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Modelling the Volatility of Banks Interest Rate Returns in Nigeria: A Comparison of the Efficacy of Different GARCH Models

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Abstract: This study examines the modelling of volatility in Nigeria's interest rate returns, comparing various GARCH models. The data used in the study were extracted from the Central Bank of Nigeria's (CBN) online statistical database on deposit bank interest rates. Both first- and second-order GARCH models were fitted to the data using EViews version 10. The results indicated that the second-order TGARCH (2,2) model provided the best fit for the data. Model selection was based on the Akaike Information Criterion (AIC), and model diagnostics were conducted using the ARCH effect test, QQ-plot, and serial correlation test to ensure robustness. The study's findings revealed a higher probability of gains than losses for individuals who obtained loans from banks during the study period. However, the variables analysed in this study exhibited extreme volatility, which suggests that users of interest rates were exposed to considerable risks. This means that bankers, customers of deposit money banks, and investors should expect rewards for holding such a risky asset. It was concluded that ARCH-GARCH models not only estimate expected returns on interest rates but also assess investors' reactions to risk, as revealed in the leverage effects captured in the second-order TGARCH (2,2) model, which was provided as the best fit for the data. Based on these findings, the study recommends further investigation into the volatility of interest rates.

Keywords: Interest Rate; Central Bank of Nigeria's (CBN); Akaike Information Criterion (AIC); Extreme Volatility; Leverage Effects; Decision-Making; ARCH-GARCH; Financial Stability; Risk Management.

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1. Introduction

Fluctuations in interest rate returns in the banking sector are a critical factor in determining financial stability, as they impact a bank's ability to manage risks, set appropriate interest rates, and adapt to economic fluctuations. The volatility of interest rate returns plays a crucial role in shaping the financial landscape of any economy, and this is especially true for banking sectors in emerging markets such as Nigeria. As the global financial environment becomes increasingly interconnected, the volatility of interest rates has the potential to create both risks and opportunities for banks, making the accurate modelling of this volatility

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essential for effective risk management, policy formulation, and investment decision-making. In Nigeria, where banks operate in a complex environment characterised by volatile exchange rates, inflationary pressures, and cyclical regulatory reforms, accurately modelling interest rate volatility is crucial for understanding market behaviour and mitigating potential risks [9]. However, despite the growing importance of understanding interest rate dynamics, the existing literature on modelling volatility of bank interest rate returns in Nigeria remains limited and often inadequately addressed. Many studies to date have focused on stock market volatility or broad macroeconomic variables, leaving a significant gap in exploring how volatility in interest rate returns specifically affects banks in Nigeria. Financial systems face unique challenges, such as inflation, interest rate volatility, and regulatory uncertainty. Furthermore, few of these numerous studies have examined interest rate volatility at the global level, and there is a notable gap in research that focuses specifically on the Nigerian banking sector. Existing studies often focus on stock market volatility, exchange rates, or general macroeconomic factors, but do not explore how fluctuations in interest rate yields specifically affect Nigerian banks. Furthermore, many studies that attempt to model financial volatility in Nigeria primarily rely on first-order GARCH models and traditional methods, which may not capture the dynamic and nonlinear nature of interest rate volatility in emerging markets like Nigeria.

The family of generalised autoregressive conditional heteroskedasticity (GARCH) models has gained popularity in financial econometrics for its ability to model time-varying volatilities in financial data [12]. However, despite its widespread use, there is limited empirical evidence on which variant of the GARCH model best captures the volatility of Nigerian banks' interest rate returns. Most studies applying GARCH models in the Nigerian context tend to focus on other financial variables, such as crude oil prices, stock prices, or exchange rates, leaving a large gap in understanding the performance of these models when applied to interest rate data [13]. Furthermore, the choice of GARCH model – whether standard GARCH, exponential GARCH (EGARCH), or first- and second-order threshold GARCH (TGARCH) – has not been rigorously compared in the context of Nigerian bank interest rates, limiting the ability of financial analysts to choose the most appropriate instrument to forecast fluctuations in this sector [1]. This study aims to fill this gap by systematically comparing the effectiveness of different GARCH models in modelling the volatility of Nigerian banks' interest rate returns [8]. By evaluating models such as standard first- and second-order GARCH, EGARCH, and TGARCH, the research will identify the approach that provides the most accurate and reliable forecasts of interest rate volatility, thereby providing valuable insights into the risk management strategies of Nigerian banks. The specific objectives of the study are to analyse the dynamics of Nigerian banks' interest rate volatility, compare the forecasting performance of different GARCH models, and recommend the most effective model for use in this context. The significance of this research lies in its potential to improve the accuracy of financial forecasts and enhance decision-making within the Nigerian banking sector. By providing a better understanding of interest rate volatility, the study will support the formulation of more robust risk management strategies, ultimately contributing to the stability and growth of the Nigerian financial system.

