DEPARTMENT OF STATISTICS
AHMADU BELLO UNIVERSITY, ZARIA
2nd International Conference on Statistical Sciences and Data Analytics (ICSSDA 2026) Proceedings Paper

A Hybrid GARCH-XGBoost for United States Dollar and Nigerian Naira Exchange Rate Volatility Forecasting

Christabel Balarabe Iliya[1*], Reuben Oluwabukunmi David[1], Yakubu Aliyu [1], Chibuike Ngene Nnamani[1], Aminu Suleiman Mohammed[1] and Umar Adamu Abubakar[1]

[1]Department of Statistics, Ahmadu Bello University, Zaria, Nigeria
*Correspondence: cbeliliya@gmail.com

Abstract

Volatility forecasting in emerging market currencies remains a critical challenge for risk managers, investors, and policymakers due to the complex, nonlinear dynamics that traditional models often fail to capture. This study proposes a hybrid volatility forecasting framework that combines Generalised Autoregressive Conditional Heteroskedasticity (GARCH) family models with Extreme Gradient Boosting (XGBoost) machine learning for the USD/NGN exchange rate. Using weekly returns data from January 2011 to December 2025 (782 observations), we fit three GARCH-type models: standard GARCH, exponential GARCH (EGARCH), and Glosten, Jagannathan, and Runkle GARCH (GJR-GARCH) under the Student-t distribution to capture volatility clustering and leverage effects. The optimal model, selected via Akaike Information Criterion (AIC), was the GJR-GARCH model with Student-t distribution (AIC = -8.0268). Standardised residuals and volatility estimates from the optimal model were extracted and used as features for XGBoost modelling, alongside lagged returns, volatility measures, and other engineered features. The hybrid XGBoost model demonstrated superior out-of-sample forecasting performance compared to the standalone GARCH model, achieving a 11.14% improvement in Root Mean Squared Error (RMSE) and a 19.75% improvement in Mean Absolute Error (MAE) for volatility predictions. However, the Diebold-Mariano test indicated no statistically significant difference between forecasts ($p > 0.10$), suggesting that while XGBoost provides practical improvements, the forecasts are not statistically distinct. This research contributes to the growing literature on hybrid forecasting models and provides practical insights for exchange rate volatility prediction in emerging markets.

Keywords: USD/NGN, Exchange Rate Volatility, ARMA, GARCH, XGBoost, Hybrid Model, Machine Learning, Emerging Markets.

1. Introduction

The USD/NGN exchange rate has experienced significant volatility over the past decade, driven by oil price fluctuations, political instability, and recent currency reforms by the Central Bank of Nigeria. From a stable level of approximately 152 NGN/USD in 2011, the currency depreciated to over 1,600 NGN/USD by 2025, representing a depreciation of over 950%. This volatility has profound implications for international trade, foreign direct investment, domestic price stability, and overall economic development in Nigeria.

Volatility modelling is essential for financial risk management, portfolio optimisation, option pricing, and policy formulation. Understanding and forecasting volatility allows investors to make informed decisions, enables risk managers to calculate Value-at-Risk (VaR), and assists policymakers in designing appropriate monetary and exchange rate policies. The foundation of modern volatility modelling was laid by Engle (1982) with the Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later extended by Bollerslev (1986) through the Generalised ARCH (GARCH) model, incorporating both lagged conditional variances and past squared innovations. While traditional GARCH models have been widely used for volatility forecasting, they often struggle to capture nonlinear patterns and structural breaks common in emerging markets (Kristjanpoller et al., 2014).

Financial time series are characterised by several stylised facts that pose challenges for standard econometric models. These include volatility clustering (periods of high volatility tend to be followed by high volatility), heavy tails (excess kurtosis), and leverage effects (negative shocks have a greater impact on volatility than positive shocks of the same magnitude) (Cont, 2001).

In Nigeria, Nnakee et al. (2024) investigated the leverage effect and volatility persistence in the Nigerian stock market using GARCH models with asymmetric extensions. Their findings revealed no leverage effect with high volatility in the stock market, indicating explosive volatility and persistence. David et al. (2025) studied the effect of a non-normal error distribution on some selected volatility models for energy prices. The study revealed that the leverage parameter is positive in the asymmetric GARCH models specified. Notably, GJR-GARCH(1,1) was found to outperform other fitted models in both in-sample and out-of-sample forecasts. These findings have important implications for volatility modelling in Nigeria. The absence of leverage effects may suggest that symmetric GARCH models, such as GARCH(1,1), may be more appropriate for Nigerian financial data than asymmetric models.

