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MODELING VOLATILITY OF NIGERIA STOCK EXCHANGE USING GARCH MODELS

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Abstract: **Financial and economic variables fluctuate owing to a variety of causes, including economic conditions, market pressures, government policies, global effects, industry-specific factors, and even random events. Addressing these fluctuations requires the development of accurate forecasting models to help market participants and policymakers adapt to the dynamic nature of stock market volatility. This research models the conditional mean and variance of Nigeria Stock Exchange Banking Index (NGX-BANK) by obtaining the ARIMA model that captures the linear dependency in the return and the optimal Symmetric or Asymmetric GARCH model that captures the time-varying volatility. The research obtained the Value at Risk and forecast future volatility. Ten years daily closing price were used to obtain the estimate of the ARIMA-GARCH, ARIMA-IGARCH, ARIMA-EGARCH and ARIMA-TGARCH models. The returns from the daily price were stationary but not normally distributed showing the asymmetric nature of the returns. ARIMA(2,0,1) captures the linear dependencies and temporal patterns present in the returns of the series. It was established that ARIMA(2,0,1)+EGARCH(4,4) was the optimal model that can capture the structured information regarding conditional mean and volatility. There were no indication of heteroscedasticity or autocorrelation in the ARIMA-EGARCH model's residual. Meanwhile, there exist 1% chance that the loss from the asset will exceed 860.07 in 10 days.**

Keywords: **ARIMA, Forecast, GARCH, Heteroscedasticity, Time Series, VaR, Volatility.**

I. INTRODUCTION

Economic data analysis is often performed in economics using a branch of statistics known as Econometrics. It involves using statistical models to predict and test economic theories. The relationship between economic variables are analyzed, and future economic trends are forecasted using the econometric models. Multiple techniques, which includes panel data analysis, time series analysis, regression analysis, among others are used in econometrics research. These techniques are used to describe economic relationships and to present models that describe those relationships. Econometric models can be used to analyze numerous economic variables including economic growth, inflation, unemployment, trade, financial markets and more. Financial and economic variables is subject to variation due to several known factors and some unexpected and random occurrences. Analyzing and forecasting these variations is strongly reliant on volatility modeling which is a critical component of econometrics. Modeling volatility of financial time series and also predicting its future trend has become more prevalent in recent years. Volatility is an integral abstraction in numerous economic and financial applications, these applications includes the management of associated risk, pricing of assets, portfolio optimisation and so on. Volatility is determined by the conditional variance of the returns on an asset under consideration and it represents the relative rate of change in stock prices [1]. It shows how much the price or value of an asset fluctuates over time. It serves as a statistical indicator of how unpredictable a financial investment can be.

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Stock market revolves around the challenges and uncertainties posed by the fluctuations in stock prices over time. Several key issues closely tied to stock market volatility include the fact that investors face increased uncertainty and risk due to stock market volatility. High volatility can lead to significant losses, making it crucial for investors to effectively manage and mitigate risk. One great challenge encountered by investors is the stock market volatility, this debar the investors from making informed investment decisions. The fluctuating stock prices make it difficult to accurately assess the value of investments and project future returns, impacting asset allocation and portfolio management. Excessive stock market volatility can have destabilizing effects on financial markets, raising concerns about systemic risk. Large price swings and market disruptions can trigger panic selling, market crashes, and contagion effects, posing risks to market stability and overall economic well-being. It can also present challenges for algorithmic, high-frequency traders and raises concerns for regulatory bodies and policymakers who are to monitor excessive volatility which are essential to maintain market integrity, protect investors, and ensure financial stability. Addressing these challenges requires the development of accurate forecasting models to help market participants and policymakers adapt to the dynamic nature of stock market volatility and increase investors' confidence. Hence, the purpose of this research is to model the volatility of Nigeria stock exchange by obtaining the optimal Symmetric or Asymmetric GARCH models that capture the time-varying volatility, estimate the Value at Risk (VaR) and forecasting future volatility of the stock exchange.