2. Methodology

2.1. Model Specification

Modelling involves identifying the key features of the real-world economy and making appropriate simplifications or assumptions to effectively capture those features. Model specification in statistical modelling is the process of selecting and defining the structure of the statistical model that will be used to analyse data [15]. Thus, the structural formulation of the model used in this study is derived as follows: suppose we let be the log return of an interest rate at time index t.

$$\mathrm{RITRT} = \mathrm{Log}\left(\frac{\mathrm{Interest_t}}{\mathrm{Interest_{t-1}}}\right)\mathrm{x}100$$

Where $\mathrm{Interest_t}$ is the interest rate at present (t) and $\mathrm{Interest_{t-1}}$ is the interest rate at the previous time $(\mathrm{t}-1)$, and in the volatility study $\mathrm{r_t}$ is either taken as serially uncorrelated or with minor lower-order serial correlations, but it is a dependent series. The conditional mean and variance of $\mathrm{r_t}$ given the information set available at the time $\mathrm{t_{t-1}}$ as $\mathrm{I_{t-1}}$ are specified as thus:

$$\mu_t = \mathrm{E}(\mathrm{r_t}/\mathrm{I_{t-1}})$$

$$\sigma^2 = \mathrm{Var}(\mathrm{r_t}/\mathrm{I_{t-1}}) = \mathrm{E}[(\mathrm{r_t}-\mu_t)^2/\mathrm{I_{t-1}}]$$

Since the serial dependence is weak, we can say that it follows a simple time series model, such as a stationary ARMA (p, q) model. The model becomes:

$$\mathrm{r_t} = \mu_t + \mathrm{e_t}$$

$\mu_t = c + \sum_{i=1}^{p} \varphi_i r_{t-1} - \sum_{i=1}^{q} \theta_i e_{t-1}$

Where p and q are non-negative integers and et are innovations or error terms. This is the mean equation for. The order (p, where p and q are non-negative integers and et are innovations or error terms, $e_t \sim N(0, \sigma_t^2)$. This is the mean equation for r_t. The order (p, q) of an ARMA model may depend on the frequency of the return series. The variance can be specified as:

$\sigma_t^2 = Var(r_t/I_{t-1}) = Var(e_t/I_{t-1})$

2.2. ARCH Model

One of the key assumptions underlying least squares regression is homoscedasticity, which means that the variance of errors remains constant across all observations. However, when this assumption is violated, while the estimates remain unbiased, they no longer yield the minimum variance estimates. This results in misleadingly narrow standard errors and confidence intervals, creating a false sense of precision. To address this issue, ARCH and related models step in by explicitly modelling the volatility within the framework itself, thus correcting the limitations of the least squares approach. The ARCH models, as introduced by Engle [10] and further developed by Tsay [11], consist of both mean and volatility equations, and are formulated as follows:

$r_t = \mu_t + e_t e_t = \sigma_t \in_t, , \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2$

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \in_t, t = p + 1, \ldots\ldots\ldots, T$

where e_t denotes the error term, and T is the sample size. This is called the ARCH (p) model. The next step is to check the ARCH effects by using the residuals of the mean equation. For us to do that, we apply the usual Ljung-Box statistics Q(p) to the $\{e_t^2\}$ series or apply white's test of significance of $\alpha_i = 0 (i = 1, \ldots\ldots, P)$ by F-statistic under the null hypothesis given as Ho : α1 = ... = αp = 0.This F-statistic is distributed as χ2 distribution. If ARCH effects are found to be significant, we can use the PACF of e_t^2 to determine the ARCH order. After specifying the volatility model, we jointly estimate the mean and volatility models. Lastly, we evaluate the fitted model and refine it further. The standardised residuals $\hat{e}_t = \frac{e_t}{\sigma}$ can be seen to check the adequacy of a fitted ARCH model. We can evaluate the QQ plots of $\hat{e}_t$ and e_t^2 to check the validity of the mean and variance equations, respectively. After determining the model's parameters, predictions can be made.

2.3. GARCH Model

Bollerslev [12] proposed a useful extension to the ARCH model, otherwise referred to as the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model. Bollerslev [12] and Tsay [11] respectively opined that the e_t obtained follows a GARCH (p, q) model, given that;

$e_t = \sigma_t \in_t; \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum \beta_j \sigma_{t-1}^2$

In addition to ARCH conditions, we also have βj ≥0, and $\sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_j) < 1$. The restriction on $\alpha_i + \beta_j$ implies that the unconditional variance of e_t is finite, whereas its conditional variance σ_t^2 evolves. The α_i and β_j are ARCH and GARCH parameters, respectively. Like ARCH models, GARCH models also exhibit volatility clustering, a leverage effect, and heavier tails. Specifying the order of a GARCH model is not straightforward, and most applications use only lower-order GARCH models. Two types of GARCH were considered under the symmetric GARCH framework, based on their error distribution assumption, and they include GARCH. The GARCH (p, q) model in its generalised form is written as: thus:

$\sigma_t^2 = w + \sum_{t=1}^{q} \alpha_i \quad \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$

Such that P is the order of the GARCH terms, σ^2 and q is the order of the ARCH term ε_{t-1}^2 where, α_i and β_j>.0; $\sigma_t{}^2$ is the conditional variance and ε_t disturbance term, the reduced form of the equation, i.e., GARCH(1,1), is given as thus:

$\sigma_t^2 = w + \alpha_i \varepsilon_t^2 + \beta_j \sigma_{t-1}^2$

Where w, α, and β_jd are non-negative parameters to be estimated, and $\alpha + \beta < 1$ to be stationary.

