JOURNAL OF STATISTICAL MODELING & ANALYTICS (JOSMA)
(ISSN: 2180-3102)
UNIVERSITI MALAYA

Volatility Modeling of Monthly USD Exchange Rate Returns for Maximized Earnings

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Received 20 Feb 2025
Accepted 06 Aug 2026
Published 20 Nov 2026

RESEARCH ARTICLE

Abstract

Studying the exchange rate (EXR) volatility is crucial in macroeconomics research, due to the frequent instability in the exchange of foreign currencies, particularly the United States Dollar (USD) in developing countries. Thus, this study analyzed the dynamic relationship between the volatility index of the USD forex market based on key economic indicators of monetary policy rate (MPR) and inflation rate (IR) in Nigeria. Data comprising 122 weekly Naira-to-Dollar exchange rates were sourced from January 2022 to April 2024 and analyzed using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Exponential (E-GARCH), and Asymmetric (A-GARCH) models. Model performance is assessed using AIC, BIC, Log-Likelihood, and RMSE. Both MPR and IR had a significant impact on A-GARCH and E-GARCH, in contrast to the insignificance of the GARCH model, indicating that a higher MPR increases market volatility, whereas a higher IR reduces it. Although the traditional GARCH model explains some characteristics of Forex volatility; still, the A-GARCH and E-GARCH models give a better indication of the persistence of volatility and asymmetric effects in the exchange rate series, with the A-GARCH model showing that the series' volatility is more persistent in response to MPR and IR. Therefore, the A-GARCH was applied to a 12-month forecast, where each term of the forecast was identical, meaning that the forecasted returns remained stable throughout the year without any significant changes or fluctuations.

Keywords: Forecast, Forex Market Volatility, GARCH Model, Monetary Policy Rate, Inflation Rate.

1. Introduction

Understanding forex market volatility is essential for creating effective trading strategies that can help maximize returns while minimizing risk (Olowe, 2011). The foreign exchange (Forex) market is the largest and most liquid financial marketplace globally, where exchange of foreign currencies takes place without hindrance. The future of this trading has however been established to be affected by various

macroeconomic factors such as inflation, monetary policy, and geopolitical events, making it a potential opportunity and risk for traders (Baruník et al., 2017).

Under the Bretton Woods system of fixed forex trading, exchange rates were relatively stable until 1971. But the fall of the system put in place floating exchange rates, which caused a lot of volatility in the market as the values of the currency were determined by the market forces, the economic situation, and the geopolitical changes (Cespa et al., 2022). A further increase in volatility was experienced in the eighties, which was occasioned by speculative trading, macro-economic factors, and other events, such as the Plaza Accord in 1985 (Chaboud et al., 2023), algorithmic and/or high-frequency trading, which can magnify price fluctuations in response to price signals (Han et al., 2020), etc.

Managing volatility has become a key challenge in forex management. Factors such as unstable exchange rates, uncertainty about the economy, geopolitical instability, finding lucrative investment opportunities, risk management, etc. are some of the top issues major traders need to deal with, to achieve maximized earnings in their trading activities.

Economic indicators are among the most prevalent factors known to have influenced the forex market volatility; hence its study has become imperative in the evaluation of the forex market. The rates of inflation affect the money's purchasing power and can cause sudden changes in the market when inflation data appear to be contrary to what was anticipated (Ha et al., 2022). In the same way, changes in central bank monetary policy can greatly impact exchange rates through similar mechanisms. When central banks raise interest rates, they tend to attract foreign investment and, therefore, bolster the currency, while a lower interest rate might lead to a larger capital outflow and thus make the currency more volatile. Additionally, geopolitical events can cause volatility in the market, which may lead to capital flight (Chaboud et al., 2023).

The level of exchange rate volatility has been studied by various econometric models. Danladi et al. (2015) investigated the relationship between exchange rate volatility and international trade and reported that there was a bidirectional relationship. Without consideration of macroeconomic variables, Olowe (2011) indicated that there was forex volatility on a daily and weekly basis. Mohnot (2019) in related papers used the traditional GARCH model to predict exchange rate volatility and found that the shocks to exchange rate volatility were stronger during the crisis periods, thereby making forecasting less accurate.

Volatility issues have been explored in several studies through various econometric methods. Danladi et al. (2015) studied the relationship between exchange rate volatility and international trade and concluded that there exists bidirectional causality between the two. However, Olowe (2011) observed that forex markets continued to be volatile even without the consideration of macroeconomic factors. The few related studies reviewed examined the use of the classical GARCH model to predict exchange rate volatility, as shown by Mohnot (2019), who found that volatility shocks are more severe during crisis periods, making forecasting more difficult.

