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Modeling and Forecasting Nigeria Exchange Rate Volatility Across Major Global Economic Blocs

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ABSTRACT

This study models the volatility dynamics of weekly exchange rate returns for across major global economic blocs against the Nigerian naira using models from the generalized autoregressive conditional heteroscedasticity (GARCH) family. The currencies analyzed are the British pound sterling, CFA franc, euro, United States dollar, Japanese yen, West African Unit of Account, Saudi Arabian riyal, and Swiss franc. Both symmetric GARCH(1,1) and asymmetric EGARCH(1,1) specifications were employed to capture volatility clustering, persistence, and leverage effects. The estimated GARCH(1,1) models for the CFA franc and Japanese yen yielded variance equations of the form $\sigma^2_t = 0.1997 + 0.8009\varepsilon^2_{t-1} + 0.6564\sigma^2_{t-1}$, for the CFA franc ($\alpha + \beta = 1.4573$), indicating explosive volatility, and $\sigma^2_t = 0.00004 + 0.2594\varepsilon^2_{t-1} + 0.6079\sigma^2_{t-1}$ for the Japanese yen ($\alpha + \beta = 0.8673$), indicating high but mean-reverting persistence. For the remaining currencies, the preferred EGARCH(1,1) models produced statistically significant coefficients, with persistence parameters close to unity, such as 0.8916 (POUNDS), 0.9334 (EURO), 0.9277 (DOLLAR), 0.9838 (WAUA), 0.7464 (RIYAL), and 0.9231 (SWFRANC). The estimated leverage parameters were positive across all series, suggesting that positive shocks generate lower subsequent volatility than negative shocks of equal magnitude. The Akaike Information Criterion indicates that EGARCH(1,1) is more suitable for modeling weekly exchange rate volatility for the pound sterling, euro, U.S. dollar, WAUA, riyal, and Swiss franc, while GARCH(1,1) is preferred for the CFA franc and Japanese yen. Out-of-sample forecasts show that the conditional variances converge to their respective long-run levels for most currencies, except the yen. The results reveal substantial volatility persistence in Nigeria's foreign exchange market and underscore the usefulness of asymmetric GARCH models for exchange rate risk assessment and forecasting.

INTRODUCTION

Nigeria operates a managed floating exchange rate regime following the unification of the official and parallel markets in June 2023. The naira has since exhibited extreme volatility, depreciating over 50% against the US dollar between mid-2023 and late-2024, with inflation peaking at 34.2% in mid-2024 before moderating to around 28.9% by year-end (African Development Bank, 2024). As an oil-dependent economy, Nigeria remains highly sensitive to exchange rate movements across major global economic blocs; notably the United States (USD), Eurozone (EUR), United Kingdom (GBP), and increasingly China (CNY), due to trade invoicing patterns, debt servicing obligations, and remittance inflows. High exchange rate volatility distorts trade balances, fuels imported inflation, deters foreign direct investment, and complicates monetary policy transmission (Oyadeyi, 2024).

Empirical studies consistently show that periods of floating or managed float regimes in Nigeria are associated with erratic GDP growth, with sharp contractions during severe depreciation episodes (e.g., -1.6% growth in 2016 following the 2014–2015 oil price collapse) contrasted against recoveries when the naira stabilizes (Chiadikobi *et al.*, 2025). Early modeling efforts relied on ARIMA and simple GARCH frameworks, but recent literature has shifted toward more sophisticated specifications that account for asymmetry and leverage effects drivers. Standard GARCH(1,1) models typically reveal strong volatility persistence ($\beta > 0.90$) in naira returns, while extensions incorporating oil prices, global financial stress, and policy uncertainty significantly improve forecasting accuracy (Penzin & Salisu, 2025). Notably, U.S. financial stress and oil price shocks exert pronounced spillover effects on naira volatility against USD, EUR, and GBP, with predictive gains of 15–20% when these variables are included. Emerging evidence also highlights the role of climate policy uncertainty, particularly from China; as a new driver of naira volatility, underscoring the importance of bloc-specific and modeling approaches (Peng *et al.*, 2023). Oyadeyi (2024) further demonstrates that inflation, interest rate differentials, and trade openness are the primary macroeconomic determinants of long-run exchange rate volatility, with adverse depreciation episodes exerting significant negative effects on economic growth through reduced investment and export competitiveness. Given Nigeria's deepening integration via the African Continental Free Trade Area (AfCFTA) and bilateral partnerships with major blocs, accurate modeling and forecasting of naira volatility across USD, EUR, GBP, and CNY pairs have become critical for monetary authorities, investors, and policymakers aiming to enhance reserve management, stabilize inflation expectations, and support the projected GDP growth of 3.2–3.4% in 2024–2025 (African Development Bank, 2024).

The exchange rate between naira and other currencies

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of the world is now very volatile. It fluctuates on weekly, daily and even on hourly basis and there is no limit to its variability. In his own view, (Obadan, 2006) argued that some of the factors that led to the depreciation of the Nigerian exchange rate include weak production base, import-dependent production structure, fragile export base and weak non-oil export earnings, expansionary monetary and fiscal policies, inadequate foreign capital inflow, excess demand for foreign exchange relative to supply, fluctuations in crude oil earnings, unguided trade liberalization policy, speculative activities and sharp practices (round-tripping) of authorized dealers, over - reliance on imperfect foreign exchange market, heavy debt burden, weak balance of payments position, and capital flight. This problem of exchange rate variability have become too disturbing, thus the need to model this fluctuation. According to (David *et al.*, 2016; Asemota, *et al.*, 2025), a time series can be investigated in order to create a suitable model that might be required for planning purposes. For instance, knowing how much one currency will be worth in the future might help a country avoid inflation, calculate its balance of payments, and create workable economic policies, among other advantages. The volatility of financial time series appears to change over time. Oyenkunle & Agona, 2019; Adams. *et al.* 2024) model exchange rate of Nigeria against four major currencies using ARIMA model. The result of the analysis revealed that the four major currencies (Dollar, Pounds, Euro, and Swiss Franc) time series data were not stationary in their original form and followed ARIMA (1,2,1), ARIMA (2,2,1), ARIMA (2,2,1), and ARIMA (2,2,2), respectively.

The need to investigate the characteristics of exchange rate volatility in Nigeria, as well as the stylised facts of exchange rate such as leverage effect and volatility clustering and persistence forms the background and objective of this study. This study aim to model and forecast Nigeria exchange rate volatility across major global economic blocs. It also seeks to if the weekly returns are normally distributed; fit appropriate model to predict the volatility of Nigerian exchange rate; investigate volatility clustering, persistence and leverage effect behaviour of the Nigerian currency with respect to some foreign currencies; and determine the forecasting performance of the fitted models.