Tsay [11] emphasised that the primary purpose of an asymmetric GARCH model is to address the shortcomings found in symmetric GARCH models. These shortcomings include the inability of symmetric models to capture the leverage effect, the differential impact of good and bad news, and long memory. To overcome these limitations, this study considers two types of asymmetric GARCH models: the EGARCH and TGARCH models. The Exponential GARCH (EGARCH) model can be specified generally as follows:

$$\text{Log}\,(\sigma_t^2) = \beta_0 + \sum_{1=1}^{q} \left\{ \alpha i \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right| + \gamma_{i} \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right|_i \right\} + \sum_{j}^{p} \beta; \log\left(\sigma_{t-j}^2\right)$$

The reduced form of the generalised EGARCH will be stated as thus:

$$\text{Log}\,(\sigma_t^2) = \beta_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right| + \gamma_i \frac{\varepsilon_{t-1}}{\sigma_{t-1}^{\;2}} + \beta_1 \log\left(\sigma_{t-1}^{\;2}\right)$$

Where $\alpha_{1;}\, \gamma_i \geq_0 \varepsilon_{t-1} >_0$ and $\varepsilon_{t-1} > 0$ and $\varepsilon_{t-1} < 0$ simply good news and bad news, whereas the total effects are given as $(1 + \gamma_i)$ $|\varepsilon_{t-1}|$and $(1\text{-}\gamma_i)|\varepsilon_{t-1}|$ respectively. $\gamma_i < 0$ is the expectation when bad news has a higher impact on volatility. Similarly, the EGARCH model usually has variance stationarity when $\sum_{j=1}^{p} \beta, < 1$, and then the null hypothesis will be rejected. When $\gamma_i = 0$, it shows the presence of the leverage effect. According to Atoi [6], this means that bad news has a stronger effect on good news than the volatility of interest rate return. The threshold GARCH (TGARCH) model; this is generally specified as TGARCH (p,q):

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i\ \varepsilon_{t-1}^2 + \sum_{i=1}^{q} y_i\, I_{t-i}\ \varepsilon_{t-1}^2 + \sum_{j=1}^{\rho} \beta_j \sigma_{t-j}^{e}$$

Where $I_{t-1} = 1$ if $\varepsilon_{t-1}^2 < 0$ and O otherwise $\varepsilon_{t-1}^2 > 0$ Implies good news where $\varepsilon_{t-1}^2 < 0$ bad news, and according to Atoi [6], there exist two shocks of equal size with differential effects on the conditional variance. He further opined that bad news increases volatility when $I_i > 0$, which means the existence of the leverage effect in the jth order; and when Ii > 0, the news impact is asymmetric.

2.4. Source of Data

This study utilises the monthly interest rate for Nigeria, sourced from and extracted from the Central Bank of Nigeria's online website (www.cbn.ng). The variable was the interest rate, and it covered the period from July 1997 to July 2024. The data were analysed with the aid of STATA and EViews software, version 10.

2.5. Model Estimation Technique/Procedure

The procedure for estimating the GARCH model in this study follows a structured econometric analysis approach, starting with a detailed examination of the time series data. The first step involves assessing the behaviour of the data through visual inspection with a time series plot, which helps identify trends, patterns, and irregularities in the data over the specified time period. This is followed by the estimation of an ARMA (Autoregressive Moving Average) model, where the residuals are extracted from an ordinary least squares (OLS) regression to evaluate the conditional mean and variance. The ARMA model is represented as a dynamic equation that captures the relationship between past values and errors. Once the ARMA model is established, the next phase of the analysis focuses on volatility clustering, which is a common feature in financial time series. This is assessed by transforming the residuals obtained from the ARMA model and plotting them to identify periods of high and low volatility. The presence of volatility clustering helps in understanding how volatility persists over time and justifies the use of GARCH-type models for further analysis.

Subsequently, a Normality Test is performed to examine whether the residuals follow a normal distribution. The Jarque-Bera test, which is based on skewness and kurtosis, is used to test for deviations from normality. If the normality test fails, indicating that the residuals are not normally distributed, the study follows the recommendation by Kwiatkowski et al. [4] to use GARCH models with alternative error distributions to better capture the non-normal characteristics of the data. The presence of heteroskedasticity, a condition where the variance of the residuals changes over time, is then tested using the ARCH effects test. Engle [10] LaGrange Multiplier (LM) test is applied, where the squared residuals from the ARMA model are regressed on their own lags. The test statistic, based on the number of observations multiplied by the R-squared value ($n \times R^2$), is compared to a Chi-square distribution with q degrees of freedom. A significant result ($n*R^2 >$ Chi-square) would indicate the presence of ARCH effects, confirming that the data exhibit time-varying volatility—a key feature that GARCH models are designed to capture. After verifying the presence of ARCH effects, the study proceeds to estimate the parameters of the GARCH model.

This includes symmetric models, such as the GARCH (p, q) model developed by Bollerslev [12], which captures the relationship between past squared errors and conditional variance.

The study also explores asymmetric models, such as the EGARCH (Exponential GARCH) model by Epaphra [8] and the TGARCH (Threshold GARCH) model by Fleming and Klagge [9], both of which are designed to account for asymmetric volatility reactions to good and bad news, as well as leverage effects. Model selection is performed using the Akaike Information Criterion (AIC), a method commonly employed to compare the fit of competing models. These criteria help identify the most appropriate model by penalising models for complexity, with the AIC being defined as -2 times the log-likelihood function plus 2 times the number of parameters. The SIC, which imposes a heavier penalty for additional parameters, is also considered, following the suggestion of Ehrmann and Fratzscher [7], who recommend using SIC to avoid overfitting and to select a more parsimonious model. Through these steps, the study ensures a comprehensive procedure for estimating and selecting the most appropriate GARCH model to analyse the volatility of Nigeria's interest rate returns, considering key econometric tests and model selection criteria.