This study investigates the effects of key macroeconomic variables on the volatility of the Nigerian forex market from January 2022 to April 2024. Specifically, it analyzes the impact of the Monetary Policy Rate (MPR) and the inflation rate (IR) on the volatility of the exchange rate of the U.S dollar on the basis of the GARCH, A-GARCH, and the E-GARCH models. The models offer more insights into volatility dynamics and the asymmetric reaction of the forex market to economic shocks. Results suggest that the MPR has a strong influence on forex volatility, and inflation, on the other hand, shows different effects in the various models, suggesting a complex correlation between macroeconomic indicators and forex volatility. The research outcomes equally offer valuable insights into how these fluctuations impact the trading landscape, the significance of good risk management practices like diversification, position sizing, and stop-loss orders in reducing losses during market volatility, which could help improve trading strategies and individual/government policy decisions (Ogundipe et al., 2019; Zhao, 2022; Liu et al., 2020).

2. Materials and methods

2.1 Data Sources and Method of Collection

This study utilizes time series data consisting of 122 weekly Naira-to-Dollar exchange rates sourced from the History Exchange Report website, between January 2022 to April 2024. The weekly data was aggregated into 28 monthly data for ease of forecasting and policy recommendations. The choice of economic indicators that depict the independent variables are the Monetary Policy Rate (MPR) and the Inflation Rate. The analytical techniques employed to explain the volatility structure of the exchange rate are the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), the Asymmetric GARCH (A-GARCH), and the Exponential GARCH (E-GARCH). Model parameters were estimated by the Maximum Likelihood Estimation (MLE) method, while model performance was assessed by Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Log-Likelihood (LogL), and Root Mean Square Error (RMSE). The techniques assisted in determining the relationships between MPR, inflation, and exchange rate fluctuations. The methodology provided robustness, including model diagnostics for testing the reliability of findings, including autocorrelation tests and normality tests.

2.2 Volatility Models

2.2.1 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Volatility persistence, in the sense that high (low) volatility in one period is likely to be high (low) in the next, is most well represented by the GARCH model. This is an important feature as it allows for the modelling of long-term trends and variations in inflation rates, which is necessary to understand the inflation volatility over time. The foundational model is the GARCH (1,1) as opined by Bollerslev (1986), which is expressed mathematically as

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (1)$$

where σ_t^2 is the conditional variance, $\omega > 0$ is a constant, α (the ARCH term) captures the reaction to news (the impact of past squared shocks), and β (the GARCH term) captures volatility persistence. The sum $\alpha + \beta$ measures the overall persistence of volatility shocks, with values close to 1 indicating highly persistent volatility.

2.2.2 Asymmetric Generalized Autoregressive Conditional Heteroskedasticity (A-GARCH Model)

The A-GARCH model is one of the extensions of the conventional GARCH model, which explicitly considers the asymmetry of the volatility response to shocks in time series data. In the data analysis, the statistical formula of the A-GARCH model contains a conditional variance equation, where the asymmetry parameter is added to account for asymmetrical reactions to market shocks. Below is the general conditional variance equation of the A-GARCH model

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} a_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (2)$$

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma(y_{t-1}^2 I_{t-1}) + \gamma|\epsilon_{t-1}|\delta \quad (3)$$

where ω is the constant term, βj are the GARCH coefficients, γ is the asymmetry parameter, which determines the impact of current volatility on future volatility. $|\epsilon_t|$ is the absolute value of the error term at time t, δ is the power of the absolute value term, controlling the degree of asymmetry in volatility responses.

The term $\gamma|\epsilon_{t-1}|\delta$ is added to the equation to make it asymmetric by giving different reactions to negative and positive shocks. Positive shocks ($\delta > 0$) exert a larger effect on future volatility than do negative shocks, and vice versa for negative shocks ($\delta < 0$).

2.2.3 Exponential Generalized Autoregressive Conditional Heteroskedasticity (E-GARCH Model)

The E-GARCH model is a very useful econometric model that can be applied to model and evaluate time series data when studying the volatility of inflation in Nigeria. This model covers the phenomenon of volatility clustering rather well, in which periods of moderate volatility are followed by low volatility, and times of high volatility are followed by high volatility. The ability of the E-GARCH model to capture asymmetries in the volatility response to both positive and negative shocks is one of its main advantages. This model recognizes that negative economic shocks, such as poor inflationary pressures, have a larger impact on the volatility of a country than positive shocks. This is especially applicable in the study of inflation volatility, where adverse economic events can result in greater uncertainty and volatility in the pricing of goods and services. The Exponential GARCH (EGARCH) by Nelson (1991) models the logarithm of the conditional variance, which naturally ensures σ_t^2 without parameter restrictions. Its standard form is:

$$ln(\sigma_t^2) = \omega + \beta ln(\sigma_{t-1}^2) + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \quad (4)$$

where σ_t^2 is the conditional variance at time t, $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is the lagged error term from the mean equation, ω is the constant term, α captures the magnitude effect (the impact of the size of the shock), γ captures the asymmetric (leverage) effect: If $\gamma < 0$, negative shocks increase volatility more than positive shocks of the same magnitude, and if $\gamma = 0$, the model reduces to a symmetric GARCH, β measures the persistence of volatility over time, and the term $\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|$ ensures that the model is always positive without parameter restrictions.

