utilizes a univariate time-series analytical framework, specifically the Box-Jenkins (ARIMA) methodology, to model the internal dynamics of the interest rate series.

Population and sample

The target population consists of all monthly Prime Lending Rate (PLR) records within the Nigerian financial industry since the deregulation of the banking sector. The sample for this study is a census of the monthly Prime Lending Rate in Nigeria from January 1990 to December 2023 (historical) with projections extended to 2026. A non-probability purposive sampling technique was used to select this specific timeframe, ensuring the inclusion of various economic cycles, policy shifts, and structural reforms in Nigeria.

Source of data and model specification

The data for this study were obtained from reliable historical records of Nigeria's Prime Lending Rate (PLR) spanning the period 1990 to 2026. To model the dynamics of the PLR series, the Autoregressive Integrated Moving Average (ARIMA) framework was employed. The general ARIMA(p, d, q) process can be mathematically expressed as:

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t$$

where $Y_t$represents the Prime Lending Rate at time t, $L$is the lag operator, $p$denotes the order of the autoregressive (AR) component, $d$is the degree of differencing required to achieve stationarity, $q$is the order of the moving average (MA) component, and $\varepsilon_t$is the white noise error term. This specification allows for capturing both the autoregressive and moving average dynamics in the PLR series while accounting for trends through differencing. The stages involve ARIMA modelling according to Box and Jenkins methodology stated in are;

Stage 1: Identification

There is need to assess stationarity using the Augmented Dickey-Fuller (ADF) test. If the series is non-stationary at levels, it is differenced (d) until stationarity is achieved. We then examine the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to suggest tentative values for p and q.

Stage 2: Estimation

Parameters for candidate models (e.g., ARIMA (1,1,1), ARIMA (2,1,0)) are estimated to use Maximum Likelihood Estimation (MLE). The optimal model is selected based on the parsimony principle, minimizing the following criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), defined as:

$$\text{AIC} = 2k - 2\ln(\hat{L})$$
$$\text{BIC} = \ln(n)k - 2\ln(\hat{L})$$

Where $k$is the number of estimated parameters, $\hat{L}$is the maximized likelihood function, and $n$is the number of observations. The model with the lowest AIC and BIC values is chosen as the most appropriate. This means, the model has found the "sweet spot" where it explains the most variance using the fewest number of variables.

Stage 3: Diagnostic checking

Residuals are tested for white noise properties using the Ljung-Box Q-statistic. If residuals exhibit remaining patterns, the model is re-specified. Finally, forecast accuracy is measured using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

