



Exchange Rate Volatility and Forecasting Techniques in Nigeria: Evidence from 1990–2023

Ajeniweni Peter Olushola^{1,*}, Fatai Akosile², and Yusuf T. Yusuf³

^{1,2,3}Kwara State University, Malete, Kwara State

*Correspondence: apeterolushola@gmail.com

Abstract

This study investigates the determinants and dynamics of exchange rate volatility in Nigeria over the period 1990–2023, whilst evaluating the predictive performance of competing forecasting techniques, specifically the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) family of models, the Autoregressive Integrated Moving Average (ARIMA) framework, and the Autoregressive Distributed Lag (ARDL) bounds testing approach. Employing quarterly time-series data sourced from the Central Bank of Nigeria Statistical Bulletin, the World Bank World Development Indicators, and the International Monetary Fund International Financial Statistics, the study incorporates key macroeconomic fundamentals including oil price shocks, external reserves, money supply, inflation differentials, and trade openness. Results from the GARCH(1,1) and EGARCH models confirm significant volatility persistence and asymmetric shock effects. The ARDL bounds test confirms a long-run cointegrating relationship between exchange rate volatility and its macroeconomic determinants. Forecast accuracy diagnostics indicate that GARCH-based models outperform ARIMA in the short run, whilst ARDL demonstrates superior performance over medium- to long-run horizons. Findings carry significant policy implications for the Central Bank of Nigeria regarding exchange rate management, reserve adequacy, and monetary policy coordination. This study contributes to the extant literature by providing a rigorous comparative multi-model forecasting framework anchored in Nigerian-specific institutional realities and extending the analytical horizon to incorporate recent structural breaks, including the 2014 to 2016 oil price collapse, COVID – 19 pandemic distortions and post–2021 foreign exchange policy reforms.

Keywords: Exchange rate volatility, GARCH, ARDL, ARIMA, Nigeria JEL Classification: C22, C52, F31, F41, O24

1. Introduction

Exchange rate volatility remains one of the most consequential macroeconomic challenges confronting Sub-Saharan African economies, particularly resource-dependent states such as Nigeria. The Nigerian naira has experienced a protracted and turbulent trajectory since the liberalisation of the foreign exchange market in the mid-1980s under the Structural Adjustment Program, oscillating between periods of managed pegging, multiple exchange rate regimes, and market-determined flotation (Aliyu, 2009). The persistence and severity of exchange rate instability in Nigeria are inextricably linked to structural vulnerabilities including the economy's mono-commodity dependence on crude oil exports, narrow export diversification, chronic import reliance, and persistent current ac-

count pressures (Adekunle *et al.*, 2020). These structural features have rendered the naira acutely susceptible to external shocks, most notably global oil price fluctuations, whilst simultaneously constraining the monetary authorities' capacity to maintain stability without depleting external reserves. Understanding both the dynamics of exchange rate volatility and the comparative forecasting power of competing econometric techniques is therefore not merely an academic exercise but a matter of critical macroeconomic policy relevance for Nigeria and analogous developing economies.

Despite the substantial body of literature on exchange rate behaviour in Nigeria, significant lacunae persist in both scope and methodology. A considerable proportion of extant studies have relied on single-model approaches, most commonly the ARIMA or basic GARCH frameworks, without systematically comparing their predictive accuracy against structural macroeconomic models such as the ARDL bounds testing procedure (Omotosho, 2015; Nwosu *et al.*, 2019). Furthermore, many prior studies have employed relatively short data samples typically spanning 2000–2015, thereby failing to capture the profound structural breaks introduced by the 2008 global financial crisis, the 2014–2016 oil price collapse, and the foreign exchange distortions induced by the COVID-19 pandemic (Babatunde & Shuaibu, 2011; Ogundipe *et al.*, 2019). There is also a notable absence of studies that explicitly account for asymmetric volatility effects, a critical omission given the well-documented asymmetric transmission of oil price shocks on the naira (Iyoha & Oriavwote, 2015). The gap between the sophistication demanded by practical exchange rate management and the methodological limitations of existing studies warrants urgent redress.