2.3 Model Evaluation

To evaluate and compare the performance of the GARCH, AGARCH, and EGARCH models, several metrics are utilized.

2.3.1 Akaike Information Criterion (AIC)

The measure of relative goodness of fit of a statistical model is the Akaike Information Criterion (AIC). According to Akaike (1974), he suggested measuring the goodness of fit for some particular model by balancing the error of the fit against the number of parameters in the model. It is defined as:

$$AIC = 2k - 2ln(L) \quad (5)$$

where k is the number of parameters in the statistical model, and L is the maximized value of the likelihood function for the estimated model. The AIC is applied in model selection, in which the model with the least AIC is selected as the best candidate model.

2.3.2 Bayesian Information Criterion (BIC)

This is also known as the Schwartz criterion.

$$BIC = \left[\frac{-2lnL + kln(n)}{n}\right] \quad (6)$$

Under the assumption that the model error is normally distributed

$$BIC = ln\left(\frac{RSS}{n}\right) + k\left(\frac{lnn}{n}\right) \quad (7)$$

It penalizes true parameters more strongly than the AIC.

2.3.3 Root Mean Square Error (RMSE)

To differentiate the best model after procedure of prediction, the RMSE is the most frequently used measure to draw conclusions about forecasting methods. The RMSE is calculated by squaring the individual errors and adding them together, divided by the number of individual errors and then square rooted. This gives a single number that summarizes the overall error. It is defined as;

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{X}_i - X_i)^2}{n}} \quad (8)$$

where $\left(\hat{X}_i - X_i\right)$ is the residuals, X_i and $\hat{X}_i$ are observed and predicted values respectively.

2.3.4 Log-Likelihood (Log L)

For a normally distributed error term, the log-likelihood function for an E-GARCH model is given by:

$$\ln L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2}\right] \quad (9)$$

where $\ln L(\theta)$ is a log-likelihood function, θ is a vector of model parameters, T is a number of observations, ε_t is residual/error term at time t, and σ_t^2 is a conditional variance from the E-GARCH model.

3. Results

3.1 Results from Exploratory Analysis

Table 1 presents a descriptive summary of the economic indicators considered in this study. The variability of MPR is found to be moderate with an average of 16.98 and standard deviation of 3.64. The standard deviation of inflation is 5.59, with a mean of 23.37, which implies a large variation in the level of inflation. The median inflation rate is 21.98, which means half of the observations are below 21.98, and the mode is 34.19, which indicates a peak observation. MPR and inflation rates have near-zero kurtosis values and are normally distributed, while price per USD has a positive kurtosis value, which is more peaked. The skewness values show that the MPR and inflation rates are moderately positively skewed, while the Price per USD has a stronger positive skew with a number of high outlier values. Price per USD has the highest dispersion (1085.53), meaning large differences in exchange rate values for this indicator compared to other indicators. The overall results indicate that there have been significant economic fluctuations over the period of study, and that attention is needed to these variables in economic policy and decision making.

Table 1. Descriptive Summary Table

	MPR	*Inflation rate*	*Price/USD*
Mean	16.98214286	23.37321429	642.7915714
Standard Error	0.687776949	1.05571499	60.32847998
Median	17.75	21.975	459.82925
Mode	18.75	34.19	1499.9375
Standard Deviation	3.639373529	5.58631864	319.22831
Sample Variance	13.24503968	31.20695595	101906.7139
Kurtosis	-0.001012361047	-0.3844615881	1.604815412
Skewness	0.2749213792	0.6529143433	1.536802481
Range	13.25	18.59	1085.5255
Minimum	11.5	15.6	414.412
Maximum	24.75	34.19	1499.9375

The exchange rate, monetary policy, and inflation rates are aggregated into months showing fluctuations over time, as shown in Figures 1 and 2. After a relatively stable period until mid-2023, the exchange rate sharply increased. It reaches its peak in late 2023 and has a notable decrease after that. The overall trend indicates that the price has been fluctuating and changing rapidly with some stable periods in between. The pattern of the inflation rate is relatively stable until mid-2023, when there is a significant jump in late 2023, with possibility of a future decline. The MPR slowly rise with its highest increase experienced around mid-2024.