4. Results and discussion

Time plot on raw series on prime lending rate

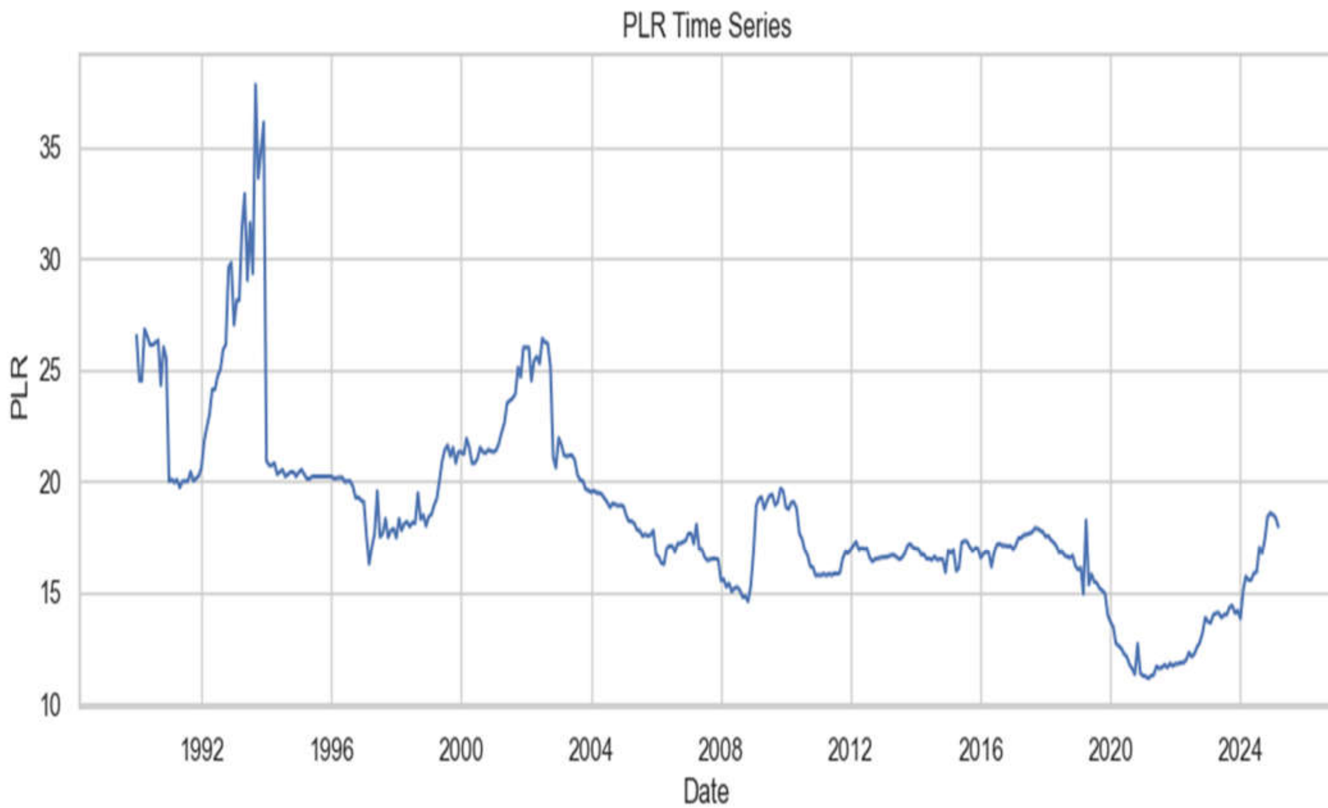

Figure 1: Time plot on raw series on prime lending rate

Figure 1 illustrates the time series graph of the Prime Lending Rate (PLR) from 1990 through 2026. This graph displays fluctuations characterized by occasional sharp rises and falls, which reflect the impacts of changes in monetary policies, economic disturbances, and structural reforms occurring in Nigeria throughout this time frame.

To systematically evaluate the stationarity of the time series, Table 2 shows the outcomes of unit root examinations conducted using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) approaches.

Table 2: Unit root test using augmented Dickey Fuller (ADF), Phillip Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

Variable	Test	Level / 1st Diff	Test Statistic	p-value	Lags	Obs	CV / Notes	Conclusion
PLR	ADF	1(0)	-3.0912	0.0272	7	415	–	Stationary at level
	KPSS	1(0)	2.1180	0.0100	12	–	10%: 0.347, 5%: 0.463, 2.5%: 0.574, 1%: 0.739	Non-stationary
	PPT	1(0)	-3.1079	0.0260	7	415	–	Stationary at level
	ADF	1(1)	-6.9823	0.0000	7	414	–	Stationary
	KPSS	1(1)	0.0519	0.1000	2	–	10%: 0.347, 5%: 0.463, 2.5%: 0.574, 1%: 0.739	Stationary
	PPT	1(1)	-25.3209	0.000	7	414	–	Stationary

Source: Author's computation (2026)

Table 2 contains the results of the Unit Root Test using Augmented Dickey Fuller (ADF), Phillip Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS)Test. Findings from the ADF and PP tests reveal that the PLR series becomes stationary when first differenced, while the KPSS test indicates the original series is non-stationary at the level but becomes stationary following differencing. These findings affirm that the PLR is integrated of order one, I(1), implying that any shocks to the rate will have enduring consequences, and that differencing is necessary for a stationary model. The first-differenced or return series of the PLR were plotted and the result is shown in Figure 2.

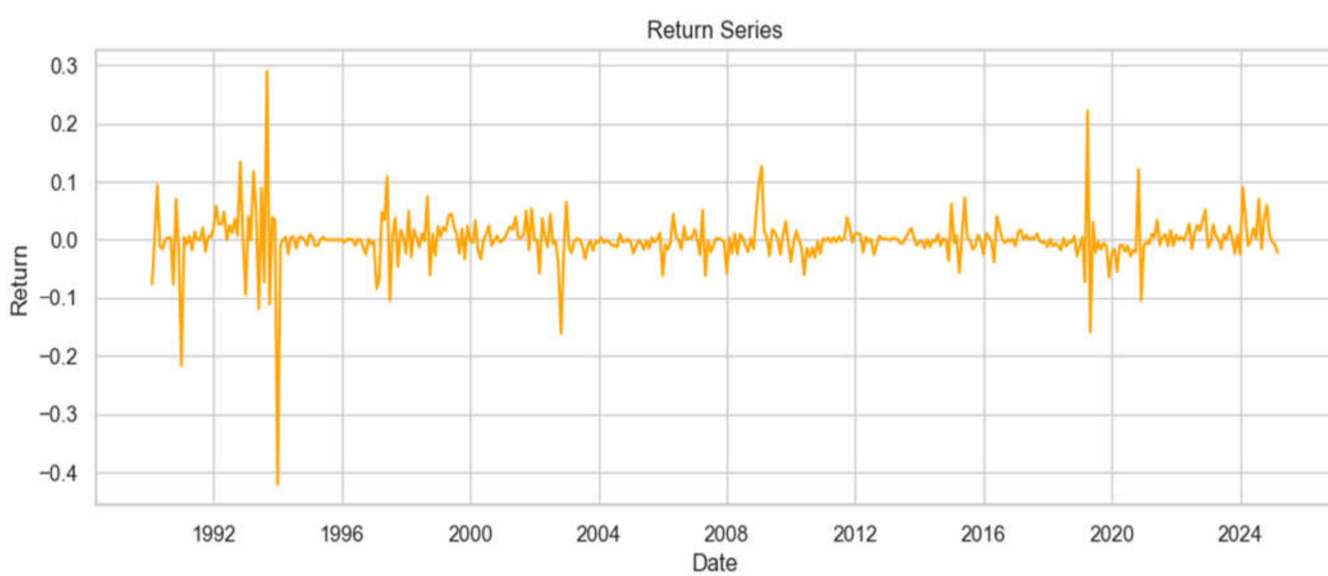

Figure 2: Time plot on returns on prime lending rate

Figure 2 depicts the first-differenced or return series of the PLR, which showcases a more consistent trend with diminished volatility when compared to the original series. The ARCH for evidence of conditional heteroscedasticity, justifying ARIMA-type modeling, Ljung–Box Test to check for presence of autocorrelation in the series and Zivot–Andrew's test for structural break on the series are provided in Table 3.