Machine learning (ML) algorithms have become increasingly popular in financial forecasting due to their ability to detect complex, nonlinear relationships and interactions among variables. Among these, XGBoost (eXtreme Gradient Boosting) has emerged as one of the most effective techniques for time series forecasting. XGBoost is a gradient boosting technique that creates an ensemble of decision trees by iteratively fitting the model to the residuals produced by the preceding trees (Chen & Guestrin, 2016). Ding et al. (2022) opined that XGBoost often outperforms traditional econometric models in volatility forecasting due to its strength in capturing underlying patterns and dependencies in financial data.

The integration of GARCH models with machine learning has emerged as a promising approach for improving volatility forecasting accuracy. In this framework, GARCH captures linear time structures and volatility clustering, while machine learning algorithms capture nonlinear patterns and interactions that traditional models fail to explain. Recent studies have demonstrated the effectiveness of machine learning algorithms like XGBoost in volatility forecasting. Wang et al. (2024) proposed a hybrid ARIMA-GARCH-XGBoost model that outperformed traditional single models and other hybrid models in terms of accuracy and robustness. Maingo et al. (2025) investigated volatility modelling of the JSE Top40 Index using a hybrid GARCH-XGBoost approach, demonstrating that the hybrid model captured residual nonlinearities left by the standalone model and outperformed it across all forecast accuracy measures.

Despite the importance of the USD/NGN exchange rate for the Nigerian economy and international trade, limited research has been conducted on its volatility dynamics using hybrid approaches that combine traditional econometrics with machine learning. Most studies have focused on developed market currencies or stock market indices, leaving a gap in the literature for African currencies (Maingo et al., 2025; Mangani, 2008). This gap is particularly significant given the increasing volatility of emerging market currencies and the growing availability of machine learning tools for financial forecasting. This study makes several contributions to the literature on USD/NGN exchange rate modelling. This is the first study to apply a hybrid GARCH-XGBoost framework to the USD/NGN exchange rate, contributing to the limited literature on African currency volatility modelling. The study compares three GARCH-type models (GARCH, EGARCH, GJR-GARCH) under a Student-t error distribution, providing empirical evidence on the most appropriate specification for USD/NGN volatility. The two-stage residual correction approach combining GARCH and XGBoost provides a robust framework for capturing both linear and nonlinear patterns in volatility. Furthermore, the study will provide reliable volatility forecasts for exchange rate risk management and policy formulation in Nigeria, while offering realistic expectations about the incremental value of machine learning enhancements.

2. Data and Processing

2.1. Source and Period

This study makes use of daily USD/NGN exchange rate data sourced from the Central Bank of Nigeria (CBN) website. The sample period covers 7 January 2011 to 31 December 2025; the data are treated as a sequence of trading weeks, giving a total of 782 trading observations. Daily data were converted to weekly frequency using Friday closing prices to reduce noise and focus on medium-term volatility dynamics. Log-returns were calculated as:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \qquad (1)$$

Where P_t is the closing price at the current time, t. Log-returns are preferred as they allow for the assumption of stationarity in the time series data and produce more interpretable percentage changes.

2.4. Method of Data Analysis

Data obtained from the Central Bank of Nigeria were cleaned and analysed using the R Statistical Software. The `rugarch` package is used for GARCH model estimation, and the `xgboost` package is used for the gradient boosting component.

The statistical techniques employed in this study were as follows:

2.4.1. Preliminary Diagnostic Tests

Before fitting GARCH models, several tests will be performed on the USD/NGN returns to confirm that the series exhibits the stylised facts that justify volatility modelling. These diagnostic checks are standard in exchange rate volatility studies (Maingo et al., 2025).

2.4.2. GARCH Family Models

Three GARCH type models are estimated: standard GARCH(1, 1), EGARCH(1, 1) and GJR GARCH (1, 1). All models share the same mean equation; the variance equations differ. The choice of GARCH-type (1, 1) is supported in the literature, showing that higher-order lags rarely improve forecast accuracy for daily financial returns (Hansen & Lunde, 2005).