3. Results

Figure 1 shows the raw interest rate data plotted against years (in months) from 1990 to 2025. The graph illustrates that interest rates have fluctuated significantly over time, with notable peaks in 1995 and 2022. Between 2008 and 2015, there was a dramatic decline, followed by an improvement. The rate reached its lowest point around 2020 and then rebounded.

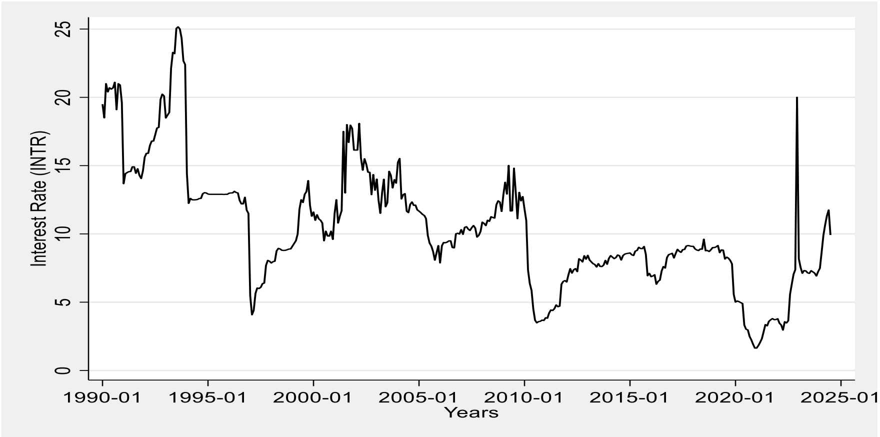


Figure 1: Raw interest rate data plotted against years (months)

Figure 2 illustrates the returns on interest rate data over the same period, demonstrating how the rates fluctuate and their associated volatility. The graph shows abrupt rises and falls, indicating that there were periods of significant change.

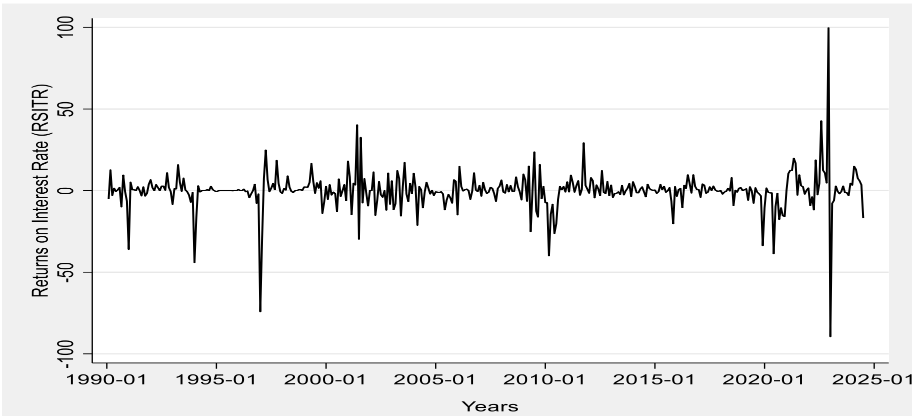


Figure 2: Returns on interest rate data plotted against years (months)

Around 2022, there are significant gains and losses, which align with major market changes. The returns plot illustrates how interest rates fluctuate over time in a dynamic and unstable manner.

Table 1 presents the descriptive statistics for interest rate returns, indicating a negative mean (-0.000376) and skewness (-0.945294), which suggests left-skewed data with elevated kurtosis (10.8268). The Jarque-Bera (JB) value of 648.33 and the p-value of 0.000 indicate that the data is not normally distributed.

Table 1: Summary descriptive statistics for interest rate return

Mean	Median	Min	Max	StdD.	Skewnes	Kurtosis	JB	P-value
-0.000376	0.002331	-0.731762	0.446647	0.116447	-0.945294	10.8268	648.3318	0.000

The normality plot in Figure 3 indicates that the distribution is leptokurtic, meaning that most values are close to the mean, while a few are far away from it.

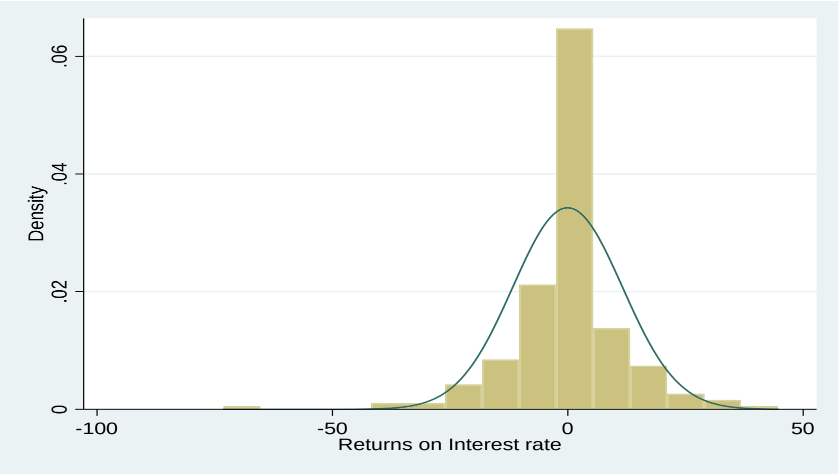


Figure 3: Normality plot of the returns on interest rate

The ARMA Model as obtained from the linear regression model in equation (3.1), we have;

$$\text{Interate} = \underset{(0.060)}{0.205448} + \underset{(0.000)}{0.965\,02}\text{Interate}_{t-1} + \mu_t$$