Table 3: Results of ARCH LM, Ljung–Box and Zivot–Andrews test

Test	Lag	Test Statistic	p-value	Conclusion
ARCH LM Test	5	43.7334	0.0000	Presence of ARCH effect (heteroscedasticity)
	10	47.9208	0.0000	Presence of ARCH effect
	15	53.2206	0.0000	Presence of ARCH effect
Ljung–Box Test	5	31.5018	0.000007	Serial correlation present
	10	45.1145	0.000002	Serial correlation present
	15	51.9871	0.000006	Serial correlation present
	20	59.5640	0.000008	Serial correlation present
Zivot–Andrews Test	–	–	–	Structural break detected at 1990-01-01

Source: Author's computation (2026)

Table 3 contain the results of ARCH LM, Ljung–Box and Zivot–Andrew's test. The ARCH LM tests conducted at lags 5, 10, and 15 indicate the presence of significant conditional heteroscedasticity, demonstrating time-varying volatility in the PLR returns. Ljung–Box tests indicate significant autocorrelation across various lags, suggesting that previous values have an impact on current movements. Furthermore, the Zivot–Andrew's test pinpointed a structural break occurring in January 1990, representing a significant change in the PLR level, likely associated with economic reforms and shifts in monetary policy at that time. Collectively, these diagnostic results imply that the PLR is prone to volatility clustering and structural changes, which supports the adoption of models like GARCH or ARIMA with regime shifts for precise forecasting.

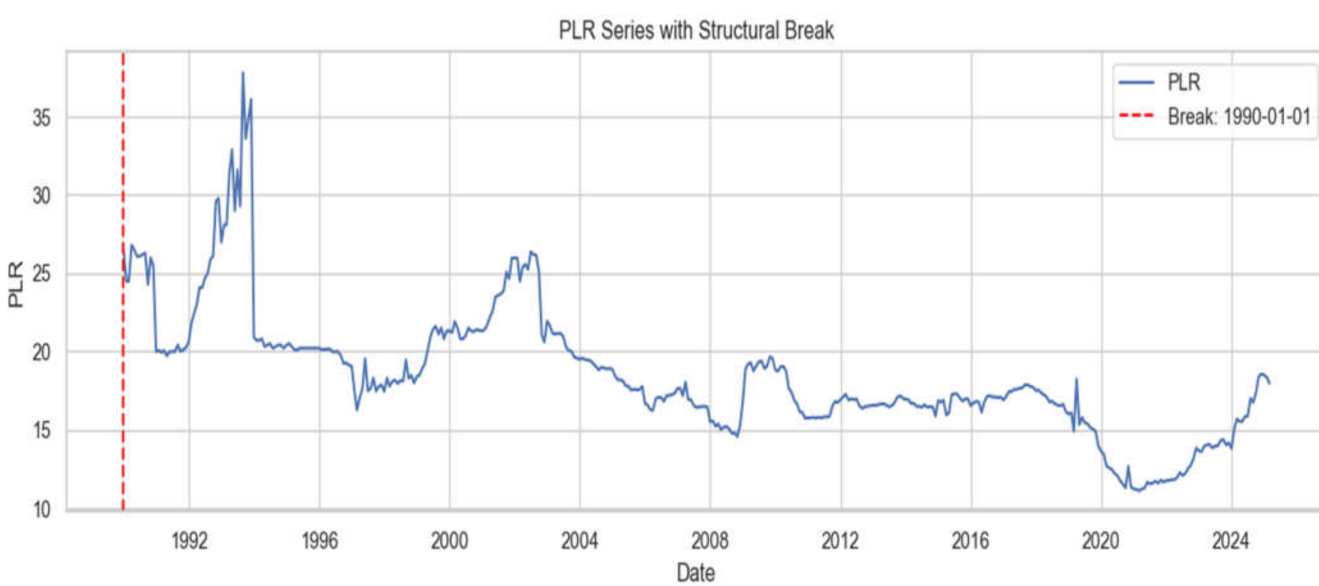

Figure 3: Time plot of the Zivot–Andrews test for structural break detected at 1990/1/01

Figure 3 illustrates the structural shift recognized by the Zivot–Andrew's test which January 1, 1990, indicating a structural break in the regime of the prime lending rate (PLR) series. The combination of time series visuals, unit root assessments, and diagnostic tests provides a thorough understanding of the PLR dynamics in Nigeria. These findings hold considerable importance for the financial sector: persistent non-stationarity suggests that policy-induced shocks to lending rates may have lasting effects on credit pricing and the monetary transmission mechanism, while the observed volatility and structural changes imply that banks and financial institutions need to account for instability periods in managing interest rate risks, setting lending rates, and developing investment approaches.