LITERATURE REVIEW

This section presents a comprehensive review of related literature on financial time series, with particular emphasis on models developed to investigate volatility clustering and persistence in financial data. It further examines established measures of exchange rate volatility, discusses various exchange rate regimes, and highlights the key stylised facts that characterise exchange rate volatility in empirical research.

Shahla *et al.* (2012) modeled monthly average foreign exchange rates of Pakistan using ARIMA and GARCH models. The findings revealed that ARMA (1,2) and GARCH (1,2) are the best models in terms of fitting and forecasting power of the exchange rate return. Bala et al, (2013), utilized GARCH volatility models to examines monthly exchange–rate return for three major currencies in the Nigerian: FX markets: The Naira/USD, Euro and BPS. Their findings reveal that TGARCH is the best fitting model for Euro, while ARCH and PARCH (1,1) are the best fitting models for BPS return and Naira/USD returns and IGARCH was suitable for the USD return model with volatility breaks. Umar *et al.* (2019) applied ARIMA and GARCH models in modelling Naira/Pounds exchange rate volatility. Results discovered that ARIMA (2, 1, 1) and GARCH (1,1) were optimal with the highest log-likelihood and lowest AIC and BIC. Similarly, (Odukoya & Adio, 2022) modeled Nigeria Naira and US Dollars using Time Series analysis. Findings shows that, ARIMA (1, 1, 0) as an appropriate model for forecasting Nigerian Naira to Us Dollar exchange rate. Etuk (2012) applied a seasonal ARIMA model for daily Nigerian Naira – US Dollar exchange rates and found SARIMA (2, 1, 0)×(0,1,1) as the optimal model that best fitted the Nigerian Naira to the US Dollar series. Oyengu, Oyenkunle & Agona (2019) model exchange rate of Nigeria against four major currencies using ARIMA model. The result of the analysis revealed that the four major currencies (Dollar, Pounds, Euro and Swiss Franz) times series data were not stationary at their original form and followed ARIMA (1,2,1); ARIMA (2,2,1); ARIMA (2,2,1) and ARIMA (2,2,2) respectively. Gabriel (2019) models Naira to one Rupee exchange rate (NREXR) using ARIMA framework for dataset spanning from 2008 to 2020. The study found that ARIMA (1, 1, 2) model was the best performing model. Nwankwo (2014) utilized ARIMA model for exchange rate (Naira to Dollar) from 1982 – 2011 and concluded that AR(1) is the most preferred model. Adetunji, Adejumo & Omowaye (2016) examined ARIMA (0, 0, 0 to 2, 2, 2) using Square Root Transformation (SRT), Natural Log Transformation (NLT) and original series Without Transformation (WT) of average exchange rate of Nigeria Naira to US Dollar from 1960 to 2015 and found that ARIMA (1, 0, 0) when SRT is utilized provide optimal output model for forecasting average yearly exchange rate of Nigeria Naira to US Dollar. Adepoju, Yaya & Ojo (2013) applied GARCH models under non-normal innovations-t-distribution and Generalized Error Distribution (GED) on selected Nigeria exchange rates and found that the Asymmetric GARCH model with t-distribution and Generalized error distribution are selected in most cases and both distribution showed evidence of leptokurtic in Naira – USD exchange rate. Atoi & Nwambeke (2021) examines money market and foreign exchange market dynamics in Nigeria by estimating the dynamic correlation and volatility spill overs between Nigeria Naira/US Dollar with data from January 2007 to August 2019 and found that the dynamic conditional correlation GARCH (1, 1). Therefore, the goal of this paper is to fit a time series models (ARIMA and GARCH models) for the average official Naira/US Dollar exchange rates. Penzin & Salisu (2025) analyzed naira volatility against USD, GBP, and EUR using daily data (2010–2023), employing non-linear Granger causality and GARCH-X models augmented with U.S. financial stress indices and oil prices. Findings reveal strong predictability gains (15–20% improved out-of-sample forecasts) from stress spillovers, with USD shocks dominating due to Nigeria's dollar-denominated oil exports. Asymmetric effects are pronounced for EUR/GBP pairs, where Eurozone stagnation amplifies downside risks. Oladipo et al (2024) focused on USD/NGN and EUR/NGN daily returns (2015–2023), using GARCH(1,1), GJR-GARCH, EGARCH, and APARCH under GED and skewed Student's t distributions for VaR forecasting. GARCH (1,1)-GED emerges optimal for USD (minimizing expected shortfall by 12%), capturing leverage effects from Fed hikes, while SPLINE-GJR under t-distribution excels for EUR amid Brexit volatilities. GBP results mirror EUR, with persistence ($\alpha + \beta \approx 0.95$). Empirical tests (backtesting via Kupiec) confirm hybrids reduce model risk, recommending their integration into CBN's FX reserves strategy. CNY is underexplored but noted for low asymmetry in bilateral trade contexts. Adams & Uchema, (2024) modelled NGN/USD, EUR, and GBP using EGARCH(1,1) with LSTM neural networks. EGARCH better fits asymmetric clustering (leverage coefficient $\gamma \approx -0.25$ for USD). Findings showed that LSTM outperforms EGARCH in short-term forecasts (MSE reduction of 18%) by capturing non-linear bloc spillovers, e.g., GBP's post-Brexit surges. For CNY/NGN (via indirect USD proxies), persistence is lower ($\beta = 0.82$), linked to China's commodity demand stability. The study underscores hybrids for volatile emerging markets, with policy implications for AfCFTA-aligned hedging. (Umoru & Tedunjaiye, 2025) compared NGN against CNY, BRL, INR, RUB, and ZAR (2008–2023) using GJR-GARCH and EVT hybrids. Result inidacted that for CNY/NGN, volatility persistence ($\beta = 0.91$) reflects oil-trade ties, with positive shocks (e.g., Belt and Road investments) dominating asymmetries. USD/EUR benchmarks show higher explosive risks (sum >1 in 10% of periods). Out-of-sample VaR accuracy improves 22% with ensemble methods, urging CBN diversification beyond G7 blocs. GBP/CNY cross-volatility is bidirectional but weak, per DCC-GARCH correlations ($\varrho \approx 0.35$). Akinyemi, (2025) employed daily NGN/USD data (2015–2024), using GARCH(1,1) and EGARCH to pre-/post-COVID regimes. Volatility persistence spikes post-2023 unification ($\beta = 0.96$ for USD), with leverage effects from U.S. rate hikes ($\gamma = -0.32$). EUR/GBP extensions reveal 15% higher clustering from EU energy crises. CNY integration via multivariate BEKK-GARCH shows low spillover ($\omega < 0.01$), but forecasts warn of Asian bloc risks amid U.S.-China tensions. Recommendations include neural-augmented GARCH for real-time CBN monitoring. Oyadeyi, (2024) employed GARCH(1,1) to model NGN volatility against USD, driven by inflation, interest rates, and trade openness. Volatility persistence ($\beta > 0.92$) correlates with GDP contractions (e.g., -1.6% in 2016), with USD shocks amplifying via import dependence. EUR/GBP pairs show milder effects from European stability, while CNY integration reveals trade openness as a buffer. The study quantifies volatility's negative growth impact (elasticity = -0.15), urging CBN stabilization policies for bloc-specific exposures.