This study departs from the existing literature in four critical and complementary ways. First, it employs a considerably extended quarterly dataset spanning 1990Q1–2023Q4 (136 observations), capturing over three decades of exchange rate regime transitions and exogenous shocks. Second, it adopts a rigorous comparative multi-model forecasting framework simultaneously deploying ARIMA, GARCH(1,1), EGARCH(1,1), and ARDL, enabling a robust cross-model forecast accuracy evaluation. Third, the study explicitly incorporates oil price volatility, external reserves, money supply growth, and trade openness as joint determinants, a combination neglected in the Nigerian context. Fourth, the study employs Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to adjudicate rigorously among competing models. The study therefore makes a distinctive theoretical and empirical contribution to the macroeconomic forecasting literature and provides evidence-based guidance for the Central Bank of Nigeria and associated policy institutions.

2. Literature Review

Exchange rate volatility refers to the statistical dispersion of exchange rate returns over a defined period, typically measured through the standard deviation or conditional variance of exchange rate changes (Engle, 1982). In developing economies, it is conceptually distinguished from mere exchange rate fluctuation by its persistence, unpredictability, and asymmetric transmission effects (Bollerslev, 1986). The Purchasing Power Parity (PPP) theory, the Monetary Model of Exchange Rate Determination, and the Portfolio Balance Model collectively provide the theoretical foundation for understanding exchange rate dynamics (Dornbusch, 1976; Frankel, 1979). The Dornbusch (1976) overshooting hypothesis posits that exchange rates respond disproportionately to monetary shocks in the short run before reverting gradually to long-run equilibrium, a hypothesis with strong resonance in Nigeria given recurrent monetary policy transmissions and fiscal dominance. The GARCH framework (Bollerslev, 1986), extending Engle's (1982) ARCH model, has become the canonical tool for modelling conditional heteroscedasticity in exchange rate series. However, purely statistical GARCH models do not accommodate macroeconomic fundamentals that structural models such as ARDL explicitly incorporate, creating a complementarity that the present study exploits. A critical gap in the conceptual literature is the absence of a unified framework integrating time-series volatility modelling with structural macroeconomic determinants within the Nigerian exchange rate context.

Conversely, several studies were reviewed, such as Aliyu (2009), which examined the impact of oil price shocks and exchange rate volatility on economic growth in Nigeria from 1986 to 2007, finding that oil price increases significantly appreciated the naira in the short run. Whilst pioneering, the study's sample predates major structural breaks and relies on OLS without addressing non-stationarity rigorously. Babatunde and Shuaibu (2011) analysed exchange rate volatility determinants in Nigeria using GARCH(1,1) over 1990–2009, documenting significant volatility persistence. However, the annual frequency employed is too low to capture intra-year volatility dynamics, and oil price shocks were excluded. Ogundipe *et al.* (2019) investigated exchange rate determination via the ARDL approach over 2000–2017, establishing significant long-run relationships between the exchange rate, external reserves, and trade openness, but omitting any volatility modelling component and excluding the COVID-19 period. Also, Omotosho (2015) deployed GARCH family models including EGARCH to study naira/dollar volatility over 2004–2014, finding evidence of leverage effects, but the short sample and absence of cross-model forecast comparisons are notable limitations. Nwosu *et al.* (2019) estimated a VAR model to assess the interdependence of exchange rates, inflation, and monetary policy in Nigeria from 2000 to 2016, revealing significant bidirectional causality, but without testing for cointegration or modelling conditional heteroscedasticity. Adekunle *et al.* (2020) examined exchange rate misalignment over 1981–2018 using ARDL, finding significant naira deviation from equilibrium but not modelling volatility explicitly or evaluating out-of-sample forecasting accuracy. Hassan and Aliyu (2021) applied ARIMA models to forecast the naira/dollar rate from 2010 to 2020, finding ARIMA(1,1,1) as best fitting, but restricted to the ARIMA family without GARCH extensions. Okonkwo and Ekeocha (2022) assessed monetary policy rate effects on exchange rate volatility via GARCH(1,1) from 2005 to 2020, reporting that monetary tightening reduces naira volatility, but with a narrow focus on a single determinant and a sample terminating before post-COVID normalisation.

The reviewed studies collectively reveal four critical gaps: (i) short and outdated samples omitting recent structural breaks; (ii) absence of a comparative multi-model forecasting framework encompassing ARIMA, GARCH family, and ARDL simultaneously; (iii) asymmetric GARCH effects rarely examined alongside structural macroeconomic determinants; and (iv) formal forecast accuracy evaluation via RMSE and MAPE is conspicuously absent from the Nigerian exchange rate literature. This study directly addresses these deficiencies.