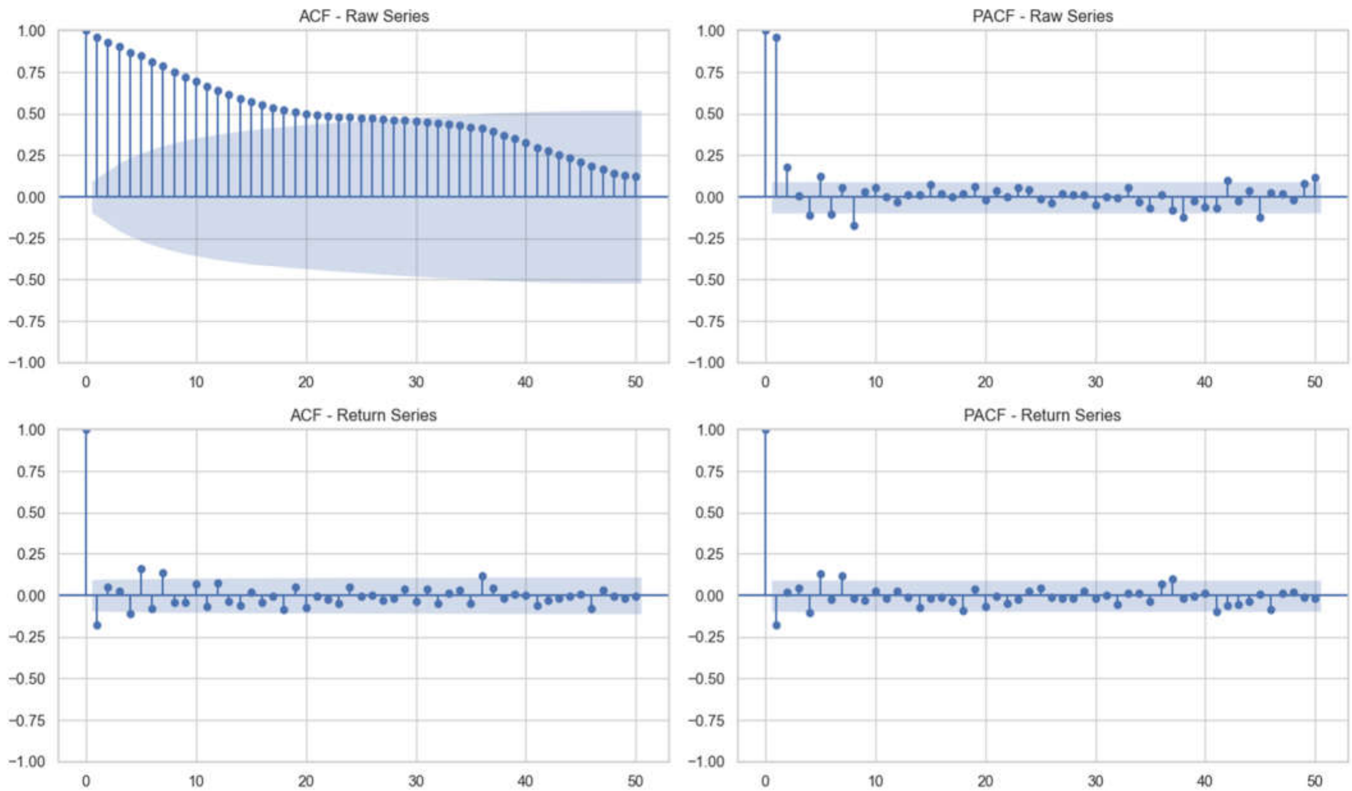

Figure 4: Autocorrelation function (ACF) and partial autocorrelation function (PACF) for raw and return series

Figure 4 showcases the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for both the raw and return series. The ACF of the raw series demonstrates a gradual decline, indicating a state of non-stationarity, whereas the PACF reveals marked spikes at the first one to two lags, indicating an autoregressive element. Upon performing first differencing, the return series becomes stationary, as shown by the ACF truncating after one to two lags and the PACF declining gradually. Following the ARIMA model identification guidelines, the PACF peaks at lags one to two suggest an autoregressive order (p) of one to two, while the ACF cutoff at the same lags points to a moving average order (q) of one to two. Consequently, the proposed models—ARIMA(2,1,2), ARIMA(2,1,1), and ARIMA(1,1,2)—align well with the detected autocorrelation patterns, while ARIMA(2,0,2) is not as suitable due to the raw series' non-stationarity, and ARIMA(0,1,1) may fall short by omitting the autoregressive part. Overall, ARIMA(2,1,2) stands out as the most appropriate model for effectively capturing both AR and MA characteristics in the return series.