3.1. Test for Heteroskedasticity (ARCH Effect)

Table 2: Testing for the presence of an ARCH effect

Estimator	Lag 1
F-statistic	61.139
Prob F (1,237)	0.0003
$n*R^2$	49.012
$X^2(1,1)$	0.00

Source: *Researcher's Computations,2024*

3.2. Different Estimated GARCH Models

3.2.1. ARCH (1,1)

$\hat{\mu}$ = -0.5125,

$\sigma_t = 58.2190 + 0.9549\hat{\mu}_{t-1}^2$

p value $= (0.000)\ \ (0.000)$

AIC=7.5527

3.2.2. ARCH (2,2)

$\hat{\mu} = -0.58519,$

$\sigma_t = 50.977 + 0.705\hat{\mu}_{t-1}^2 + 0.1799\hat{\mu}_{t-2}^2$

p value = (0.000) (0.00 0) (0.0586)

AIC=7.5277

3.2.3. GARCH (1, 1)

$\hat{\mu} =$ -0.3275- $0.1434\hat{\mu}_{t-1}^2$

$\hat{\sigma}_t^2 = 9.9253 + 0.26094\hat{\mu}_{t-1}^2 + 0.7028\sigma_{t-1}^2$

p value = (0.000) (0.000) (0.000)

AIC= 7.5102

3.2.4. GARCH (2,2)

$\hat{\mu} =$ -0.3213 - $0.0627\hat{\mu}_{t-1}^2$

$\hat{\sigma}_t^2 = 1.672 + 0.6793\hat{\mu}_{t-1}^2$-$0.6286\hat{\mu}_{t-2}^2 + 1.0912\sigma_{t-1}^2 - 0.1413\sigma_{t-2}^2$

p value = (0.0169) (0.000) (0.000) (0.000) (0.1853)

AIC= 7.4687

3.2.5. EGARCH (1,1)

$\hat{\mu} =$ -0.3093 - $0.14759\hat{\mu}_{t-1}^2$

Log (σ_t^2) $= 0.1996 + 0.3004 \left|\frac{\mu_{t-1}^2}{\sigma_{t-1}^2}\right| - 0.1228 \left|\frac{\mu_{t-1}^2}{\sigma_{t-1}^2}\right| + 0.94144 \log\left(\sigma_{t-1}^2\right)$

p value = (0.1219) (0.5563) (0.0001) (0.000),

AIC= 7.477558

3.2.6. EGARCH (2,2)

$\hat{\mu} =$ -0.3845 - $0.1748\hat{\mu}_{t-1}^2$

Log (σ_t) =$2.1315 + 0.9032 \left|\frac{\mu_{t-1}^2}{\sigma_{t-1}^2}\right| + 0.4873 \left|\frac{\mu_{t-1}^2}{\sigma_{t-2}^2}\right| + 0.3209 \left|\frac{\mu_{t-2}^2}{\sigma_{t-2}^2}\right| - 0.2364 \log(\sigma_{t-1}^2) + 0.5473 \log(\sigma_{t-2}^2)$

p value =, (0.5563) (0.000) (0.0001) (0.000) (0.4238) (0.000)

3.2.7. TGARCH (1,1)

When p = 1 and q = 1, the GJR-GARCH (p,q) model is written as follows:

$\hat{\mu} =$ -0.2876 -$0.2127\hat{\mu}_{t-1}$

$\sigma_t^2 =$ -0.2876 $+ 0.0351\varepsilon_{t-1}^2 + 0.2378\sigma_t^2 + 0.8024 I_{t-1}\varepsilon_{t-1}^2$

p value $= (0.1219), (\ 0.5563), (0.000), (0.0001),$

$$I_{t-1} = \begin{cases} 1 \text{ when } \varepsilon_{t-1} < 0 \\ 0 \text{ when } \varepsilon_{t-1} \geq 0 \end{cases}$$

AIC=7.4783

3.2.8. TGARCH (2,2)

$\hat{\mu} = 0.7040$ -0.0197$\hat{\mu}_{t-1}$

$\sigma_t^2 = 3.5986 + 0.3519\varepsilon_{t-1}^2 - 0.0301 I_{t-1}\varepsilon_{t-1}^2-0.4905\varepsilon_{t-2}^2 + 0.3922 I_{t-1}\varepsilon_{t-2}^2 + 0.9157\sigma_{t-1}^2 + 0.00193\sigma_{t-2}^2$

p value $= (0.1219), (\ 0.5563), (0.000), (0.0001), (0.000), (0.4238), (0.000), (0.000), (0.0000), (0.8163)$

$$I_{t-1} = \begin{cases} 1 \text{ when } \varepsilon_{t-1} < 0 \\ 0 \text{ when } \varepsilon_{t-1} \geq 0 \end{cases}$$

AIC=7.290230

Table 3 shows the model fitness and selection outcomes for several ARCH, GARCH, EGARCH, and TGARCH models based on their AIC values. The TGARCH (2,2) model had the lowest AIC value of 7.290 among all the models tested. This indicates that the TGARCH (2,2) model is the most suitable for interest rate returns.