A research by [2] looked into the daily closing value of the shares of Al-Rajhi Bank, a major participant in the banking and financial sectors featured on the Saudi stock market. Their study indicated that the AR(1) model accurately described the patterns in the shares over the period. Despite this, additional testing for the ARCH impact on the residuals indicated heteroscedasticity in the residual series, suggesting the use of ARCH models for future investigation. Various statistical tests, including those for heteroscedasticity and model fit criteria such as R-squared, Akaike, Schwarz, and Hannan-Quinn statistics, confirmed the GARCH (1, 1) model's adequacy for capturing the conditional variance of the Bank's closing values. According to the research, Positive innovations aligning with favorable situations, results in lighter swings than negative innovation happening during unfavourable situations. Importantly, the analysis discovered that the bank's share prices were unaffected by the negative innovations resulting from the COVID-19 crisis, which spanned the study period from February 1, 2018, to September 23, 2022. Furthermore, another research by [3] models and predicts the volatility of the USD/XAF and CNY/XAF exchange rates between 01 January 2017 and 30 September 2022. While GARCH model is used to capture heteroscedasticity, the EGARCH and GJRGARCH models are employed to capture asymmetry and leverage effects in the data. The findings suggest the presence of conditional heteroscedasticity and persistent volatility in both exchange returns where shocks are felt further in the future. Thus, by the Akaike Information Criteria, the USD/XAF exchange rate volatility can be adequately estimated by the ARMA(0,1)+GJR-GARCH(1,1)-SGED model and that for the CNY/XAF exchange rate by the ARMA(1,1)+GJR-GARCH(2,2)-SGED model.

An investigation by [4] delves into numerous GARCH-type models to scrutinize how volatility fluctuations influence the US stock exchange, with a specific focus on the S&P 500 index. The study covers two time periods: 2002 to 2010 and 2012 to 2020. Several empirical conclusions arise from the detailed analysis of each coefficient in these GARCH-type models. Leverage effects had a significant effect on S&P 500 returns during both the 2008 global financial crisis (GFC) and the COVID-19 pandemic. In terms of conditional variance persistence, volatility during the 2008 global financial crisis outperformed the COVID-19 crisis. However, in terms of the rate of change in conditional variance, the COVID-19 crisis resulted in substantially more volatility than the 2008 GFC. This suggests that financial crises largely caused by non-financial reasons frequently result in severe but short-term index swings, whereas those caused primarily by financial causes have longer-term consequences. The paper also compares the effectiveness of several GARCH-type models in volatility estimation using the Akaike Information Criterion and the Bayesian Information Criterion. It discovers that the GJR-GARCH model exhibits superior performance during the 2007-2008 financial crisis period, while the EGARCH model fares better during the COVID-19 financial crisis. Owing to the presence of leverage effects, asymmetric GARCH-type models demonstrate enhanced efficacy in volatility estimation across diverse financial crisis scenarios compared to symmetric models. In a study by [5] incorporated the EGARCH model alongside the ARCH and GARCH models to analyze Bitcoin returns. The selection of the most appropriate model among these volatility models was based on Akaike Information Criterion. The findings revealed that the GARCH (1,1) model emerged as the prevalent model for Bitcoin returns. Following this, the GARCH (1,1) model was succeeded by the GARCH (1,3) model and then the EGARCH (1,1) model. Notably, the γ parameter in the EGARCH (1,1) model exhibited statistical significance at 5% level, suggesting that shocks produced exerted an asymmetrical effect on return volatility. EGARCH(1,1) model was recommended as alternative in instances where the GARCH (1,1) and GARCH (1,3) proved inadequate.

In contribution to these literatures, this study will establish which models is better at capturing Nigeria Stock Exchange Banking Index volatility dynamic and will give insights into which model performs better in terms of accuracy. Accurate forecasting is essential for individuals, organizations, and financial institutions engaged in the exchange because it allows them to make well-informed choices and effectively mitigate risk A precise projection of the exchange rate can help guide policy decisions. In addition, the study will bridge the sector-specific analysis gaps in our knowledge of financial econometrics and forecasting.