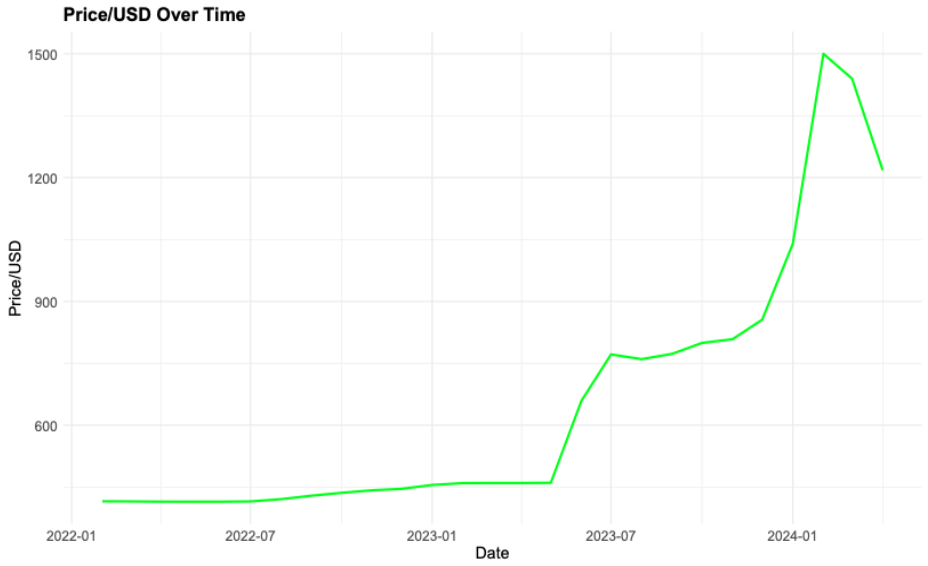

Figure 1. Time Plot of Exchange Rate (USD) Over Months

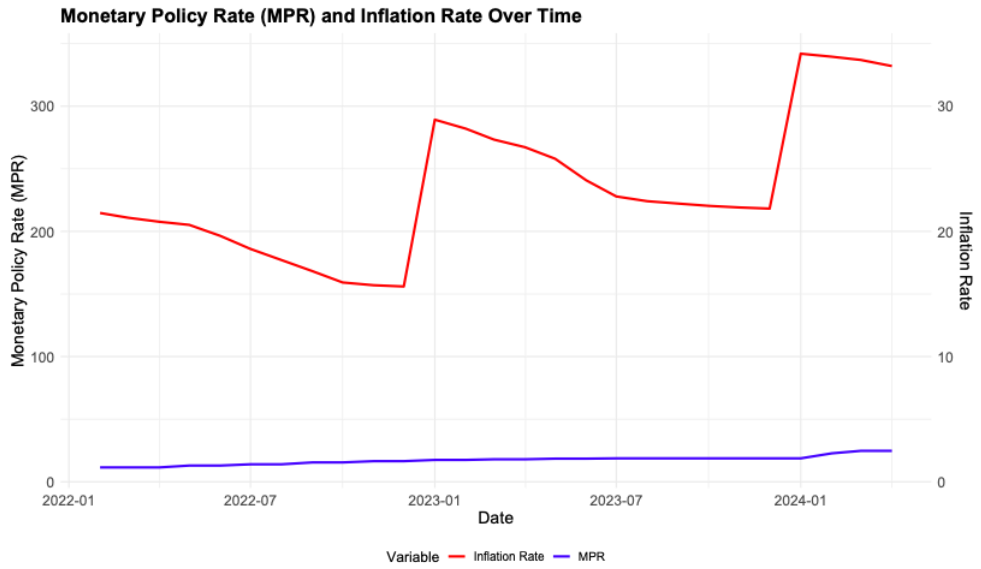

Figure 2. Time Plot of Monetary Policy and Inflation Rate

The correlation matrix displayed in Figure 3 shows that there are strong interrelationships among the indicators. MPR and Inflation Rate is moderately positively correlated (0.696), implying that a high MPR will bring about a corresponding high inflation rate, and vice-versa. The relationship between the exchange rate and MPR is positive and strong (0.835), and the relationship between the exchange rate and inflation rate is also positive and strong (0.711). This implies that the fluctuations in the MPR and inflation are strongly correlated with the fluctuations in the exchange rate, which has been observed, with higher MPR and inflation leading to a higher price of USD.