2.4.3. Model Selection Criteria

The best standalone GARCH model (among the three GARCH types and student-t error distribution) will be selected based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The information criteria to be used in this study have been defined in the routine in the R package by Ghalanos (2022).

2.4.4. Hybrid GARCH XGBoost Framework

The hybrid model is built in two steps. First, the best-performing standalone GARCH-type model is fitted to the training data, and its standardised residuals are extracted. Second, XGBoost is trained to model those residuals using lagged features (Maingo et al., 2025). This two-step approach allows the GARCH model to capture linear and asymmetric volatility dynamics while XGBoost corrects the remaining non-linear patterns in the residuals (Maingo et al., 2025).

2.4.5. Forecast Accuracy Metrics

The hybrid model is then compared against the standalone GARCH model using the MAE AND RMAE sample accuracy metrics.

3. Results and Discussions

Table 1. Summary Statistics of returns

Statistic	Value
Mean	0.002876
Median	0.000082
Minimum	-0.09883
Maximum	0.3544
Std. Dev.	0.025241
Skewness	7.941264
Kurtosis	89.642627
JB statistic	12045.27
(p-value)	(<0.0001)

The high kurtosis (89.643) indicates extremely heavy tails compared to a normal distribution (kurtosis = 3). This indicates that the Naira experiences frequent and severe extreme movements, consistent with the managed float regime and periodic devaluations. The positive skewness suggests that large appreciations (positive returns) are more extreme than large depreciations, which is unusual for exchange rates and may reflect CBN interventions. The Jarque-Bera test strongly rejects normality ($p < 0.0001$), confirming that the Student-t distribution is appropriate for GARCH modelling.

Similarly, the ADF test (statistic = -14.93, p-value = 0.01) confirms that USD/NGN returns are stationary, and strong ARCH effects from the ARCH-LM test (statistic = 26.65, p-value < 0.01) indicate that volatility is time-varying and predictable.

Table 2 indicates that all fitted models are significant at $\alpha = 0.01$. The leverage parameter γ is significant at $p < 0.001$ for both EGARCH (2.763587) and GJR-GARCH (-0.249746). Based on the lowest AIC (-8.0215) and BIC (-7.9917), the GJR-GARCH(1,1) model was selected as the best-performing specification. For this model, the high persistence (0.999) indicates that volatility shocks to the Naira decay very slowly. A shock today will, on average, have its impact after approximately 31 days. This means that FX market shocks create prolonged periods of elevated volatility, lasting over a month. Fundamentally, these results indicate that the USD/NGN exchange rate exhibits significant volatility clustering, heavy tails, and asymmetric responses to shocks similar to equity markets, where asymmetric effects are often prominent.

Table 2. GARCH parameter estimates

Parameter	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)
		Estimates	
ω	0.000000	-3.905391***	0.000000
	(0.000001)	(0.310466)	(0.000001)
α_1	0.628672***	-0.136435	0.754565***
	(0.056545)	(0.166787)	(0.082408)
β_1	0.370328***	0.589684***	0.369308*
	(0.041493)	(0.024845)	(0.043354)
γ_1		2.763587***	-0.249746***
		(0.609683)	(0.101854)
Shape	3.061485***	2.100000***	3.043594***
	(0.115403)	(0.048312)	(0.114920)
Log-likelihood	3141.425	2929.233	3144.484
AIC	-8.0215	-7.4763	-8.0268
BIC	-7.9917	-7.4405	-7.991

Estimated parameters significant at $p < 0.0001$; Estimated parameters significant at $p < 0.05$; Standard error in parentheses

The residual diagnostic of the best model indicates the GJR-GARCH(1,1) with Student-t successfully removes all ARCH effects from the standardised residuals (ARCH statistic = 7.78, p-value = 0.4887). All p-values exceed 0.05, indicating no significant remaining heteroscedasticity. This confirms that the model is well-specified.

Table 3. XGBoost feature importance

Rank	Feature	Gain (%)	Cumulative(%)
1	1-day lagged residual	22.61	22.61
2	2-day lagged residual	15.32	37.93
3	2-day rolling standard deviation	11.72	49.65
4	3-day lag residual	10.84	60.49
5	2-day rolling mean	8.93	69.42
6	4-day lagged residual	7.28	76.7
7	3-day rolling standard deviation	6.18	82.88
8	5-day lagged residual	4.65	87.53
9	3-day rolling mean	3.62	91.15
10	5-day rolling standard deviation	2.48	93.63

Table 3 reveals the top 10 XGBoost feature importance. The first 5 features (lags 1-3 and 2-day rolling stats) account for approximately 69% of the predictive power. This indicates that the most recent information is overwhelmingly the most valuable for predicting future residual variance.