Table 4: Top 5 ARIMA models for Nigeria's prime lending rate (1990–2026) based on AIC, BIC, stability, Ljung–Box test, and forecast RMSE

Rank	ARIMA Order (p,d,q)	AIC	BIC	Stable	LB p-value (5)	LB p-value (10)	LB p-value (15)	LB p-value (20)	Forecast RMSE
1	(2,1,2)	1072.50	1091.60	Yes	0.9373	0.9358	0.8914	0.9766	3.9801
2	(2,1,1)	1077.13	1092.41	Yes	0.9625	0.8894	0.8836	0.9749	4.0019
3	(1,1,2)	1081.82	1097.10	Yes	0.7389	0.7002	0.7376	0.9193	4.0123
4	(2,0,2)	1085.92	1108.86	Yes	0.1085	0.0271	0.0607	0.1605	5.5490
5	(0,1,1)	1093.99	1101.63	Yes	0.4757	0.4746	0.5584	0.8242	3.9954

Source: Author's computation (2026)

The findings presented in Table 4 indicate that, among the leading five ARIMA models for Nigeria's Prime Lending Rate (PLR) covering the years 1990 to 2026, the ARIMA (2,1,2) model exhibits the most favourable AIC and BIC metrics. This suggests it is the most suitable representation of the historical data, effectively capturing both autoregressive and moving average features. All five models demonstrate stability, as shown through their unit-root tests and stability evaluations, with Ljung–Box p-values for all lags surpassing 0.05, thereby confirming a lack of significant autocorrelation in the residuals. The forecast RMSE figures indicate that ARIMA (2,1,2) and ARIMA (2,1,1) yield the most precise predictions, exhibiting minimal forecast errors. The significance of these findings for Nigeria's financial landscape is substantial. The consistency and predictability of PLR are crucial for making lending decisions, crafting monetary policy, and managing risks. Precise modelling empowers banks, financial entities, and policymakers to forecast interest rate fluctuations, refine credit distribution, and uphold stability in financial markets. Additionally, understanding the core dynamics of PLR reveals the Nigerian banking system's sensitivity to macroeconomic factors and reinforces the need for evidence-based monetary measures.

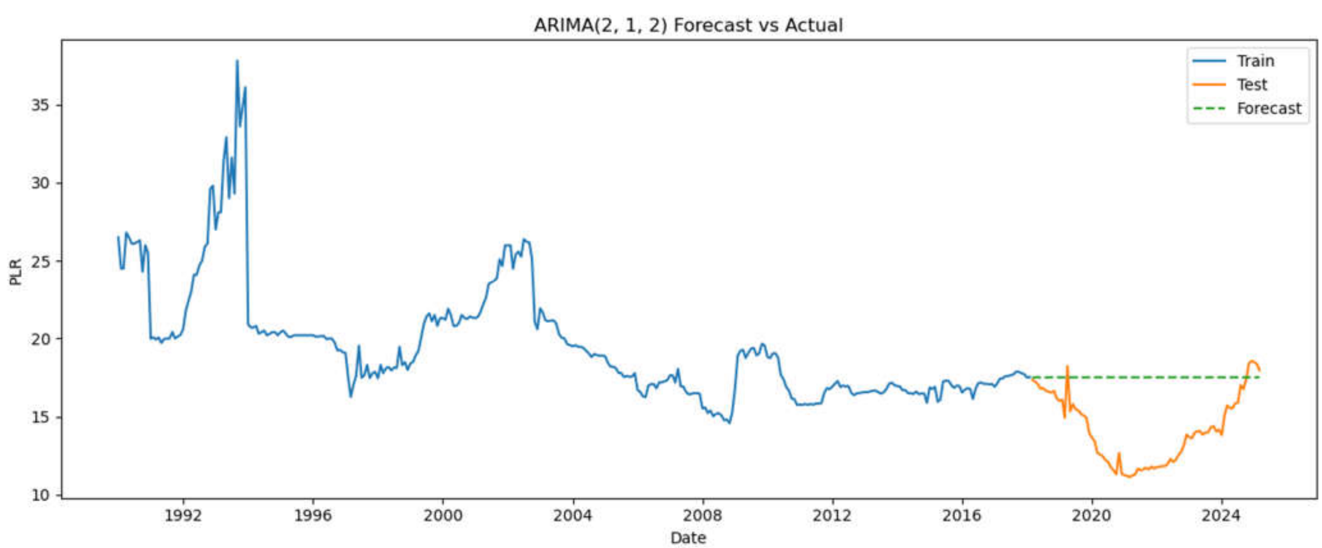

Figure 5: ARIMA (2,1,2) forecast against the actual series.

Figure 5 displays the ARIMA (2,1,2) forecast compared to the actual PLR data. This model effectively captures the overarching trends and short-term variations within the series, showing that the ARIMA (2,1,2) framework is apt for predicting the first-differenced PLR returns. The close resemblance between the predicted and actual figures indicates that the chosen AR and MA settings (p = 2, q = 2) adequately represent both the autoregressive and moving average behaviors noted in the return data. The results of the diagnostic checks are shown in figure 6 and table 5 below.