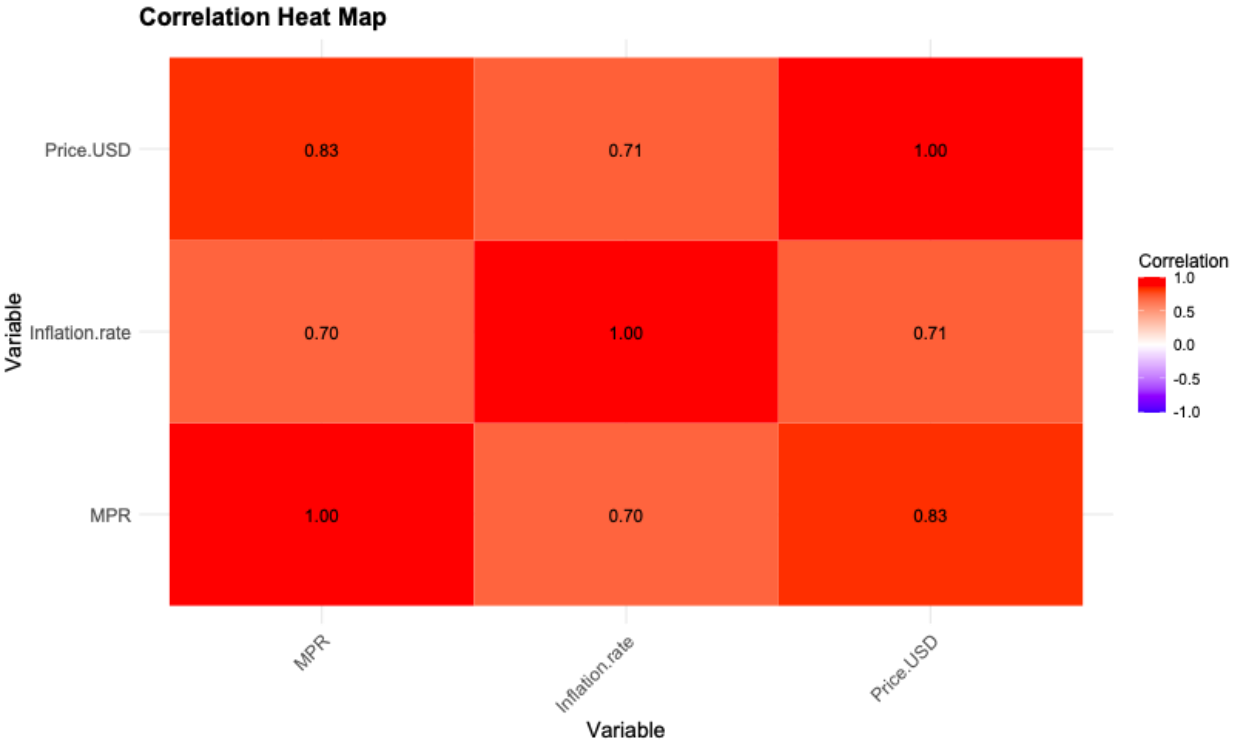

Figure 3. Correlation Heatmap

3.2 Volatility Model Results

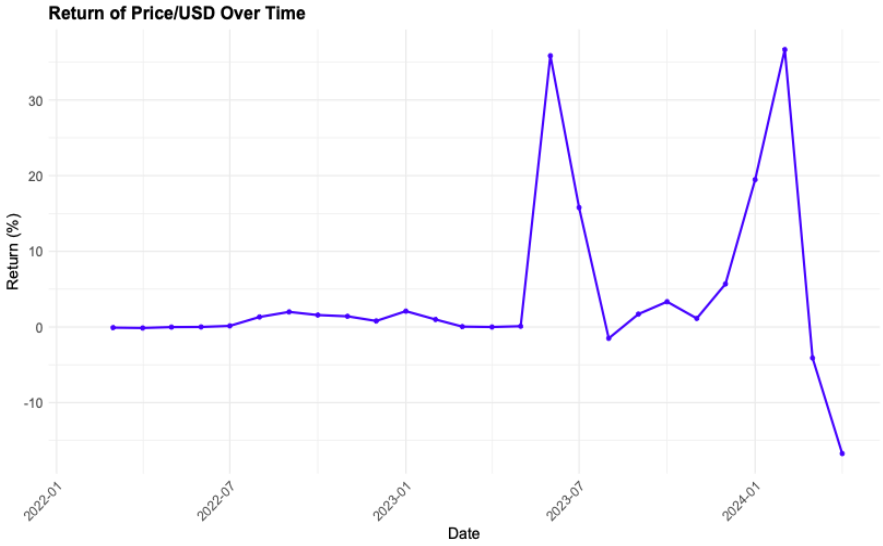

Figure 4. Trend for Returns of Exchange Rate (USD) Over Months

Figure 4 presents the fluctuation pattern of the USD returns over time. The chart highlights how volatile the market is and how difficult it could be for investors looking for steady profits. Notable spikes and reductions in returns are observed, with significant price fluctuations due to volatility as indicated by the period's numerous peaks and troughs, which implies that the market is generally unstable and that price reversals occur frequently. Even if there are times when returns are good, there are also times when they are negative, which indicates that the investment has a high level of risk.

Table 2 presents the parameter estimates of the GARCH, A-GARCH, and E-GARCH techniques used to model USD return volatility. The average USD return (μ) is insignificant in the GARCH model, whereas the A-GARCH and E-GARCH models show highly significant mean estimates. The α_1 parameter, which measures the effect of past shocks on current volatility, is only marginally significant in the GARCH model but highly significant and negative in both A-GARCH and E-GARCH models, suggesting stronger volatility responses to past shocks in the asymmetric models. Similarly, the β_1 parameter, which captures volatility persistence, is insignificant in the GARCH model but highly significant and positive in the A-GARCH and E-GARCH models, indicating strong persistence of volatility over time. The γ_1 parameter, representing leverage or asymmetry effects, is highly significant in both A-GARCH and E-GARCH models, confirming that positive and negative shocks affect Forex volatility differently. In addition, the shape parameter is statistically significant across all three models, indicating a leptokurtic distribution of returns and supporting the suitability of these models for capturing exchange rate volatility dynamics.