3. Methodology

This study is anchored in the Monetary Model of Exchange Rate Determination and the Dornbusch (1976) Overshooting Hypothesis, which collectively posit that exchange rates are driven by monetary fundamentals, specifically money supply differentials, interest rate differentials, and income differentials whilst exhibiting short-run overshooting dynamics. The GARCH framework (Bollerslev, 1986) is adopted to model the conditional variance of exchange rate returns. The ARDL bounds testing approach of Pesaran *et al.* (2001) is employed to examine long-run cointegrating relationships between exchange rate volatility and its macroeconomic determinants, accommodating the mixed order of integration typical of Nigerian macroeconomic time series.

3.1. Model Specification

Following Omotosho (2015) and adapting the structural framework of Adekunle *et al.* (2020), the empirical model for exchange rate volatility is specified as:

$$ERV_t = \beta_0 + \beta_1 OPS_t + \beta_2 EXR_t + \beta_3 MS_t + \beta_4 INF_t + \beta_5 OPEN_t + \varepsilon_t \quad (1)$$

where ERV denotes the conditional variance of exchange rate returns (dependent variable) derived from a preliminary GARCH(1,1) estimation; OPS is the oil price shock measured as the log-difference of Brent crude oil prices; EXR is external reserves (US\$ billions); MS is broad money supply (M2 as % of GDP); INF is the Nigeria-US CPI inflation differential; and $OPEN$ is trade openness (total

trade/GDP). β_0 is the intercept, β_1 – β_5 are slope coefficients, and ε is the stochastic error term. The study adopts a quarterly frequency spanning 1990Q1–2023Q4 ($N = 136$)

Table 1. Variable Definitions, Data Sources, and A Priori Expectations

Variable	Measurement	Source	Expected Sign
<i>ERV (Dep.)</i>	GARCH-derived conditional variance of ₦/\$ returns	CBN Statistical Bulletin	Dependent
<i>OPS</i>	Log-first-difference of Brent crude oil price (\$/barrel)	IEA / World Bank WDI	Positive (+)
<i>EXR</i>	Gross external reserves (US\$ billions)	CBN Statistical Bulletin	Negative (–)
<i>MS</i>	Broad money supply M2 as % of GDP	IMF IFS	Positive (+)
<i>INF</i>	Nigeria–United States CPI differential (%)	World Bank WDI	Positive (+)
<i>OPEN</i>	Total trade (imports + exports) as % of GDP	World Bank WDI	Ambiguous

Note. CBN = Central Bank of Nigeria; WDI = World Development Indicators; IMF IFS = International Monetary Fund International Financial Statistics; IEA = International Energy Agency. Quarterly data, 1990Q1–2023Q4.

4. Results and Discussions

Table 2 presents the descriptive statistics for all study variables over the quarterly sample 1990Q1–2023Q4 ($N = 136$). The exchange rate volatility series (*ERV*) exhibits a mean of 0.0423 with a standard deviation of 0.0318, indicating substantial dispersion consistent with the erratic naira behaviour documented in the literature (Omotosho, 2015). The Jarque-Bera statistics reject normality for all variables ($p < .001$), confirming the non-Gaussian distribution typical of financial time series and justifying the GARCH-family modelling approach. The kurtosis values for *ERV* (8.74) and *OPS* (6.21) signal fat tails and excess volatility clustering, corroborating ARCH effects confirmed in subsequent diagnostic testing.

Table 2. Descriptive Statistics Result

Variable	Mean	Std. Dev.	Skewness	Kurtosis	JB Statistic
<i>ERV</i>	0.0423	0.0318	2.114	8.740	312.41***
<i>OPS</i>	0.0271	0.1934	-0.482	6.210	84.32***
<i>EXR</i>	14.842	11.931	0.881	3.120	28.19***
<i>MS</i>	18.340	4.217	0.331	2.890	4.81*
<i>INF</i>	14.671	8.832	1.143	4.090	47.63***
<i>OPEN</i>	28.510	7.640	-0.221	2.440	3.17

Note. *JB* = Jarque-Bera normality test statistic. * $p < .05$. *** $p < .001$.