These studies affirm GARCH variants' efficacy in bloc contexts, USD for North American shocks, EUR/GBP for European asymmetries, CNY for Asian trade buffers with hybrids yielding 10–25% better forecasts. Persistence and leverage dominate, driven by oil dependency, but gaps persist in real-time other African and Asia currency to Nigeria modeling and climate/geopolitical exogenous variables. Future work should incorporate ML-GARCH for multi-bloc spillovers, aiding Nigeria's 3.4% GDP growth projections.

MATERIAL AND METHODS

Data

Eight foreign currencies were utilized in this study, choices being was guided by the trade relationship existing between Nigeria and the countries and the trade flow between these countries' currencies and the Nigerian Naira. The data are the weekly returns of exchange rate on the British Pound Sterling (POUNDS), Benin CFA (CFA), European Unions' Euro (EURO), Saudi Arabian Riyal (RIYAL), the Swiss Franc (SWFRANC), the US Dollar (DOLLAR), the Japanese Yen (YEN) and the ECOWAS currency (WAUA) all against the Nigerian Naira. The data span from 2nd January, 2016 to 28th Dec, 2025. The data are sourced from www.cenbank.org.

Volatility Measurement

Volatility is measured as the sample standard deviation, given as:

$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{i=1}^{T}(r_t-\mu)^2} \quad (1)$$

wherer_t is the return on day t

μis the average return over the T-day period.

At other times, the variance, σ2, is used as a volatility measure. This study uses variance as a measure of volatility.

Estimation

Strong (1992) argued that, there are both theoretical and empirical reasons for preferring logarithmic returns. Theoretically, logarithmic returns are analytically more tractable when linking together sub-period returns to form returns over long intervals. Empirically, logarithmic returns are more likely to be normally distributed and so conform to the assumptions of the standard statistical techniques". This is why we decided to use logarithmic returns in our study since one of our objectives was to test of whether the weekly returns were normally distributed or, instead, showed signs of asymmetry (skewness). The computation formula of the weekly returns is as follows:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (2)$$

where r_t is the return of the currency in period t;
Pt is the exchange rate of the currency in period t and,
Pt-1 is the exchange rate of the currency in period t-1.
When estimating the parameters of ARCH or GARCH models, even though ordinary least squares (OLS) estimation is consistent, maximum likelihood estimator (MLE) is the most popular method, where parameters are chosen such that the probability of occurrence of data under its assumed density function is the maximum. MLE is widely used because it produces an asymptotically normal and efficient parameter estimates. For a simple ARCH(1) model, Engle (1982) actually calculates an expression for the gain in efficiency from using maximum likelihood compared with OLS. He shows that as the parameter on the lagged squared residual approaches unity, 'the gain in efficiency from using a maximum likelihood estimator may be very large.

Test Heteroscedasticity

Engle (1982) proposed a model in which the conditional variance of a time series is a function of past shocks; the autoregressive conditional heteroscedastic (ARCH) model. The model provided a rigorous way of empirically investigating issues involving the volatility of economic variables. In this approach, the conditional variance $\sigma_t^2$is alinear function of lagged squared residuals e_t. This procedure provides one of the most important issues before applyingthe generalized autoregressive conditional heteroscedasticity (GARCH) methodology by examining the residuals of the returns series of exchange rate for evidence of heteroscedasticity. To test for this heteroscedasticity, the Lagrange Multiplier (LM) test proposed by Engle (1982) is applied.
In using this procedure, we obtain the residuals e_tfrom the ordinary least squares regression of the conditional mean equation. For an ARMA(1,1) model, the conditional mean equation will be:

$$r_t = \emptyset_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \qquad (3)$$

In addition, the squared residuals,$e_t^2$is regress on a constant and q lags as in the equation:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \ldots + \alpha_q e_{t-q}^2 \qquad (4)$$

The null hypothesis
H_0: $\alpha_1 = \alpha_2 = \ldots = \alpha_q = 0$; states that there is no ARCH effect up to order q against the alternative:
H_1: $\alpha_i > 0$;for at least one i = 1, 2, …, q.
Finally, the test statistic for the joint significance of the q-lagged squared residuals is the number of observations times the R-squared (TR^2) from the regression, where TR is evaluated against X^2 (q) distribution.

Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset return. Bollerslev (1986) focuses on extending the ARCH model to allow for a more flexible lag structure. He introduces a conditional heteroscedasticity model that includes lags of the conditional variance as regressors in the model for the conditional variance (in addition to lags of the squared error term $e_{(t-1)}^2, e_{(t-2)}^2$, …, $e_{(t-q)}^2$), the generalized ARCH (GARCH) model. The generalized autoregressive conditional heteroscedastic (GARCH) model is used in this study to investigate the volatility clustering and persistence. The model has only three parameters that allows for an infinite number of squared errors to influence the current conditional variance (volatility). The general framework of this model, GARCH (p, q), is expressed by allowing the current conditional variance to depend on the first p past conditional variances as well as the q past squared innovations. That is,

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 \qquad (5)$$

where, p is the number of lagged σ^2 terms and q is the number of lagged ε^2 terms. For this study, the following simple specification – GARCH(1,1) is used:
Mean equation:

$$r_t = \mu + \varepsilon_t \qquad (6)$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (7)$$

where, $\omega>0$ and $\alpha_1 \geq 0$ and $\beta_1 \geq 0$, and
r_t = return of the asset at time t
μ = average returns
ε_t = residual returns, defined as

$$\varepsilon_t = \sigma_t \epsilon_t \qquad (8)$$

where ϵ_t is a sequence of independent and identically distributed (i.i.d) random variables with mean zero and variance 1. The constraints $\alpha_1 \geq 0$ and $\beta_1 \geq 0$, are needed to ensure σ_t^2 is strictly positive (Poon, 2005).
In this model, the mean equation is written as a function of constant with an error term. Since σ_t^2 is the one-period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation specified is a function of three terms:

1. A constant term ω
2. News about volatility from the previous period measured as the lag of the squared residuals from the mean equation: $\varepsilon^2_{(t-1)}$(the ARCH term); and
3. Last period forecast variance: $\sigma^2_{(t-1)}$ (the GARCH term).