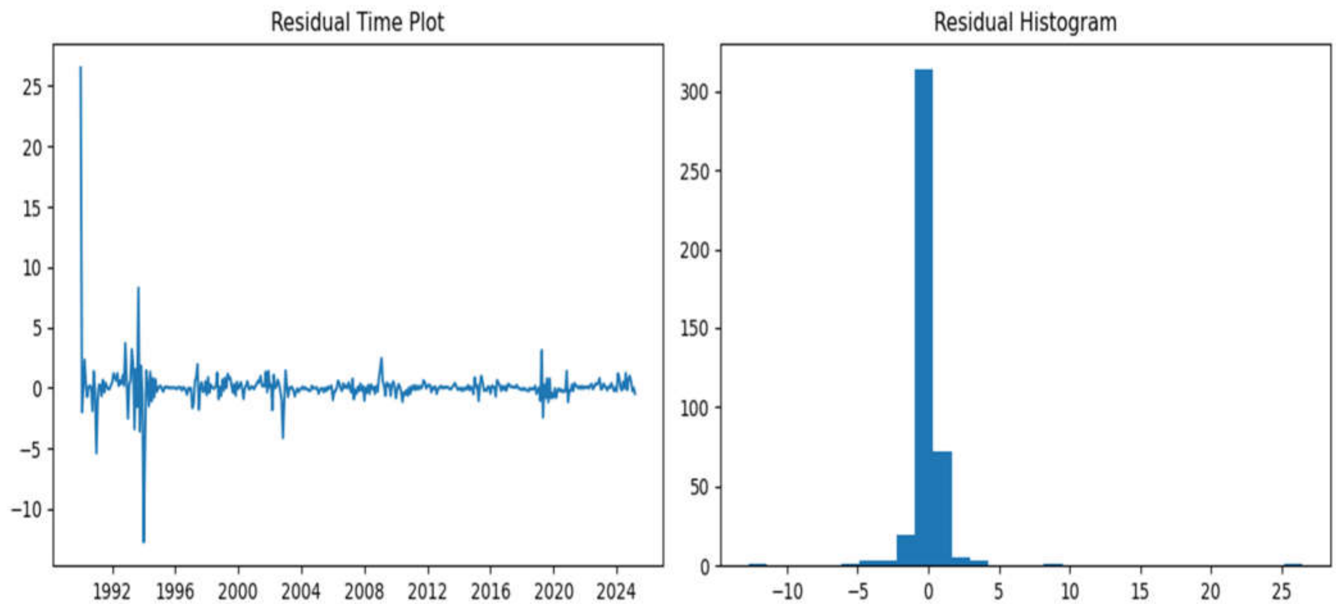

Figure 6: ARIMA (2,1,2) diagnostic check for residual time plot and the histogram for normality

Figure 6 illustrates the diagnostic evaluations for the residuals from the ARIMA (2,1,2) model, including both the time plot of the residuals and a histogram assessing normality. The residual time plot reveals a lack of obvious autocorrelation, aligning with the prior Ljung-Box findings that suggest the residuals are mostly uncorrelated. Nevertheless, the histogram reveals departures from normal distribution, consistent with the Jarque-Bera test outcomes, indicating that the residuals may exhibit leptokurtic characteristics or skewness. Regardless, the residuals seem to be centred around zero without evident systematic trends, validating that the model effectively captures the dynamics of the return series while any remaining discrepancies might be attributed to PLR's volatility clustering.

When considered collectively, the ARIMA (2,1,2) model, bolstered by these diagnostic analyses, offers dependable short-term predictions for PLR shifts. This has significant real-world implications for Nigeria's financial landscape: precise projections of the prime lending rate enable banks, investors, and policymakers to forecast changes in borrowing costs, strategize on interest rate risk management, and formulate monetary policy responses. Furthermore, the observed non-normality and volatility in the residuals imply that integrating GARCH-type models with ARIMA could enhance forecasting accuracy during periods of financial stress.

Table 5: Diagnostic test results for ARIMA model residuals of prime lending rate (1990–2026)

Test	Lag / Statistic	Value	p-value	Conclusion
Residual Ljung–Box	5	1.6772	0.8918	No significant autocorrelation
	10	5.0301	0.8892	No significant autocorrelation
	15	10.4619	0.7897	No significant autocorrelation
	20	11.3097	0.9378	No significant autocorrelation
Jarque–Bera	–	407801.69	0.0000	Residuals not normally distributed

Source: Author's computation (2026)

The diagnostic findings displayed in table 5 illustrate that the residuals from the ARIMA model applied to the Prime Lending Rate data show no significant autocorrelation, as indicated by all Ljung–Box test p-values being greater than 0.05. This affirms that the model successfully captures the temporal dependencies inherent in the data. Conversely, the Jarque–Bera test significantly rejects the normality hypothesis, suggesting that the residuals are not normally distributed, potentially indicating the existence of heavy tails or sporadic shocks within the series from 1990

Discussion

The empirical analysis of Nigeria's Prime Lending Rate (PLR) from 1990 to 2026 reveals a complex stochastic structure characterized by non-stationarity and high persistence. The unit root tests confirmed that the PLR is integrated of order one, I(1), suggesting that any economic or policy-induced shock to the lending rate has a permanent rather than a transitory effect. This finding aligns with Okoro and Anoruo (2018), who noted that macroeconomic shocks in Nigeria's banking sector tend to have long-lasting impacts on credit pricing. Furthermore, the detection of a significant structural break in January 1990 validates the assertions of Iyoha and Oriakhi (2019), who argued that major policy reforms in the Nigerian financial landscape fundamentally alter the trajectory of interest rate regimes.