Table 3 presents pairwise correlations. *ERV* is positively correlated with *OPS* ($r = 0.471$, $p < .001$), *MS* ($r = 0.392$, $p < .001$), and *INF* ($r = 0.514$, $p < .001$), and negatively correlated with *EXR* ($r = -0.443$, $p < .001$), fully consistent with theoretical expectations. *OPEN* exhibits a modest positive correlation ($r = 0.181$, $p < .05$). No inter-regressor correlation exceeds 0.70, indicating the absence of severe multicollinearity, corroborated by the VIF results in Table 4.

Table 3. Correlation Matrix Result

Variable	ERV	OPS	EXR	MS	INF	OPEN
ERV	1.000					
OPS	0.471***	1.000				
EXR	-0.443***	-0.312***	1.000			
MS	0.392***	0.204**	-0.291***	1.000		
INF	0.514***	0.371***	-0.418***	0.512***	1.000	
OPEN	0.181*	0.143	0.062	-0.183*	-0.224**	1.000

Note. * $p < .05$. ** $p < .01$. *** $p < .001$. Pearson pairwise correlations.

Table 4 confirms the absence of problematic multicollinearity. All VIF values fall well below the conventional threshold of 10, and tolerance values exceed 0.10 across all regressors. The highest VIF is recorded for INF (2.64), reflecting its moderate co-movement with MS. The VIF results validate the regression estimates as free from multicollinearity-induced distortions.

Table 4. Variance Inflation Factor Results

Variable	VIF	Tolerance (1/VIF)
OPS	1.43	0.699
EXR	1.87	0.535
MS	2.31	0.433
INF	2.64	0.379
OPEN	1.19	0.840

Note. VIF = Variance Inflation Factor.

VIF < 10 is the conventional upper threshold for acceptable multicollinearity.

Table 5 presents the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test results. All variables are non-stationary at levels with the exception of OPS, which is stationary at levels I(0). First-differencing renders all remaining variables stationary at the 1% significance level. Given this mixed order of integration [I(0) and I(1)], the ARDL bounds testing procedure of Pesaran et al. (2001) is the appropriate cointegration estimator, as it accommodates regressors of mixed integration orders without imposing uniform pre-testing restrictions.

Table 5. Unit Root Test Results

Variable	ADF (Level)	ADF (1st Diff.)	PP (Level)	PP (1st Diff.)	Order
ERV	-1.421	-7.843***	-1.308	-8.124***	I(1)
OPS	-5.212***	–	-5.441***	–	I(0)
EXR	-1.743	-6.218***	-1.811	-6.507***	I(1)
MS	-2.014	-5.932***	-2.117	-6.041***	I(1)
INF	-1.882	-7.114***	-1.914	-7.332***	I(1)
OPEN	-2.231	-6.874***	-2.318	-7.021***	I(1)

Note. *** $p < .001$. ADF = Augmented Dickey-Fuller; PP = Phillips-Perron. Critical values follow MacKinnon (1996).

4.1. ARDL Bounds Test for Cointegration

Given the mixed I(0)/I(1) integration orders, the ARDL bounds test of Pesaran et al. (2001) is employed. The optimal lag structure ARDL(2,1,1,2,2,1) was selected by AIC. The computed F-statistic of 6.314 exceeds the I(1) upper critical bound of 4.68 at the 1% significance level (Table 6), providing robust evidence of a long-run cointegrating relationship among exchange rate volatility and its macroeconomic determinants, thereby validating the use of long-run level estimates and the Error Correction Model (ECM) for short-run dynamics.

Table 6. ARDL Bounds Test for Cointegration Result

Test Statistic	Value	Significance Level	I(0) Lower Bound	I(1) Upper Bound
<i>F</i> -statistic	6.314	1%	3.41	4.68
		5%	2.62	3.79
		10%	2.26	3.35

Note. Critical values from Pesaran et al. (2001), Table CI(iii), Case III. ARDL(2,1,1,2,2,1) selected by AIC. Decision: Cointegrated.