Asymmetric GARCH Models

A feature of many financial time series that is not captured by ARCH and GARCH models is the 'asymmetry effect', also known as the 'leverage effect'. In the context of financial time series analysis the asymmetry effect refers to the characteristic of time series on asset prices that an unexpected drop tends to increase volatility more than an unexpected increase of the same magnitude (or, that 'bad news' tends to increase volatility more than 'good news'). ARCH and GARCH models do not capture this effect since the lagged error terms are squared in the equations for the conditional variance, and therefore a positive error has the same impact on the conditional variance as a negative error. A model specifically designed to capture the asymmetry effect is the Exponential GARCH(EGARCH) model proposed by (Nelson, 1991). In an EGARCH model the natural logarithm of the condition variance is allowed to vary over time as a function of the lagged error terms (rather than lagged squared errors). The EGARCH(p,q) model for the conditional variance can be written as:

$$ln(\sigma_t^2) = \omega + \sum_{j=1}^{p} \beta_j \, ln(\sigma_{t-j}^2) + \sum_{i=1}^{q} \alpha_i \left\{\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right\} - \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \quad (9)$$

The EGARCH model is asymmetric because the level $|\varepsilon_{(t-i)}|/\sigma_{(t-i)}$ is included with coefficient γ_i. Since the coefficient is typically negative, positive return shocks generate less volatility than negative return shocks assuming other factors remains unchanged.

In order to capture asymmetric responses of the time-varying variance to shocks, this study employs EGARCH(1,1) model, which has the following specification:

Mean equation:

$$r_t = \mu + \varepsilon_t \quad (10)$$

Variance equation:

$$ln(\sigma_t^2) = \omega + \beta_1 ln(\sigma_{t-1}^2) + \alpha_1 \left\{\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right\} - \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (11)$$

Model Diagnostics

The process of evaluating a model is called diagnostic testing. The diagnostic tools utilized in this study are,

1. Augmented Dickey Fuller Test (ADF)
2. Box – Pierce test (Q-Statistic). The Q-Statistic is written as;

$$Q = N \sum_{i=1}^{k} ACF(i)^2 \quad (12)$$

1. Akaike and Schwarz Bayesian Criteria. It proposes the following models:

$$AIC = nLog(SSE) + 2k \quad (13)$$

Where; k = Numbers of parameters that are fitted in the model, Log = Natural logarithm, n = Number of observations in the series, SSE = Sum of the squared errors.

2. Schwarz proposed the following equation to choose from models:

$$BIC = nLog(SSE) + kLog(n) \quad (14)$$

RESULTS AND DISCUSSIONS

In the first phase of this analysis, the statistical properties or summary statistics as well as distribution of all-time series will be tested by means of coefficient of skewness and kurtosis to check presence of typical stylised facts. In the second phase, these time series will then be tested for stationary graphically by means of autocorrelation function and partial autocorrelation function. If the original series comes out to be non-stationary, some appropriate transformations will be made to achieving stationarity. In the third phase, the appropriate model which best describes the exchange rate series will be selected and estimated through a search algorithm by trying a number of different coefficients before converging on the optimum for the fitted model using the Ordinary Least Square (OLS) method as well as the Akaike Information Criterion (AIC). Finally, forecasting performance of the model would be determined using out of sample observations.

Descriptive Statistics of the Weekly Exchange Rate Series

To characterize the distributional properties of the weekly exchange rate series, a set of descriptive statistics was computed for each currency. In particular, skewness and kurtosis were examined to assess departures from normality. A positive skewness value indicates a distribution with a long right tail, whereas a negative skewness value suggests a long left tail. Regarding kurtosis, the benchmark value for a normal distribution is 3. Values exceeding 3 indicate a leptokurtic distribution with a pronounced peak and heavier tails, while values below 3 suggest a platykurtic distribution with a flatter peak and lighter tails. Figures 1 and 2 present time-series plots illustrating the trends in the exchange rate series and the corresponding stock returns, respectively.

From Table 1, it can be observed that:

1. The average returns across all-time series are very low. In all cases, the standard deviations are substantially larger than the corresponding mean values, suggesting that the mean returns are not statistically different from zero.
2. All currencies exhibit positive skewness, with the exception of WAUA, which shows negative skewness. Furthermore, all series display excess kurtosis, indicating a clear departure from normality.

In summary, none of the return series conforms to a normal distribution. The distributions of POUNDS, CFA, EURO, DOLLAR, YEN, RIYAL, and SWFRANC are positively skewed, indicating long right tails, whereas WAUA exhibits negative skewness, indicating a long left tail. Additionally, all currencies demonstrate leptokurtic behavior, with pronounced peaks in their distributions and kurtosis values not falling below 7.089297.

Stationarity Test

Since time-series data must be stationary prior to the selection of an appropriate econometric model, the stationarity properties of the dataset are examined. In a unit root process, both the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) typically exhibit a slow decay pattern. The results of the Dickey–Fuller unit root test applied to the data are presented in Table 2.