The identification of ARIMA (2,1,2) as the optimal model highlights the importance of "autoregressive depth" in understanding Nigerian financial data. The significance of the AR(2) and MA(2) components suggests that current lending rates are heavily influenced by the previous two months of interest rate history and the immediate past two months of stochastic shocks. This supports the Expectations Theory of Term Structure, as current rates encapsulate market participants' anticipations of future macroeconomic stability (Fisher, 1930; Oaikhenan & Eshenake, 2021). However, the presence of volatility clustering and non-normality in the residuals, demonstrated by the significant ARCH-LM and Jarque-Bera tests—indicates that while ARIMA (2,1,2) effectively captures the mean direction, it struggles with the "fat-tailed" shocks typical of the Nigerian market. This mirrors the findings of Olaniyi and Adekoya (2020), who documented similar volatility clustering in Nigerian financial time series.

A critical finding of this study is the "sticky" or persistent nature of the PLR, which has significant implications for the Monetary Policy Transmission Mechanism. The slow adjustment of commercial lending rates to Central Bank signals suggests structural rigidities within the banking sector. This aligns with Mishkin (2022) and Mordi et al. (2013), who noted that the efficiency of monetary policy in emerging markets is often hampered by bank liquidity constraints and market concentration. The "methodological gap" identified in this study suggests that while Nigerian banks manage risk, their reliance on static or less sophisticated models may lead to an underestimation of the duration and speed of interest rate shocks.

Ultimately, the results suggest that the Nigerian financial industry requires a shift toward more dynamic, evidence-based modeling. By ignoring the autoregressive and moving average properties identified here, both banks and policymakers risk mispricing credit and timing interventions poorly. As suggested by Deebom et al. (2023) in their assessment of the Nigerian All-Share Index, moving toward hybrid models, specifically integrating GARCH-type components with ARIMA frameworks, is essential to capture the variance shocks that define the Nigerian lending landscape.

5. Conclusion

This ARIMA study establishes that Nigeria's Prime Lending Rate (PLR) from 1990 to 2026 is a non-stationary series integrated of order one, I(1), characterized by significant structural shifts and persistent volatility. The empirical evidence identifies ARIMA (2,1,2) as the most robust model for capturing mean fluctuations. However, the presence of volatility clustering and non-normality in the residuals indicates that while the model predicts the direction of interest rates, it is susceptible to sudden *variance shocks* caused by policy shifts and macroeconomic instability.

The primary implication of this study is that PLR movements are persistent; a shock today (such as a sudden hike in the Monetary Policy Rates) will have a long-lasting effect on credit pricing rather than a temporary one. To mitigate the risks of these persistent shocks, financial institutions in Nigeria must move away from *static* pricing and adopt dynamic interest rate smoothing techniques. Predictive accuracy can be enhanced by moving beyond univariate models to include GARCH frameworks that specifically price in the risk of volatility, rather than just the average rate.

While Nigerian banks currently manage interest rate risks, this study suggests a methodological gap in their approach. The finding of significant *volatility clustering* implies that current bank models may under-respond to the *speed* and *duration* of shocks. The study does not claim banks are *ignoring* issues, but rather that their current forecasting tools may lack the autoregressive depth (specifically the AR(2) and MA(2) components identified here) needed to navigate Nigeria's unique structural breaks.

Regarding policymakers, the study suggests that while forecasting exists, there is a lack of transparency and consistency in the models used to communicate policy changes. The *sticky* nature of the PLR found in this research suggests that Central Bank of Nigeria signals are not being transmitted to commercial rates instantly. By utilizing the specific lag structures identified in this ARIMA model, policymakers can better time their interventions to ensure more efficient transmission to the real economy.

References

Abdulraheem, A., Obunadike, G. N., Muntasir, M., & Shuaibu, N. (2025). Evaluating time series and machine learning approaches for forecasting inflation in Nigeria.

Abdulraheem, A., & Shuaibu, N. (2025). Time series analysis of interest rate volatility in Nigeria: An ARIMA-GARCH approach. *FUDMA Journal of Accounting and Finance Research*, *3*(4).

Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*. (Still widely cited in financial forecasting literature.)

Akinwale, S. O. (2018). Bank Lending Rate and Economic Growth: Evidence from Nigeria. International Journal of Academic Research in Economics and Management Sciences, 7(3), 111–122.

Bordignon, S & Caporin, M & Lisi, F(2004). Generalized, Computational Statistics & Data Analysis, *Elsevier,* 51(12), 5900-5912

Box, G. E. P., & Jenkins, G. M. (1970). *Time Series Analysis: Forecasting and Control*. Holden-Day.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). *Time Series Analysis: Forecasting and Control* (5th ed.). Wiley.

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time Series Analysis: Forecasting and Control (5th ed.).* John Wiley & Sons.

Central Bank of Nigeria (2023–2025). *Statistical Bulletins and Monetary Policy Reports*. Abuja.