Table 3: Model fitness and selection

MODEL	AIC	Least AIC
ARCH (1,1)	7.553	
ARCH (2,2)	7.528	
GARCH (1,1)	7.510	
GARCH (2,2)	7.469	
EGARCH (1,1)	7.478	
EGARCH (2,2)	7.415	
TGARCH (1,1)	7.478	
TGARCH (2,2)	7.290	**7.290**

Based on the minimum as well as the least Deebom et al. [14] information criterion, the best considered model was TGARCH (2,2) in the Generalised error distributional assumption, and this can be represented as follows:

TGARCH (2,2)

$\hat{\mu} = 0.7040$ -0.0197$\hat{\mu}_{t-1}$

$\sigma_t^2 = 3.5986 + 0.3519\varepsilon_{t-1}^2 - 0.0301 I_{t-1}\varepsilon_{t-1}^2-0.4905\varepsilon_{t-2}^2 + 0.3922 I_{t-1}\varepsilon_{t-2}^2 + 0.9157\sigma_{t-1}^2 + 0.00193\sigma_{t-2}^2$

p value $= (0.1219), (\ 0.5563), (0.000), (0.0001), (0.000), (0.4238), (0.000), (0.000), (0.0000), (0.8163)$

$$I_{t-1} = \begin{cases} 1 \text{ when } \varepsilon_{t-1} < 0 \\ 0 \text{ when } \varepsilon_{t-1} \geq 0 \end{cases}$$

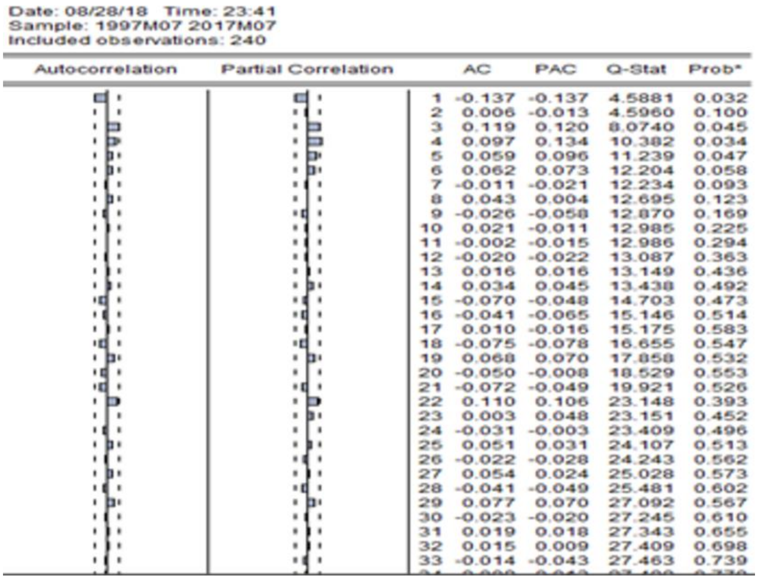
AIC=7.290230

Model diagnostics are performed to determine whether the selected model is suitable for prediction and forecasting. This confirmatory test includes the Test for Presence of ARCH Effect, the Test for Serial Correlation, and a test for normality using the QQ-plot for residuals of the selected model. Additionally, an investigation was conducted to examine the presence of ARCH effects in the selected estimated model, using the ARCH-LM test. Table 4 contains the results obtained using the ARCH-LM test for the ARCH effect. As observed, the n*X2>f-statistic indicates that the null hypothesis of no ARCH effect should be accepted at a 5% level of significance.

Table 4: Heteroskedasticity test for the best fitted GARCH (2,2) model

Models	**Heteroskedasticity Test: ARCH**	**Lag 5**	**Lag 10**
TGARCH (2,2)	F-statistic	1.151686	1.510544
	Prob. F (1,5,237, 229)	5.764434	14.83710

The result in Figure 4 indicates that there is no serial correlation, as the probability (p-values) is all greater than the standard 0.05 level of significance. Hence, there is no serial correlation. The test for Serial Correlation is done by checking the correlogram of the residual squares.



Date: 08/28/18 Time: 23:41
Sample: 1997M07 2017M07
Included observations: 240

	AC	PAC	Q-Stat	Prob*
1	-0.137	-0.137	4.5881	0.032
2	0.006	-0.013	4.5960	0.100
3	0.119	0.120	8.0740	0.045
4	0.097	0.134	10.382	0.034
5	0.059	0.096	11.239	0.047
6	0.062	0.073	12.204	0.058
7	-0.011	-0.021	12.234	0.093
8	0.043	0.004	12.695	0.123
9	-0.026	-0.058	12.870	0.169
10	0.021	-0.011	12.985	0.225
11	-0.002	-0.015	12.986	0.294
12	-0.020	-0.022	13.087	0.363
13	0.016	0.016	13.149	0.436
14	0.034	0.045	13.438	0.492
15	-0.070	-0.048	14.703	0.473
16	-0.041	-0.065	15.146	0.514
17	0.010	-0.016	15.175	0.583
18	-0.075	-0.078	16.655	0.547
19	0.068	0.070	17.858	0.532
20	-0.050	-0.008	18.529	0.553
21	-0.072	-0.049	19.921	0.526
22	0.110	0.106	23.148	0.393
23	0.003	0.048	23.151	0.452
24	-0.031	-0.003	23.409	0.496
25	0.051	0.031	24.107	0.513
26	-0.022	-0.028	24.243	0.562
27	0.054	0.024	25.028	0.573
28	-0.041	-0.049	25.481	0.602
29	0.077	0.070	27.092	0.567
30	-0.023	-0.020	27.245	0.610
31	0.019	0.018	27.343	0.655
32	0.015	0.009	27.409	0.698
33	-0.014	-0.043	27.463	0.739

Figure 4: Correlogram of standardised residuals square

The Q-Q Plots for the Residuals are done to confirm if the data set used in the estimation exhibits the characteristics of data drawn from a normal distribution. Additionally, the diagram in Figure 5 shows that the line of quantile and normality lies straight on top of each other, indicating that the model is well-fitted. This result aligns with Atoi's [6] findings in his test for the volatility of stock markets using the GARCH model.