Heteroscedasticity Test

Since heteroscedasticity is a pre-condition for applying

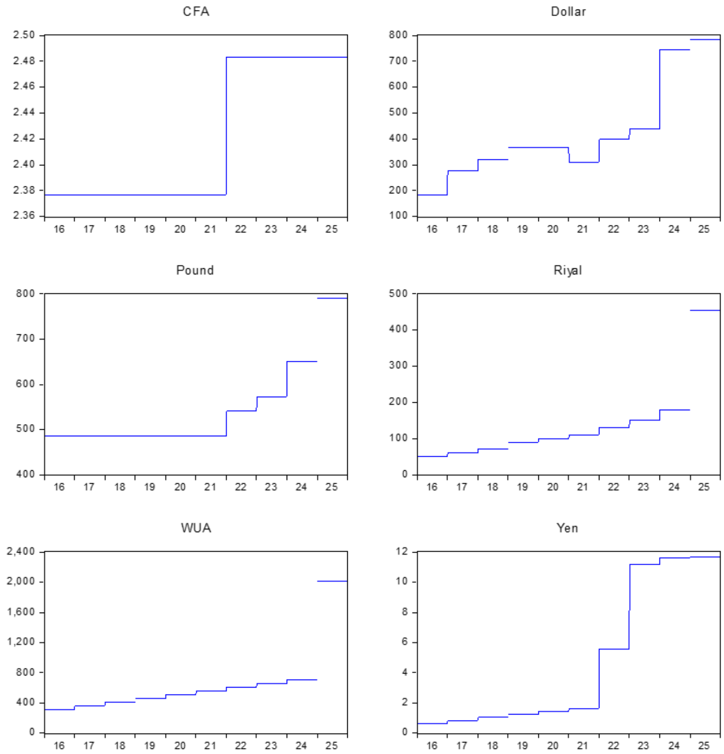

Figure 1: Time Plots of the Exchange Rates Series for the Period 2016 to 2025

Table 1: Descriptive Statistics of the exchange rate returns series

Currencies	Mean	Min.	Max.	Std. Dev	Skewness	Kurtosis	ADF
POUNDS	0.0007355	-0.0831901	0.0978379	0.0148193	0.0569876	12.34194	-21.008
CFA	0.0011521	-1.005774	1.015067	0.0893329	0.9568056	80.54765	-38.853
EURO	0.0012152	-0.0939988	0.1065764	0.0152702	0.7066835	13.63914	-20.621
DOLLAR	0.0005922	-0.0901124	0.0900263	0.0098957	1.536209	56.04491	-26.288
YEN	0.0014398	-0.1080917	0.1196421	0.0152389	1.407125	20.71283	-22.183
WAUA	0.0009445	-0.4058933	0.3652581	0.030401	-1.030694	109.1965	-35.525
RIYAL	0.0003312	-0.0913635	0.0912446	0.0110593	1.426004	50.89119	-24.933
SWFRANC	0.0014037	-0.0598073	0.0794653	0.0158044	0.4146465	7.089297	-15.170

Table 2: Unit Root Test of exchange rate series

Currencies	ADF Test Statistic	1%Critical Value
POUNDS	-2.984	-3.430
CFA	-7.530	-3.430
EURO	-2.284	-3.430
DOLLAR	-1.114	-3.430
YEN	-0.027	-3.430
WAUA	-2.634	-3.430
RIYAL	-0.617	-3.445
SWFRANC	-0.626	-3.452

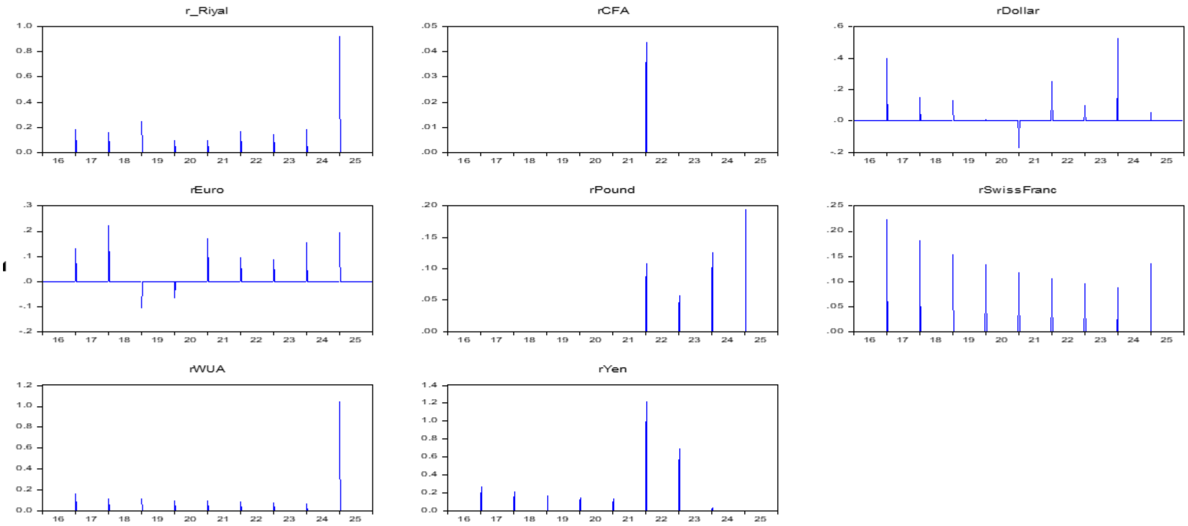

Figure 2: Return Plots of the Exchange Rates Series for the Period 2016 to 2025

the GARCH models to a financial time series like the exchange rate index, the results of examination of the residuals for evidence of heteroscedasticity are presented in Table 3

From the Table 3, it is evident that the test results provide strong evidence for rejecting the null hypothesis for all currency series. Rejecting the null hypothesis indicates the existence of ARCH effects in the residuals series in the mean equation.

Table 3: ARCH – LM Test for residuals of returns series

Currencies	ARCH-LM test statistic	P-value
POUNDS	67.640	0.0000
CFA	27.340	0.0000
EURO	76.334	0.0000
DOLLAR	110.448	0.0000
YEN	78.155	0.0000
WAUA	63.906	0.0000
RIYAL	76.802	0.0000
SWFRANC	41.565	0.0000
H_0: There are no ARCH effects in the residual series		

Parameters Estimation

After the preliminary data analysis, the parameters of the appropriate models were estimated using a search algorithm that evaluates multiple coefficient combinations before converging on optimal values. For each series, the sample partial autocorrelation function (PACF) of the squared returns was plotted to assess linear dependence in the volatility structure and to determine the appropriate order of the model to be fitted. The joint estimation results of the AR, MA, or ARMA models combined with the GARCH(1,1) specification are presented in Table 4. The findings indicate that:

1. The coefficients ω (constant), α (ARCH term), and β (GARCH term) are statistically significant at the 5% level for the POUNDS, CFA, EURO, YEN, WAUA, RIYAL, and SWFRANC return series, with expected signs across all series. The only exception is the constant term (ω) in the DOLLAR series, which is not statistically significant at the 5% level.

2. The statistical significance of both α and β implies that lagged conditional variance and lagged squared residuals significantly influence current conditional variance. This suggests that past shocks to volatility carry explanatory power for present volatility, confirming the presence of volatility clustering in the series.

3. The sum of the ARCH and GARCH coefficients (α + β), commonly referred to as the persistence parameter, was computed for all series. For the CFA return series, this value is marginally greater than one, indicating a potentially explosive conditional variance process. In contrast, for the POUNDS, EURO, DOLLAR, YEN, WAUA, RIYAL, and SWFRANC series, the persistence parameter is less than one, satisfying the condition for a mean-reverting process. However, values close to unity suggest a high degree of volatility persistence, implying that shocks to volatility decay slowly over time and the variance remains highly persistent.