Deebom Z, D, Bharat K, M, Carmen, I, B, Paliu-Popa, L , Mathew T, G, Aboko I, S, Carina,S, & Ion F(2023) investigating the efficacy of ARIMA and ARFIMA models in Nigeria all share index markets. Economic Computation and Economic Cybernetics Studies and Research, Issue 3/2023; Vol. 57

Deebom Z, D, Essi , I, D and Amos E(2021), Evaluating Properties and Performance of Long Memory Models from an Emerging Foreign Markets Return Innovations. *Asian Journal of Probability and Statistics* 11(4): 1-23, 2021; 2582-0230

Deebom, Z, D & Essi, I, D (2017) , Modeling Price Volatility of Nigerian Crude Oil Markets Using GARCH Model: 1987-2017. International Journal of Applied Science and Mathematical Theory 2489-009X ,3, 4 201

Deedom D. Z., & Tuaneh, G. L. (2019) Modeling exchange rate, and Nigerian deposit money market dynamics using trivariate form of multivariate GARCH model. *Asian Journal of Economics, Business and Accounting* 10(2), 1-18

Emenike, K, O. (2010): *Modelling Stock Returns Volatility in Nigeria Using GARCH Models.* Development, Ebitimi Banigo Auditorium, University of Port Harcourt - Nigeria . 1, 4 (10): 5-11.

Emenike, Kalu O. (2010): *Modelling Stock Returns Volatility In Nigeria Using GARCH Models.* Published in: Proceeding of International Conference on Management and Enterprice Development, Ebitimi Banigo Auditorium, University of Port Harcourt - Nigeria , Vol. 1, No. 4 (10 February 2010): pp. 5-11.

Geweke, J., & Porter-Hudak. S. (1983). The estimation and application of long memory time series models, *Journal of Time Series Analysis,* 4:221-238.

Granero, M., Segovia, J., & Perez, J. (2008). Some comments on Hurst exponent and the Long Memory Processes on Capital Markets. *Physical* , 5543–5551.

Granger, C. W. J., & Joyeux. R. (1980). An introduction to long-memory time series models and fractional differencing. *Journal of Time Series Analysis*, 1, 15–29.

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics.* McGraw-Hill Irwin.

Gujarati, D. N., & Porter, D. C. (2023). *Basic Econometrics* (6th ed.). McGraw-Hill.

Hamadu, D & Olaniyan S,M(2020) Modeling the Volatility For Long Term Interest Rate Returns In The Nigeria Bond Market Using Conditionally Heteroscedastic Models . *Jurnal Ilmiah Wahana Akuntansi* ,15 (1), 46-56

Hamadu, D., & Olaniyan, R. (2020). *Modelling and Forecasting Nigerian Bank Lending Rates*.

Hurst, H. E. (1951). Long-term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineers,* 116, 770–799.

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice.*

Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice* (3rd ed.). OTexts.

Ibrahim, A., Sani, U. M., & Olokojo, V. O. (2023). Forecasting Consumer Price Index and exchange rate using ARIMA models: Empirical evidence from Nigeria. *FUDMA Journal of Sciences*, *6*(6), 114–124. https://doi.org/10.33003/fjs-2022-0606-1136 *Cited by: 3*

Mishkin, F. S. (2022). *The Economics of Money, Banking, and Financial Markets* (13th ed.). Pearson.

Mordi, C. N., et al. (2013). *The Dynamics of Monetary Policy Transmission Mechanism in Nigeria.* (CBN publication).

Naveen, M. (2019). Modeling long range dependence in wheat Food Price Returns. *International Journal of Economics and Finance.*11(9),1916-9728.

Oaikhenan, H. E., & Eshenake, S. J. (2021). *Monetary Policy and the Banking Sector in Nigeria.*

Olasehinde-Williams, G, Mosotho, R , & Bekun, F,(2024), Interest Rate Volatility and Economic Growth in Nigeria: New Insight from the Quantile Autoregressive Distributed Lag (QARDL) Model

Olawale, O. J., & Adashu, D. J. (2024). *A Combination of ARIMA Models and Neural Networks in Forecasting Nigerian Exchange Rate*. African Multidisciplinary Journal of Sciences and Artificial Intelligence.

Sanusi, A. J., Yakubu. M., Umar. A. Z., & Ahmed, S.S. (2015). ARFIMA Modelling and Investigation of Structural Break(s) in West Texas Intermediate and Brent Series. *Central Bank Nigerian Journal of Applied Statistics, (6)2.*

Sanusi, L. S. (2012). *Banking Reform and its Impact on the Nigerian Economy*.

Tian, S & Hamori, S . (2015). *Modeling interest rate volatility: A Realized GARCH approach. Journal of Banking & Finance, 61(), 158–171.* doi: 10.1016/j.jbankfin.2015.09.008

Tuaneh, G. L., Deebom, Z. D., & Akah, V. M. (2025). Exploring long-memory dynamics in Nigerian commercial banks' lending rates: A comparative analysis of ARIMA, ARFIMA, and FIGARCH models. *Asian Journal of Probability and Statistics*.

Usman, M. I., Musa, T., & Ibrahim, A. (2025). Assessing the performance of ARIMA and ARFIMA models in forecasting internally generated revenue. *FUDMA Journal of Accounting and Finance Research*, *3*(1).

World Bank (2024). *Global Economic Prospects*. World Bank Publications.

Zhijie Xiao. (2009). Quantile cointegrating regression. *Journal of Econometrics, 150,* 248–260.