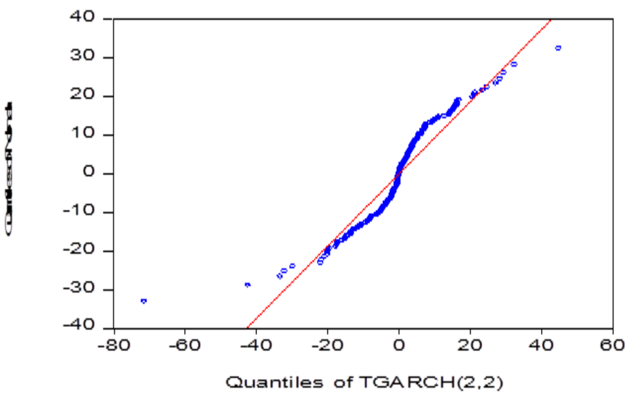


Figure 5: QQ-plot for residuals of normal distribution

4. Results and Discussion

The study utilises Nigeria's interest rate data, extracted from deposit money banks, as reported on the Central Bank of Nigeria (CBN) online statistical database. The data spans from July 1997 to July 2024. Conditional variance models were fitted to the conditionally compounded monthly interest rate data. In total, eight different GARCH models were estimated, assuming normally distributed errors. Several conditions were considered when estimating the model, and these were incorporated into the estimation technique. Some of these conditions include time plots, summary descriptive statistics, tests for ARCH effects, model estimation and selection, and diagnostic tests. Figure 1 shows the dynamics of the time plot for monthly interest rates from 1997 to 2024. The graph reveals that the variable exhibits trends, with an upward projection followed by a decline in 2001 and a subsequent rise in 2003. The fluctuations in the series continue across the years. Similarly, Figure 2 shows evidence of clustering in the time plot of the returns series, with sharp increases followed by sharp decreases, indicating instability in the rate of returns on interest rates over the study period. These results are consistent with the findings of Meher et al. [1], who investigated oil price macroeconomic volatility in Nigeria and found volatility clustering in oil price returns. Similarly, the interest rate returns variable in this study was subjected to descriptive tests, and the results indicated that the variable did not meet the assumptions of a normally distributed variable.

Table 1 presents summary statistics for interest rate returns from July 1997 to July 2024. The estimated mean (-0.000376) has a negative sign, indicating that the variable is negatively mean-reverting in nature. The standard deviation (0.116447) measures the degree of risk associated with the variable. A higher standard deviation implies greater volatility persistence and associated risk. The 117.8409% difference between the minimum and maximum returns on interest rates shows the level of variation and the fairness of returns within the sampled period. The skewness coefficient (-0.945294) is negative, indicating that the variable is negatively skewed to the left, a common feature of fair returns. Kurtosis (10.82680), which is greater than three, suggests that the variable does not exhibit the characteristics of normally distributed data. The Jarque-Bera statistic (648.3318), with a corresponding probability value of 0.0000, leads to the rejection of the null hypothesis of normality and the acceptance of the alternative hypothesis. As suggested by Mandelbrot [2], it is necessary to use alternative statistics when modelling the volatility of interest rate returns. Thus, the study employs GARCH family models, based on the assumption of a normal error distribution, with a fixed degree of freedom incorporated into the models. The variable under investigation was further subjected to an Auto-Regressive Moving Average (ARMA) model to obtain the residuals from the estimation of the returns series. The results show that the intercept (0.205448) is significant at the 10% level, and the ARCH component (0.965) is significant at the 5% level, like the findings of Eke [3] on oil price-macroeconomic volatility in Nigeria.

In another development, Table 2 shows the test for heteroskedasticity (ARCH effect) of the residuals obtained from the model in equation (4.1). The test indicates the persistence of ARCH effects. The F-statistic (61.139) is greater than its corresponding chi-square statistic (49.012), resulting in the rejection of the null hypothesis and the acceptance of the alternative hypothesis. This confirms the presence of ARCH effects in the return series of interest rates, supporting the assertion by Kwiatkowski et al. [4] that variables with such effects can be estimated using GARCH models. As previously mentioned, interest rate returns exhibit persistent shocks and continuous volatility clustering. To capture these volatility characteristics, eight different GARCH models were used in the estimation. These models were estimated with normal error distribution assumptions to better understand the specific behaviour of interest rate returns under different error distribution assumptions. The result in model (4.1) confirms that time-varying volatility includes a constant (58.2190) and an ARCH component that depends on past errors. The ARCH effect is statistically significant at the 5% level, and since the constant is not greater than one but lies between zero and one, the ARCH effect is not explosive. The model suggests an ARCH (1) effect, with an AIC of 7.5527. Model (4.2) shows that time-varying volatility includes a constant (50.977) and ARCH components that depend on immediate and second-past errors. The ARCH effects are statistically significant at the 5% level, and since the constant values lie between zero and one, the ARCH effect is not explosive.