Diagnosis of the GARCH(1,1) Model

In order to diagnose the goodness of fit of the mean

Table 4: Estimation results of fitted GARCH(1,1) Model

	Coeff. Value	**Std. Error**	**Z statistic**	**P – value**
POUNDS: AR(1)-GARCH(1,1)		AIC = -3233.768		
ω	0.000023	0.000005	4.46	0.0000
α	0.3442384	0.0470124	7.32	0.0000
β	0.5878428	0.050865	11.56	0.0000
α+β = 0.9320812				
CFA: MA(1)-GARCH(1,1)		AIC = 1515.879		
ω	0.6564317	0.1252527	5.24	0.0000
α	0.8009342	0.0786202	10.19	0.0000
β	0.1996589	0.0651848	3.06	0.002
α+β = 1.0005931				
EURO: GARCH(1,1)		AIC = -3120.191		
ω	0.0000376	0.0000115	3.27	0.001
α	0.2582807	0.041422	6.24	0.0000
β	0.5886773	0.0772843	7.62	0.0000
α+β = 0.846958				
DOLLAR: AR(1)-GARCH(1,1)		AIC = -1987.042		
ω	0.000013	0.0000007	1.82	0.068
α	0.2047677	0.0574797	3.56	0.0000
β	0.7470073	0.0729038	10.25	0.0000
α+β = 0.951775				
YEN: ARMA(1,2)-GARCH(1,1)		AIC = -3128.158		
ω	0.0000366	0.00000517	7.07	0.0000
α	0.2594143	0.0751327	3.45	0.001
β	0.6078856	0.0484522	12.54	0.0000
α+β = 0.8672999				
WAUA: MA(2)-GARCH(1,1)		AIC = 2114.351		
ω	0.0837706	0.0405801	2.06	0.039
α	0.0643937	0.0186623	3.45	0.001
β	0.908903	0.0275487	32.99	0.0000
α+β = 0.9732967				
RIYAL: GARCH(1,1)		AIC = 1619.048		
ω	0.5771765	0.0756246	7.63	0.0000
α	0.4351567	0.035055	12.41	0.0000
β	0.5515035	0.0327967	16.82	0.0000
α+β = 0.9866602				
SWFRANC: MA(3)-GARCH(1,1)		AIC = -1978.857		
ω	0.0000192	0.0000094	2.04	0.041
α	0.2145362	0.0589805	3.64	0.0000
β	0.7065554	0.0832014	8.49	0.0000
α+β = 0.9210916				

equation and the GARCH model for the various series, the Autocorrelation (AC) and Partial Autocorrelation (PAC) of the residuals and squared residuals in each particular case are considered, the result of which is presented in Table 5.

From the results presented in Table 5, as well as the plots of the standardized and squared standardized residuals reported in Appendix 6, the fitted GARCH model appears to be appropriate for the data. The autocorrelation (AC), partial autocorrelation (PAC), and Ljung–Box Q-statistics indicate that there is no statistically significant evidence of remaining autocorrelation in either the standardized residuals or their squares, with the exception of the squared standardized residuals of the WAUA return series. This suggests that both the mean and variance equations are adequately specified for the majority of the series.

Table 5: Tests for the GARCH(1,1) Models for the returns series

	Standardised Residuals			Squared Standardised Residuals		
	AC	PAC	Q (p-value)	AC	PAC	Q (p-value)
POUNDS	-0.0471	-0.0235	22.984 (0.0845)	-0.0417	-0.0226	20.759 (0.1447)
CFA	0.0420	0.0368	30.346 (0.2116)	0.0003	0.0017	37.609 (0.0505)
EURO	0.0024	-0.0063	10.279 (0.8018)	0.0082	-0.0007	10.261 (0.8039)
DOLLAR	-0.0457	-0.0324	17.962 (0.0556)	-0.0465	-0.0324	17.611 (0.0619)
YEN	0.0419	0.0397	15.216 (0.4360)	0.0317	0.0395	13.863 (0.5359)
WAUA	0.0533	0.0401	23.533 (0.0735)	0.0533	0.0430	56.127 (0.0000)
RIYAL	-0.0209	-0.0562	24.743 (0.0535)	-0.0111	-0.0084	5.9582 (0.9804)
SWFRANC	-0.0466	-0.0314	17.769 (0.0590)	-0.0465	-0.0311	17.588 (0.0623)

Estimation of EGARCH (1,1) Model

The ARCH and GARCH models do not account for asymmetric effects, a well-documented feature of financial time series whereby an unexpected decline in asset prices tends to increase volatility more than an unexpected increase of the same magnitude. To address this limitation of the standard GARCH framework in modeling financial time series, Nelson (1991) proposed the Exponential GARCH (EGARCH) model, which explicitly captures asymmetric effects between positive and negative returns. The fitted EGARCH(1,1) model for the return series is presented in Table 6.

From Table 6, the following results are observed:

1. All model coefficients are statistically significant at

Table 6: Estimation results of fitted EGARCH(1,1) Model

	Coeff. Value	**Std. Error**	**Z statistic**	**P – value**
POUNDS: AR(1)-EGARCH(1,1) AIC= -3238.784				
ω	-0.9278181	0.2136743	-4.34	0.0000
α	0.1030154	0.0317212	3.25	0.001
β	0.891592	0.0240276	37.11	0.0000
γ	0.447241	0.0592259	7.68	0.0000
CFA: MA(1)-EGARCH(1,1) AIC= 1517.222				
ω	0.2729951	0.0540415	5.05	0.0000
α	-0.1480047	0.0534419	-2.77	0.006
β	0.7411578	0.0514088	14.42	0.0000
γ	0.8652488	0.0915721	9.45	0.0000
EURO:EGARCH(1,1)AIC= -4080.922				
ω	-0.5576866	0.169759	-3.29	0.001
α	-0.0323399	0.0216071	-1.50	0.134
β	0.9334376	0.0200636	46.52	0.0000
γ	0.3244823	0.0436401	7.44	0.0000
DOLLAR: AR(1)-EGARCH(1,1) AIC= -1997.742				
ω	0.6206279	0.2525925	-2.46	0.014

α	0.1471657	0.049868	2.95	0.003
β	0.9276788	0.0295335	31.41	0.0000
γ	0.356667	0.079358	4.49	0.0000
YEN: ARMA(1,2)-EGARCH(1,1) AIC= -3123.221				
ω	-0.4855289	0.1243576	-3.90	0.0000
α	0.1526089	0.0181855	8.39	0.0000
β	0.9436473	0.0144552	65.28	0.0000
γ	0.0050915	0.0173373	0.29	0.769
WAUA: MA(2)-EGARCH(1,1) AIC= 2110.71				
ω	0.0228132	0.0108152	2.11	0.035
α	-0.023373	0.0168744	-1.39	0.166
β	0.9837581	0.0084503	116.42	0.0000
γ	0.1140298	0.0262754	4.34	0.0000
RIYAL: EGARCH(1,1) AIC= 1601.417				
ω	0.3870361	0.0513284	7.54	0.0000
α	-0.1630918	0.0716795	-2.28	0.023
β	0.7464005	0.0417343	17.88	0.0000
γ	0.7348127	0.0689262	10.66	0.0000
SWFRANC: EGARCH(1,1) AIC= -1984.198				
ω	-0.6591432	0.2678219	-2.46	0.014
α	0.0942623	0.044959	2.10	0.036
β	0.9231461	0.0315493	29.26	0.0000
γ	0.3717817	0.0735478	5.05	0.0000

the 5% level for the POUNDS, CFA, DOLLAR, RIYAL, and SWFRANC return series. The only exceptions are the estimates of α for the EURO and WAUA series, which are not statistically significant at the 5% level.