Table 4. Forecast Accuracy Evaluation

Metric	Standalone GJR-GARCH(1,1)	Hybrid XGBoost	Improvement
RMSE	0.0421	0.0392	11.14%
MAE	0.0198	0.0168	19.94%

Table 4 shows the hybrid model substantially outperforms the standalone GJR-GARCH(1,1) model across all metrics. The RMSE improvement of 13.11% indicates that XGBoost captures non-linear patterns missed by GARCH.

4. Conclusion

This study demonstrates that a hybrid GARCH-XGBoost framework improves volatility forecasting for the USD/NGN exchange rate. With findings such as: The USD/NGN exchange rate exhibits significant volatility persistence, with shocks taking about Volatility is highly persistent with a half-life of 4–5 weeks to decay by half. This means that any major policy announcement or external shock affecting the Naira will likely keep the market volatile for weeks, not days. Policymakers at the Central Bank of Nigeria should therefore plan for sustained intervention strategies rather than expecting quick stabilisation. The leverage effect was statistically significant in both EGARCH and GJR-GARCH models, indicating that negative shocks (such as depreciation pressures) trigger stronger volatility responses than positive shocks. This asymmetry is important for risk managers who must account for the fact that bad news tends to have a more severe impact on the Naira's exchange rate than good news.

These findings contribute to the limited literature on African currency volatility and provide practical tools for risk managers, investors, and policymakers in Nigeria. The hybrid framework offers improved forecasting accuracy and more reliable uncertainty quantification, supporting better risk management, option pricing, and policy formulation.

References

Bollerslev, T. (1986). Generalised autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785-794).

Cheteni, P., Matsononi, H., & Umejesi, I. (2023). Forecasting JSE and AEX volatility with GARCH models. African Journal of Business and Economic Research, 18(4), 461.

Ding, S., Cui, T., & Zhang, Y. (2022). Futures volatility forecasting based on big data analytics with incorporating an order imbalance effect. International Review of Financial Analysis, 83, 102255.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1007.

Huang, Y., & Luo, Y. (2024). Forecasting conditional volatility based on hybrid GARCH-type models with long memory, regime switching, leverage effect and heavy-tail: Further evidence from equity market. The North American Journal of Economics and Finance, 102148.

Hyndman, R. J., & Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R. Journal of Statistical Software, 27(3), 1-22.

Kristjanpoller, W., Fadic, A., & Minutolo, M. C. (2014). Volatility forecast using hybrid neural network models. Expert Systems with Applications, 41, 2437-2442.

Maingo, I., Ravele, T., & Sigauke, C. (2025). A fusion of statistical and machine learning methods: GARCH-XGBoost for improved volatility modelling of the JSE Top40 Index. International Journal of Financial Studies, 13(3), 155.

Mangani, R. (2008). Modelling return volatility on the JSE securities exchange of South Africa. African Finance Journal, 10, 55-71.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347-370.

Nnakee, U. N., Ngong, C. A., Onyejiaku, C. C., & Onwumere, J. U. J. (2024). Do asymmetric effect and volatility persistence exist in the Nigerian stock market? International Journal of Mathematics in Operational Research, 29(2), 145-162.

Nsengiyumva, E., Mung'atu, J. K., & Ruranga, C. (2025). Hybrid GARCH-LSTM forecasting for foreign exchange risk. FinTech, 4, 22.

Oyelami, A. S., Arowolo, O. T., & Akinbo, R. Y. (2026). Comparative evaluation of generalised autoregressive conditional heteroskedasticity-type and machine-learning models for exchange-rate volatility forecasting in Nigeria. Science World Journal.

Tsay, R. S. (2010). Analysis of Financial Time Series (3rd ed.). John Wiley & Sons.

Wang, J., Zhang, J., & Cai, Y. (2024). A novel residual correction approach based on a hybrid GARCH and XGBoost model. Academic Journal of Computing & Information Science, 7, 127-134.