The model suggests an ARCH (2) effect, with an AIC of 7.5527. Both models indicate positive variance, suggesting that shocks from previous periods result in greater initial innovations in absolute terms, which means smaller ARCH effects in the future. The results obtained in models (4.1) and (4.3) confirm the underlying assumptions of the ARCH effect as suggested by Engle [10] in his study on inflation in the U.K. Model (4.3) contains two components: the mean and the variance components. The intercept in the variance component is positive and statistically significant at the 5% level. Similarly, the ARCH components are positive and statistically significant at the 5% level, indicating that the interest rate return of the preceding month has a statistically significant influence on the interest rate return of the current month. This confirms that interest rate volatility is influenced by its own positive ARCH and GARCH components. The model estimates an Akaike Information Criterion (AIC) of 7.5102 and 96.37% volatility persistence. The first-order ARCH component in the variance component is positive and statistically significant at the 5% level. In comparison, the second-order ARCH component is negative but also statistically significant at the 5% level. This suggests that the preceding month's interest rate return has a positive impact on the current month's return, whereas the second-order return has a negative impact. The AIC for this model is 7.4687, and the degree of volatility persistence for the first and second orders is 177.05% and -76.99%, respectively. This shows that volatility persistence decreases in the second-order estimation, as indicated by the negative second GARCH coefficient. These results are consistent with Gujarati's [5] findings on stochastic volatility in interest rate models.

The EGARCH (1, 1) model, shown in model (4.5), estimates the volatility of interest rate returns. The coefficient of the ARCH term is positive but not statistically significant. The asymmetric term is negative and statistically significant at the 5% level. This suggests that the relationship between past returns and future volatility is positive, and that higher leverage effects due to negative returns will likely lead to lower interest rates, reflecting a higher debt-to-equity ratio. The model's AIC is 7.4776, with a volatility persistence degree of 124.184%. The EGARCH (2, 2) model, shown in model (4.6), estimates volatility with significant positive coefficients for the ARCH terms and the asymmetric term. The first-order GARCH term is negative and non-significant, while the second-order GARCH term is positive and statistically significant at the 5% level. The model estimates 66.68% volatility persistence in the first order and 103.46% in the second order, suggesting that higher-order models capture higher levels of volatility persistence. The AIC for this model is 7.3338. In the ARCH, the coefficients are positive but not statistically significant, indicating the presence of ARCH effects. Despite this, a leverage effect is observed, where negative news has a greater impact on volatility than positive news. The asymmetric term is positive and statistically significant at the 5% level, with an AIC of 7.4783. Finally, model 4.8 shows that the ARCH coefficient in the first-order model is positive but not statistically significant, while in the second-order model, it is negative and statistically significant. This confirms the presence of ARCH effects in the second-order TGARCH model. The leverage effect suggests that bad news has a greater impact on volatility than good news, with the second-order model indicating the opposite. The AIC for this model is 7.4783, consistent with Gujarati [5].

- **H01:** There is no presence of ARCH effect on monthly data returns on Nigerian Interest rate between 1997 and 2024.

To test H01, we investigate if there is an ARCH effect both P(F) and P (X2), [where P(F) and P(X2) are tail probabilities]. The p-value is less than 0.05, the level of significance. This is from the Heteroskedasticity test in Table 2.

- **H02:** There is no general comparative difference between the performance of the first and second Order GARCH models in modelling the returns on the monthly interest rate between July 1997 and July 2024.

From the values of the AIC for the various models, we have the following results: for the ARCH models, the AIC values for ARCH (1,1) and ARCH (2,2) are -7.553 and -7.528, respectively; for the GARCH models, GARCH(1,1) and GARCH(2,2) yield AIC values of -7.510 and -7.469, respectively; for the EGARCH models, EGARCH(1,1) and EGARCH(2,2) have AIC values of -7.478 and -7.415, respectively; and for the TGARCH models, TGARCH(1,1) and TGARCH(2,2) have AIC values of -7.478 and -7.290, respectively. Therefore, the model with the lowest AIC value is TGARCH (2,2). These results indicate that the TGARCH (2,2) model fits the volatility model better than the first-order GARCH model. Based on these findings, we reject the null hypothesis (H0) and uphold the view that there is a significant difference in performance between the first- and second-order GARCH models in modelling the returns on monthly interest rates from July 1997 to July 2024.

5. Conclusion

This study examines the estimation ability and performance of first- and second-order univariate GARCH models in modelling the conditional variance of interest rates. It provides some important insights into modelling the volatility of interest rate returns. The results indicate that the second-order TGARCH model (2,2) provides the best fit to the data. Model selection was based on the Akaike Information Criterion (AIC), and model diagnostics were performed using ARCH effect tests, QQ plots, and serial correlation tests to ensure robustness. From the results, we can conclude that those who obtained loans from banks during the study period had a higher probability of gaining than losing. This is because negative shocks tend to have a disproportionate effect on future volatility, and the second-order TGARCH model takes these asymmetry behaviours into account. For example, during an economic downturn, an unexpected cut in interest rates may lead to higher-than-expected volatility due to uncertainty about future economic conditions. Therefore, given the risks associated with borrowing from depository banks, investing in stocks, and pricing assets with corresponding interest income, financial analysts, investors, companies, and governments are advised to exercise caution when engaging in any business or financial activity involving interest rates.

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