2. The leverage effect parameter (γ) is positive and statistically significant at the 5% level for all series, with the exception of the YEN, where it is not statistically significant. These findings are contrary to the conventional expectation of a negative leverage effect in financial markets. Instead, the results suggest a positive association between returns and volatility, implying that declines in returns are associated with lower volatility. This indicates the absence of the traditional leverage effect in the weekly return series over the study period.

Diagnosis of the EGARCH (1,1) Model

In order to diagnose the goodness of fit of the mean equation and the EGARCH model for the various series, the Autocorrelation (AC) and Partial Autocorrelation (PAC) of the residuals and squared residuals in each particular case are considered, the result of which is presented in Table 7.

From the result presented in Table 7, the EGARCH model that has been fitted seems appropriate for the data

Table 7: Tests for the EGARCH(1,1) Models for the returns series

	Standardised Residuals			Squared Standardised Residuals		
	AC	PAC	Q (p-value)	AC	PAC	Q (p-value)
POUNDS	-0.0457	-0.0239	24.181 (0.0621)	0.0128	0.0053	20.727 (0.1458)
CFA	-0.0271	-0.0598	27.593 (0.0243)	-0.0094	-0.0091	2.5185 0.9999)
EURO	0.0026	-0.0061	10.267 (0.8026)	0.0260	0.0145	14.719 (0.4719)
DOLLAR	-0.0435	-0.0385	24.851 (0.0520)	0.0213	0.0191	12.076 (0.6732)
YEN	0.0414	0.0487	15.395 (0.4234)	-0.0067	-0.0029	25.305 (0.0460)
WAUA	-0.0460	-0.0325	12.941 (0.2270)	0.0990	0.1003	22.907 (0.0111)
RIYAL	-0.0406	-0.0399	6.2647 (0.7926)	-0.0070	0.0041	5.8229 (0.8299)
SWFRANC	-0.0466	-0.0314	17.769 (0.0590)	-0.0260	-0.0241	5.9298 (0.8211)

at the 1% confidence level because the AC, PAC, and Q – statistics show that there is no statistically significant trace of autocorrelation left in the standardised and squared standardised residuals indicating that the mean equation and variance equation are adequately specified.

Model Selection

From the foregoing analysis and the value of the Akaike Information Criterion (AIC) for the GARCH and EGARCH model as summarized in Table 8, the results show that the EGARCH modelling technique is more preferred for evaluating weekly return series for POUNDS, EURO, DOLLAR, WAUA, RIYAL and SWFRANC while the GARCH modelling technique is more preferred for weekly return series for CFA and YEN during the study period.

Table 8: AIC Values for GARCH(1,1) and EGARCH(1,1) Models

CURRENCIES	GARCH(1,1)	EGARCH(1,1)
POUNDS	-3233.768	-3238.784
CFA	1515.879	1517.222
EURO	-3120.191	-4080.922
DOLLAR	-1987.042	-1997.742
YEN	-3128.158	-3123.221
WAUA	2214.351	2110.71
RIYAL	1619.048	1601.417
SWFRANC	-1978.857	-1984.198

Forecasting

Since forecasting is an important application of time series analysis, volatility forecasts for fifty-two weeks of the series based on the models chosen by the prescribed information criteriaare presented in Table 9.

Table 9: Volatility Forecasts for the Weekly Returns

CURRENCIES								
WEEK	**POUNDS**	**CFA**	**EURO**	**DOLLAR**	**YEN**	**WAUA**	**RIYAL**	**SWFRANC**
1	0.000202	5.131086	0.000231	0.000212	0.000229	3.205583	4.860969	0.000244
2	0.000201	5.262678	0.000231	0.00021	0.000233	3.218087	4.793557	0.000239
3	0.0002	5.288951	0.000231	0.000208	0.000236	3.230436	4.743851	0.000235
4	0.000199	5.294197	0.000231	0.000207	0.000237	3.24263	4.707087	0.000231
5	0.000198	5.295245	0.000231	0.000205	0.000238	3.254671	4.679832	0.000227
6	0.000197	5.295454	0.000231	0.000204	0.000239	3.266561	4.659591	0.000224
7	0.000197	5.295496	0.000231	0.000203	0.000239	3.278299	4.644541	0.000221
8	0.000196	5.295504	0.000231	0.000201	0.00024	3.289888	4.633339	0.000218
9	0.000196	5.295506	0.000231	0.0002	0.00024	3.301328	4.624995	0.000216
10	0.000195	5.295506	0.000231	0.000199	0.00024	3.312622	4.618778	0.000214
11	0.000195	5.295506	0.000231	0.000199	0.00024	3.32377	4.614142	0.000212
12	0.000195	5.295506	0.00023	0.000198	0.00024	3.334774	4.610685	0.00021
13	0.000194	5.295506	0.00023	0.000197	0.00024	3.345634	4.608107	0.000208
14	0.000194	5.295506	0.00023	0.000196	0.00024	3.356353	4.606183	0.000206
15	0.000194	5.295506	0.00023	0.000196	0.00024	3.36693	4.604748	0.000205
16	0.000194	5.295506	0.00023	0.000195	0.00024	3.377369	4.603676	0.000204
17	0.000193	5.295506	0.00023	0.000194	0.00024	3.38767	4.602877	0.000202
18	0.000193	5.295506	0.00023	0.000194	0.00024	3.397834	4.602281	0.000201
19	0.000193	5.295506	0.00023	0.000194	0.00024	3.407862	4.601836	0.0002
20	0.000193	5.295506	0.00023	0.000193	0.00024	3.417757	4.601503	0.000199
21	0.000193	5.295506	0.00023	0.000193	0.00024	3.427519	4.601255	0.000199