Overall, while the traditional GARCH model captures only the dynamics of the exchange rate volatility, the A-GARCH and E-GARCH models provide stronger evidence of volatility persistence, influence of past shocks on current volatility, and asymmetric effects in the exchange rate series.

Table 2. Volatility Parameters Estimates for GARCH, A-GARCH and E-GARCH Models

	GARCH			A-GARCH			E-GARCH		
	Estimate	$T-$ value	$P-$ value	Estimate	$T-$ value	$P-$ value	Estimate	$T-$ value	$P-$ value
Mu	0.0026	0.0835	0.9335	-0.0443	-3845.979	0.0000	-0.0412	-64.4820	0.0000
ar1	0.2515	1.0218	0.3069	-0.0710	-2.4745	0.0133	-0.0200	-0.2460	0.8057
Omega	0.0002	0.4416	0.6588	1.0522	2.0117	0.0443	0.6560	0.62592	0.5314
alpha1	0.9321	1.7019	0.0888	-7.4002	-4.5132	0.0000	-7.3583	-2.5390	0.0111
beta1	0.0669	0.5575	0.5772	1.0000	31.7784	0.0000	1.0000	7.06786	0.0000
gamma1				10.0000	5.2896	0.0000	10.0000	2.68325	0.0073
Shape	2.3144	7.2946	0.0000	2.1532	157.3889	0.0000	2.1092	141.8460	0.0000

Table 3 below provides the parameter estimates for the economic indicators included in the three models. The estimates of MPR are 0.001728, 0.0040, and 0.00379 with corresponding values of t ($P-$ values) of 1.62036 (0.105155), 7771.3150 (0.0000), and 113.0285 (0.0000) respectively for GARCH, A-GARCH and E-GARCH models. These estimates imply that only GARCH model is not significant for the MPR estimates, though provides a positive effect on volatility, unlike the other models, which their positive changes in the MPR, strongly influences the volatility of returns in the Forex market. The Inflation Rate was estimated at -0.00115, -0.0004, and -0.0003 respectively with corresponding values of t ($P-$ values) of -0.83597 (0.403174), -312.9082 (0.0000), and -4.4925 (0.0000). As in the case of MPR, GARCH model also failed to provide a significant estimate for the IR, while the other two models provide significantly negative impacts on the volatility of the exchange rate returns. Thus, the A-GARCH and E-GARCH models revealed a more pronounced impact with both the MPR and IR. The MPR exhibits a highly significant positive relationship with volatility, indicating that increases in the MPR are strongly associated with increased market volatility. On the other hand, the inflation rate shows a significant negative impact on volatility which suggests that higher inflation rates are associated with reduced volatility, reflecting a distinct interaction compared to the non-significant weak findings exhibited by GARCH model.

Table 3. Economic Indicators' Parameter Estimates for GARCH, A-GARCH and E-GARCH Models

Indicator	GARCH			A-GARCH			E-GARCH		
	Estimate	$T-$ value	$P-$ value	Estimate	$T-$ value	$P-$ value	Estimate	$T-$ value	$P-$ value
MPR	0.001728	1.62036	0.10516	0.0040	7771.3150	0.0000	0.00379	113.0285	0.0000
Inflation Rate	-0.00115	-0.83597	0.40317	-0.0004	-312.9082	0.0000	-0.0003	-4.4925	0.0000

Table 4 compares the performance of the three models using AIC, BIC, log-likelihood, and RMSE. The A-GARCH model records the lowest AIC (-3.5734) and BIC (-3.1414), indicating the best balance between model fit and parsimony among the three models. However, its log-likelihood (-0.7292) is the lowest, suggesting a weaker likelihood-based fit relative to the alternatives. In contrast, the E-GARCH model achieves the highest log-likelihood (52.8441), indicating the strongest statistical fit to the data, although its AIC (-3.3726) and BIC (-2.9371) are higher than those of A-GARCH. The RMSE for the three models was estimated at an approximated value of 0.1, which implies that all the models have the potential of correctly predicting the volatility of the forex returns. Thus, the A-GARCH model was considered the best based on its high level of significance in estimating the predictors' effects on forex volatility returns, its parsimonious use of information, its goodness of fit, and its perceived

forecast accuracy. Furthermore, the model is selected because it gives the best AIC/BIC and captures asymmetric volatility effects, while GARCH gives slightly better RMSE.