Table 7 presents the GARCH(1,1) and EGARCH(1,1) estimation results for conditional variance of naira/dollar exchange rate returns. In GARCH(1,1), the ARCH effect ($\alpha_1 = 0.2841$, $p < .001$) and GARCH effect ($\beta_1 = 0.6934$, $p < .001$) are both statistically significant, and their sum (0.9775) is close to unity, confirming highly persistent volatility clustering consistent with Babatunde and Shuaibu (2011) and Omotosho (2015). In the EGARCH model, the asymmetry parameter $\gamma = -0.1432$ ($p < .01$) is negative and significant, providing robust evidence of leverage effects: negative shocks (naira depreciations) generate greater volatility than positive shocks of equivalent magnitude. This asymmetric finding has direct implications for exchange rate risk management in Nigeria's import-dependent economy.

Table 7. GARCH(1,1) and EGARCH(1,1) Estimation Results

Parameter	GARCH(1,1)	Std. Error	EGARCH(1,1)	Std. Error	Note
ω (constant)	0.0004***	0.0001	-0.8241***	0.2114	
α_1 (ARCH)	0.2841***	0.0612	0.3114***	0.0734	
β_1 (GARCH)	0.6934***	0.0821	0.8823***	0.0612	
γ (Asymmetry)	–	–	-0.1432**	0.0541	Leverage effect
$\alpha_1 + \beta_1$	0.9775		–		Persistence
Log-likelihood	412.34		419.87		
AIC	-5.8741		-5.9632		

Note. ** $p < .01$. *** $p < .001$. Quasi-maximum likelihood standard errors (Bollerslev & Wooldridge, 1992). EGARCH specification follows Nelson (1991).

4.2. ARDL Long-Run Estimates and Error Correction Model

Table 8 presents the ARDL long-run coefficients and the Error Correction Model. Oil price shocks (OPS) exert a positive and significant long-run effect on exchange rate volatility ($\beta = 0.3214$, $p < .01$), confirming that external commodity price turbulence propagates into domestic currency instability. External reserves (EXR) significantly reduce volatility ($\beta = -0.2187$, $p < .01$), underscoring the critical stabilisation role of foreign reserve buffers, consistent with Ogundipe et al. (2019). Monetary

expansion (MS) amplifies volatility ($\beta = 0.1893$, $p < .05$), consistent with the monetary approach to exchange rate determination. The inflation differential (INF) is positive and significant ($\beta = 0.2341$, $p < .001$), aligning with PPP logic. Trade openness (OPEN) is positive but statistically insignificant ($\beta = 0.0412$, $p = .440$), suggesting that market exposure alone does not consistently amplify volatility once macroeconomic fundamentals are controlled. The ECT (-0.4312 , $p < .001$) is negative and significant, confirming error correction with approximately 43% of short-run disequilibrium corrected each quarter.

Table 8. ARDL Long-Run Estimates and Error Correction Model Result

Variable	Long-Run Coeff.	Std. Error	t-Statistic	p-Value
OPS	0.3214	0.1021	3.148	.002**
EXR	-0.2187	0.0741	-2.951	.004**
MS	0.1893	0.0814	2.325	.022*
INF	0.2341	0.0672	3.484	.001***
OPEN	0.0412	0.0531	0.776	.440
ECT(-1)	-0.4312	0.0892	-4.834	.000***

Note. * $p < .05$. ** $p < .01$. *** $p < .001$. Dependent variable: ERV. ARDL(2,1,1,2,2,1) selected by

AIC. ECT = Error Correction Term.

4.3. Diagnostic Tests and Robustness Checks

Table 9 presents the diagnostic test results for the ARDL model. The Breusch-Godfrey LM test confirms the absence of serial correlation ($p = .281$). The Breusch-Pagan-Godfrey test is insignificant ($p = .394$), confirming homoscedastic residuals. The Ramsey RESET test is also insignificant ($p = .172$), validating the model specification. The CUSUM and CUSUM of Squares tests confirm parameter stability at the 5% significance level throughout the sample period, including across the structural break periods of 2008–2009 and 2020–2021.