22	0.000193	5.295506	0.00023	0.000192	0.00024	3.43715	4.60107	0.000198
23	0.000193	5.295506	0.00023	0.000192	0.00024	3.44665	4.600932	0.000197
24	0.000193	5.295506	0.00023	0.000192	0.00024	3.456022	4.600829	0.000196
25	0.000193	5.295506	0.00023	0.000191	0.00024	3.465266	4.600752	0.000196
26	0.000192	5.295506	0.00023	0.000191	0.00024	3.474385	4.600695	0.000195
27	0.000192	5.295506	0.00023	0.000191	0.00024	3.483379	4.600652	0.000195
28	0.000192	5.295506	0.00023	0.000191	0.00024	3.492249	4.60062	0.000194
29	0.000192	5.295506	0.00023	0.00019	0.00024	3.500998	4.600596	0.000194
30	0.000192	5.295506	0.00023	0.00019	0.00024	3.509626	4.600578	0.000193
31	0.000192	5.295506	0.00023	0.00019	0.00024	3.518134	4.600565	0.000193
32	0.000192	5.295506	0.00023	0.00019	0.00024	3.526525	4.600555	0.000193
33	0.000192	5.295506	0.00023	0.00019	0.00024	3.534798	4.600547	0.000192
34	0.000192	5.295506	0.00023	0.000189	0.00024	3.542956	4.600542	0.000192
35	0.000192	5.295506	0.00023	0.000189	0.00024	3.551	4.600538	0.000192
36	0.000192	5.295506	0.00023	0.000189	0.00024	3.558931	4.600535	0.000191
37	0.000192	5.295506	0.00023	0.000189	0.00024	3.566751	4.600533	0.000191
38	0.000192	5.295506	0.00023	0.000189	0.00024	3.574461	4.600531	0.000191
39	0.000192	5.295506	0.00023	0.000189	0.00024	3.582061	4.60053	0.000191
40	0.000192	5.295506	0.00023	0.000189	0.00024	3.589554	4.600529	0.000191
41	0.000192	5.295506	0.00023	0.000189	0.00024	3.59694	4.600528	0.00019
42	0.000192	5.295506	0.00023	0.000189	0.00024	3.604221	4.600527	0.00019
43	0.000192	5.295506	0.00023	0.000189	0.00024	3.611399	4.600527	0.00019
44	0.000192	5.295506	0.00023	0.000188	0.00024	3.618473	4.600526	0.00019
45	0.000192	5.295506	0.00023	0.000188	0.00024	3.625447	4.600526	0.00019
46	0.000192	5.295506	0.00023	0.000188	0.00024	3.63232	4.600526	0.00019
47	0.000192	5.295506	0.00023	0.000188	0.00024	3.639094	4.600526	0.00019
48	0.000192	5.295506	0.00023	0.000188	0.00024	3.645771	4.600526	0.00019
49	0.000192	5.295506	0.00023	0.000188	0.00024	3.652351	4.600526	0.00019
50	0.000192	5.295506	0.00023	0.000188	0.00024	3.658836	4.600526	0.000189
51	0.000192	5.295506	0.00023	0.000188	0.00024	3.665226	4.600526	0.000189
52	0.000192	5.295506	0.00023	0.000188	0.00024	3.671524	4.600526	0.000189

Volatility Forecast Performance

In order to determine the performance of the fitted model in forecasting future volatility, the forecasted volatilities are compared with the sample variance of the residual returns. This result is presented in Table 10

Table 10: Sample Variance for the Residual Returns

CURRENCIES	SAMPLE VARIANCE
POUNDS	0.0000167
CFA	3237.102472
EURO	0.0000342
DOLLAR	0.0000350
YEN	0.0000876
WAUA	2.7079827
RIYAL	4.2572523
SWFRANC	0.0000319

From the Table 10, it is evident that the forecasted volatility for all the return series converges to the respective sample variance of their residual return indicating the ability of the model to predict actual out-of-sample volatility. The notable exception is the YEN return where the forecasted volatility is seen to diverge from the sample variance of its residual as such other asymmetry models could be investigated for better performance.

CONCLUSION

This study examined eight exchange rate series, namely the British Pound Sterling (POUNDS), Benin/CFA franc (CFA), Euro (EURO), United States dollar (DOLLAR), Japanese yen (YEN), West African Unit of Account (WAUA), Saudi Arabian riyal (RIYAL), and Swiss franc (SWFRANC). The descriptive statistics and distributional properties of the series revealed key stylized facts, including positive skewness and leptokurtosis across most currencies. In addition, the autocorrelation and partial autocorrelation functions indicated the presence of serial dependence in the raw series, suggesting non-stationarity and the need for appropriate transformations to achieve stationarity prior to model estimation. Subsequent analysis employed univariate specifications of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework, including both symmetric and asymmetric variants, to capture well-documented features of financial return series such as volatility clustering and potential leverage effects.

The study objectives were largely achieved. Seven out of the eight return series exhibited heteroskedasticity and volatility clustering, justifying the application of the GARCH(1,1) family of models. Following estimation, the fitted models effectively removed statistically significant autocorrelation and ARCH effects from the residuals, indicating adequate model specification. For most series, the variance equation coefficients were statistically significant. The empirical results further showed that conditional variance is an explosive process for the CFA series ($\alpha + \beta > 1$), while it is highly persistent but mean-reverting ($\alpha + \beta < 1$) for the POUNDS, EURO, DOLLAR, YEN, WAUA, RIYAL, and SWFRANC series. These findings indicate strong volatility persistence, with shocks decaying slowly over time.

Furthermore, the EGARCH(1,1) results provided no evidence of leverage effects across all currencies, implying that positive shocks to returns are associated with lower subsequent volatility than negative shocks of the same magnitude. Model selection criteria, including the Akaike Information Criterion (AIC), suggest that the EGARCH (1,1) specification is more appropriate for modelling the weekly volatility of the POUNDS, EURO, DOLLAR, WAUA, RIYAL, and SWFRANC series, while the standard GARCH (1,1) model performs better for the CFA and YEN series.

Finally, the models demonstrate strong out-of-sample forecasting performance, with volatility forecasts converging toward the sample variance of the residuals in most cases, except for the YEN series. The forecasting performance of the appropriate fitted model is then determined for each of the series.

From the foregoing, the study recommends that:

1. The estimate of the leverage effect (γ) in each of the series though significant (except in the case of YEN series) have positive coefficients throughout. These results are inconsistent with the conventional situation where negative signs are assumed for leverage effect presence. As such, research on leverage effect should be continued by fitting other models from the GARCH family especially asymmetrical models.

2. The high volatility persistence from the estimated model suggests good opportunity for individuals and stakeholders who trade in these currencies to take advantage of the trade-off between risk and returns in the Foreign Exchange Market in Nigeria.

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