Table 4. Evaluation Metric Table of all models

	AIC	BIC	LogL	RMSE
GARCH	-3.0937	-2.7097	49.7649	0.1080
A-GARCH	-3.5734	-3.1414	-0.7292	0.1126
E-GARCH	-3.3726	-2.9371	52.8441	0.1130

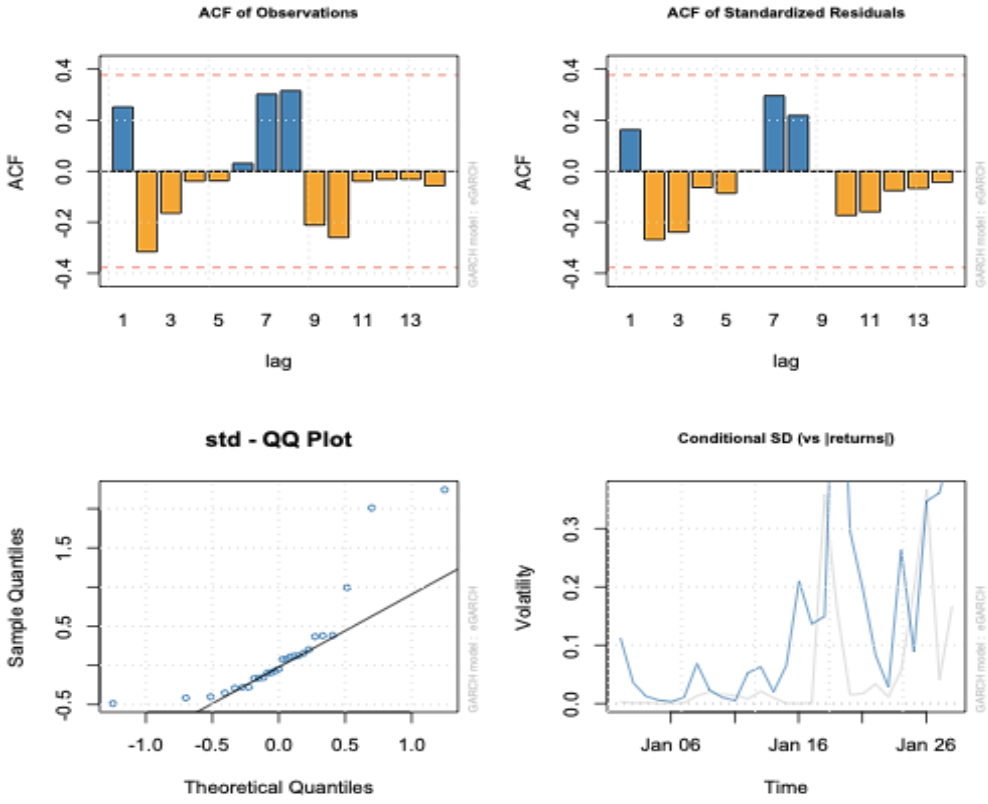

Figure 5. A-GARCH Model Diagnostic Plot

Figure 5 explores the behavior of the residuals for the chosen model, A-GARCH, by providing evidence on the adequacy of the research model in capturing the volatility dynamics of the USD returns in exchange for the local currency. The first ACF plot suggests that the model adequately captured the linear dependence structure in the return series, because the plot shows a significant autocorrelation at lag 1, with most of the autocorrelation bars lying within the confidence bounds, indicating that the residuals are largely uncorrelated. The second ACF plot assesses the remaining ARCH effects using the squared standardized residuals. It reflects that the majority of the spikes remain within the confidence limits, implying that the model successfully captures most of the volatility clustering in the data. The Q-Q plot compares the distribution of the standardized residuals with the theoretical normal distribution, implying that the residuals are approximately normally distributed occasioned by some tail departures, suggesting the presence of mild leptokurtic observations, which is common in financial return data. The last plot displays the estimated conditional volatility over time. The volatility series exhibits clear

clustering, with periods of high volatility followed by regimes of relative stability. Overall, the A-GARCH model effectively captures the expected fluctuations and asymmetric responses to shocks.

Table 5 presents the forecasted returns for the A-GARCH model for the full months of year 2024. The model gives a constant forecast across all periods with an approximated value of -0.00096745, while the forecast standard error also remains constant at 1.061784, indicating that the expected returns stabilize around a constant mean declining returns of -0.00096745, which is economically close to zero. The constant value of standard error suggests a relatively stable volatility for the forecast periods, implying that the conditional volatility process of the A-GARCH model converges to its long-run equilibrium variance.

The volatility forecasts of the A-GARCH model are computed recursively with the empirical model derived as:

$$h_t = 1.0522 - 7.4002\varepsilon_{t-1}^2 + 10.0000I_{t-1}\varepsilon_{t-1}^2 + 1.0000h_{t-1} \quad (10)$$

where h_t represents the conditional variance.