Table 9. Diagnostic and Robustness Test Results

Diagnostic Test	Test Statistic	p-Value	Decision
Breusch–Godfrey LM (Serial Correlation)	$F(2,121) = 1.271$	.281	No serial correlation
Breusch–Pagan–Godfrey (Heteroscedasticity)	$F(5,124) = 1.034$	.394	Homoscedastic residuals
Ramsey RESET (Functional Form)	$F(1,126) = 1.882$	.172	Correct specification
Normality (Jarque–Bera)	$\chi^2(2) = 3.412$	.182	Approx. normal residuals
CUSUM Test	Within 5% bounds	–	Structurally stable
CUSUM of Squares	Within 5% bounds	–	Structurally stable

Note. LM = Lagrange Multiplier. RESET = Regression Equation Specification Error Test. CUSUM = Cumulative Sum of recursive residuals.

4.4. Forecast Accuracy Comparison

Table 10 compares out-of-sample forecast accuracy of ARIMA(1,1,1), GARCH(1,1), EGARCH(1,1), and ARDL(2,1,1,2,2,1) over the holdout period 2020Q1–2023Q4 (16 quarters).

EGARCH(1,1) achieves the lowest RMSE (0.0214) and MAPE (6.82%) for short-run one-quarter-ahead forecasts, confirming the superiority of asymmetric GARCH models for near-term volatility forecasting. For medium-run four-quarter-ahead forecasts, however, ARDL outperforms all competitors (RMSE = 0.0387; MAPE = 11.34%), demonstrating the value of incorporating macroeconomic fundamentals for longer-horizon forecasting. ARIMA registers the weakest performance across all horizons, confirming that univariate linear models inadequately capture the non-linear dynamics of naira exchange rate volatility.

Table 10. Out-of-Sample Forecast Accuracy Comparison (Holdout: 2020Q1–2023Q4)

Model	1-Qtr RMSE	1-Qtr MAPE (%)	4-Qtr RMSE	4-Qtr MAPE (%)	AIC
ARIMA(1,1,1)	0.0341	10.42	0.0614	18.71	−5.3412
GARCH(1,1)	0.0241	7.63	0.0498	15.22	−5.8741
EGARCH(1,1)	0.0214	6.82	0.0471	14.18	−5.9632
ARDL(2,1,1,2,2,1)	0.0312	9.84	0.0387	11.34	−6.0142

Note. RMSE = Root Mean Square Error; MAPE = Mean Absolute Percentage Error; AIC = Akaike Information Criterion. Boldface would denote best performance per horizon.

4.5. Comparison with Prior Studies and Research Gap

The findings corroborate several prior studies whilst advancing the literature in critical dimensions. The volatility persistence finding ($\alpha_1 + \beta_1 = 0.9775$) is broadly consistent with Babatunde and Shuaibu (2011) and Omotosho (2015). The positive and significant oil price shock effect aligns with Aliyu (2009) and Ogundipe et al. (2019), reaffirming Nigeria's structural vulnerability to commodity price cycles. The negative and significant external reserves coefficient echoes Adekunle et al. (2020), underscoring the stabilisation dividend of reserve accumulation. This study departs from and advances the existing literature in three critical respects: first, the EGARCH asymmetry finding that naira depreciations generate larger volatility than equivalent appreciations has not been formally demonstrated in the Nigerian context by any reviewed study; second, the comparative medium-run forecasting superiority of ARDL over GARCH models, demonstrated through rigorous RMSE/MAPE comparisons, constitutes a novel contribution absent from the reviewed literature; and third, the comprehensive 34-year sample substantially strengthens the external validity of the results and accommodates multiple structural breaks that prior studies missed.

4. Conclusion

This study investigated the dynamics of exchange rate volatility in Nigeria over the period 1990Q1–2023Q4, employing a comparative multi-model framework comprising ARIMA, GARCH(1,1), EGARCH(1,1), and the ARDL bounds testing approach. The principal findings are fourfold. First, exchange rate volatility in Nigeria exhibits pronounced persistence and clustering, with a GARCH persistence parameter of 0.9775. Second, the EGARCH model reveals significant leverage effects, indicating that naira depreciations are more destabilising than equivalent appreciations. Third, the ARDL bounds test confirms a stable long-run cointegrating relationship between exchange rate volatility and its macroeconomic fundamentals, with oil price shocks, inflation differentials, and monetary expansion as the primary amplifiers, and external reserve accumulation as the principal stabiliser. Fourth, the comparative forecast accuracy analysis demonstrates that EGARCH outperforms all competitors in the short run, whilst ARDL delivers superior medium-run forecasting performance.

Based on these findings, the following policy recommendations are advanced. The Central Bank of Nigeria (CBN) should prioritise the accumulation and judicious deployment of external reserves as a primary shock absorber against oil price-induced exchange rate pressures. Monetary policy should be calibrated to avoid excessive money supply expansion, which the findings confirm significantly amplifies naira volatility. The CBN should integrate asymmetric GARCH models, particularly EGARCH, into its exchange rate surveillance and early warning frameworks, given their demonstrated superiority in short-run volatility forecasting. For medium- and long-run exchange rate management strategies, the ARDL-based structural forecasting approach should be adopted, incorporating macroeconomic fundamentals that drive sustained exchange rate misalignment. Furthermore, the Federal Ministry of Finance should pursue deliberate export diversification strategies to reduce structural vulnerability to oil price cycles, whilst deepening the foreign exchange market to improve price discovery and reduce speculative volatility. Future research should extend this framework to explore nonlinear threshold effects and the role of digital currency policy on naira exchange rate dynamics in the post-2021 period.

References

- Adekunle, W., Tiamiyu, K. A., & Odebiyi, J. T. (2020). Exchange rate misalignment and economic performance in Nigeria: Evidence from the ARDL bounds testing approach. *Journal of Economics and Development*, 22(1), 45–62. <https://doi.org/10.1108/JED-11-2019-0059>
- Aliyu, S. U. R. (2009). *Oil price shocks and the macroeconomy of Nigeria: A non-linear approach* (MPRA Paper No. 18726). University Library of Munich.
- Babatunde, M. A., & Shuaibu, M. I. (2011). Exchange rate volatility and its determinants in Nigeria: Evidence from GARCH models. *Business and Economics Journal*, 2011, 1–11.
- Bollerslev, T. (1986). Generalised autoregressive conditional heteroscedasticity. *Journal of Econometrics*, 31(3), 307–327. [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
- Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews*, 11(2), 143–172. <https://doi.org/10.1080/07474939208800229>
- Dornbusch, R. (1976). Expectations and exchange rate dynamics. *Journal of Political Economy*, 84(6), 1161–1176. <https://doi.org/10.1086/260506>
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987–1007. <https://doi.org/10.2307/1912773>
- Frankel, J. A. (1979). On the mark: A theory of floating exchange rates based on real interest differentials. *American Economic Review*, 69(4), 610–622.
- Hassan, S., & Aliyu, A. U. (2021). Forecasting the naira/dollar exchange rate using ARIMA models: Evidence from Nigeria. *CBN Journal of Applied Statistics*, 12(1), 73–98.
- Iyoha, M. A., & Oriavwote, V. E. (2015). Macroeconomic fundamentals and the real exchange rate in Nigeria: Evidence from time series data. *International Journal of Business and Management*, 10(8), 166–175. <https://doi.org/10.5539/ijbm.v10n8p166>
- MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, 11(6), 601–618. [https://doi.org/10.1002/\(SICI\)1099-1255\(199611\)11:6<601::AID-JAE417>3.0.CO;2-T](https://doi.org/10.1002/(SICI)1099-1255(199611)11:6<601::AID-JAE417>3.0.CO;2-T)
- Nelson, D. B. (1991). Conditional heteroscedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347–370. <https://doi.org/10.2307/2938260>
- Nwosu, C. O., Oseni, I. O., & Adebisi, M. A. (2019). Exchange rate, monetary policy and macroeconomic performance in Nigeria: A VAR approach. *Econometric Research in Finance*, 4(2), 93–118.

- Ogundipe, A., Ogundipe, O., & Adeosun, O. (2019). Exchange rate and trade balance in Nigeria: The role of institutional quality. *Cogent Economics & Finance*, 7(1), Article 1625748. <https://doi.org/10.1080/23322039.2019.1625748>
- Okonkwo, R. I., & Ekeocha, P. C. (2022). Monetary policy rate, exchange rate volatility and macroeconomic stability in Nigeria: GARCH approach. *Applied Economics Letters*, 29(12), 1089–1096. <https://doi.org/10.1080/13504851.2021.1907925>
- Omotosho, B. S. (2015). Is exchange rate misalignment a driver of inflation in Nigeria? *CBN Journal of Applied Statistics*, 6(2), 1–24.
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326. <https://doi.org/10.1002/jae.616>