It is pertinent to note that the constant forecast returns enunciates that past information has been well absorbed into current exchange rates, as already established in the results of α_1 parameter presented in Table 2 for the A-GARCH model. These forecasts also informed that no extreme volatility escalation should be anticipated during the periods, thereby suggesting a forex market transitioning toward a relatively stable regime, as a result of the estimated stable variance level. These constant forecasts and standard error are consistent with properties already established by the family of GARCH models [See the works of Bollerslev (1986); Engle and Bollerslev (1993); Chalissery et al. (2022)], where Bollerslev established that conditional variances in GARCH processes are mean reverting and converge toward long-run equilibrium. This was extended by Engle and Bollerslev that the influence of existing volatility shocks gradually decays over the forecast horizon, leading to a stable long-run forecasts. More so, Chalissery emphasized the effectiveness of A-GARCH model for volatility forecasting due to its ability to capture volatility clustering, leverage effects, and long-run variance convergence. Furthermore, the significance of α, β, and γ parameters indicate that the model successfully captures how past shocks and asymmetric responses influence current volatility. In particular, the significant leverage parameter confirms that positive and negative shocks affect Forex volatility differently, making the model more realistic than the traditional symmetric GARCH model.

Table 5. Forecast values for the complete Year 2024

Period	Forecasted Returns	Standard Error
1	-0.0009674502	1.061784
2	-0.0009674502	1.061784
3	-0.0009674502	1.061784
4	-0.0009674502	1.061784
5	-0.0009674502	1.061784
6	-0.0009674502	1.061784
7	-0.0009674502	1.061784
8	-0.0009674502	1.061784
9	-0.0009674502	1.061784
10	-0.0009674502	1.061784
11	-0.0009674502	1.061784

12	-0.0009674502	1.06178

4. Conclusion

Exchange rate volatility remains a fundamental issue for achieving macroeconomic stability, particularly in developing economies like Nigeria, where fluctuations in the USD exchange rate have widespread economic implications. This study examined the relationship between USD exchange market volatility and key economic indicators of MPR and IR in Nigeria from January 2022 to April 2024. The study provides a robust analysis of volatility dynamics and predictive modeling using the established volatility models of GARCH, E-GARCH, and A-GARCH, estimated through the Maximum Likelihood (ML) technique. With considerable negative impacts exhibited by the IR and the strong positive impacts exhibited by the MPR in the GARCH framework, recent trends show that both economic indicators are highly significant and have occasioned a causal effect on the volatility of USD exchange rates, based on the results of both A-GARCH and E-GARCH. A positive and significant association between MPR and volatility suggests that higher monetary policy rates contribute to increased forex market fluctuations, reflecting heightened market reactions to changes in Central Bank policies. Conversely, IR exhibited a negative relationship with volatility, implying that higher inflation is linked to reduced fluctuations, possibly due to market adjustments and expectations aligning with inflationary trends. This demonstrates how intricately economic indicators and forex market behavior are related, underscoring the need for traders and policymakers to take these dynamics into account when making choices.

The significance of the estimated parameters observed in the A-GARCH and E-GARCH models is consistent with earlier findings that volatility in emerging forex markets tends to subsist for long periods. This persistence is often attributed to structural weaknesses such as policy uncertainty, lower market depth, dependence on foreign capital, vulnerability to external shocks, etc. Once volatility increases, it tends to remain high because investors continuously adjust expectations in response to economic uncertainty. In emerging markets, negative news such as rising inflation, currency shortages, declining foreign reserves, or political instability often triggers stronger market reactions than positive developments. Investors and speculators typically respond more aggressively to adverse shocks because these economies are perceived as riskier and more sensitive to uncertainty. Consequently, exchange rate depreciation or unfavorable monetary conditions have been established to produce disproportionately large increases in volatility (Ayodeji, 2025).

The evaluation of model performance using criteria such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Log-Likelihood, and Root Mean Square Error (RMSE) revealed that while A-GARCH performed best in terms of information criteria, it shared a common feature of providing best predictive accuracy based on RMSE, with other GARCH models.

The monthly forecasts for the year 2024, using the A-GARCH model, revealed a constant return, with no significant variations in volatility. This implies the forecasted returns remained stable throughout the year without any significant changes or fluctuations. This stable outlook suggests that while the forex market remains volatile, external shocks or unexpected macroeconomic changes would be required to disrupt the observed pattern. Furthermore, the constant forecasted variance posits that long-run forecasts eventually converge to a constant (stable) variance level, occasioned by the equilibrium structure of the A-GARCH model. This is useful for risk management, policy analysis, and portfolio decisions because it provides an estimate of the expected long-run volatility level.

Based on the findings, this research highlights the complex interaction between MPR, IR, and EXR volatility in Nigeria, offering valuable insights for economists, financial analysts, and policymakers. The research pattern of volatility and forecast outputs will provide useful insights in the

areas of risk management techniques as suggested by Liu et al. (2020), Zhao (2022), and Pellegrino et al. (2024), among others.

This research has exposed the needs for enhanced monitoring and periodic analyses of key economic indicators of MPR and IR given their established correlations with the volatility of the EXR. Future research could extend this research by incorporating additional macroeconomic factors such as foreign direct investment, trade balance, and external reserves to substantiate this research or provide additional understanding of exchange rate dynamics.

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