II. DATA AND METHODOLOGY

A. Data

Data from the daily closing price of Nigeria Stock Exchange Banking Index (NGX-BANK) from March 24, 2014 to March 22, 2024 excluding weekends and holiday was used for the research. The Autoregressive Integrated Moving Average (ARIMA) model was used to model the conditional mean by examining the linear relationship between the current value and its lagged values, as well as the previous error terms to estimate the expected value at a given time point. The symmetric and asymmetric GARCH models were used to measure the volatility dynamics in The symmetric GARCH includes standard GARCH and Integrated GARCH (IGARCH) while the asymmetric GARCH are Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH).

B. Methodology

The stock returns will be calculated by subtracting the natural logarithm of the previous day's closing value from the natural logarithm of the closing value.

$$Y_t = log\ CP_t - log\ CP_{t-1} \quad (1)$$

where Y_t is the stock returns, CP_t is the closing value, CP_{t-1} is the previous day's closing value.

$$\text{Let } \mathcal{E}_t = Y_t - \bar{Y} \quad (2)$$

$$\text{And } \mathcal{E}_t = \sigma_t u_t \quad (3)$$

where $\mathcal{E}_t$ is the residual from mean at time t, $\bar{Y}$ is the mean, σ_t^2 is the conditional variance at time t, u_t is a white noise error term $u_t \sim N(0,1)$

The ARIMA (p,d,q) model is as follows:

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \mathcal{E}_{t-j} \quad (4)$$

where Y_t is the value at time t, μ is a constant term, Y_{t-i} is the lagged autoregressive term (i=1,2, …, p), $\mathcal{E}_{t-j}$ is the lagged moving average term (j=1,2, …, q), d is the order of the differencing, ϕ_i and θ_j are parameters to be estimated.

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model - GARCH(p,q) is given in equation 4 below:

$$\sigma_t^2 = \lambda_0 + \lambda_1 \mathcal{E}_{t-1}^2 + \lambda_2 \mathcal{E}_{t-2}^2 + \dots + \lambda_q \mathcal{E}_{t-q}^2 + \kappa_1 \sigma_{t-1}^2 + \kappa_2 \sigma_{t-2}^2 + \dots + \kappa_p \sigma_{t-p}^2 \quad (5)$$

where σ_t^2 is the conditional variance at time t, λ_0 is a constant term, λ_i and κ_j are parameters to be estimated, $\mathcal{E}_t$ is independently and identically distributed N(0, σ_t^2) for all t.

The Integrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH) model broadens the GARCH model with the clause that:

$$\lambda_1 + \lambda_2 + \dots + \lambda_q + \kappa_1 + \kappa_2 + \dots + \kappa_p = 1 \quad (6)$$

The Exponential Generalized Autoregressive Conditional Heteroscedasticity model - EGARCH(p,q)is given in equation 7 below:

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$$log\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q}(\lambda_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}) + \sum_{j=1}^{p}\kappa_j log\sigma_{t-j}^2 \quad (7)$$

where $log\sigma_t^2$ is the log of the conditional variance at time t, $\lambda_0, \lambda_i, \gamma_i, \kappa_j$ are parameters to be estimated.

The Threshold Generalized Autoregressive Conditional Heteroscedasticity model - TGARCH(p,q) is given as:

$$\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q}(\lambda_i \varepsilon_{t-i}^2 + \gamma_i I_{t-i}\varepsilon_{t-i}^2) + \sum_{j=1}^{p}\kappa_j \sigma_{t-j}^2 \quad (8)$$

where I_{t-i} is 1 if $\mathcal{E}_{t-1}$ is less than 0, I_{t-i} is 0 if $\mathcal{E}_{t-1}$ is greater than or equal to 0

The parameters of the models were estimated using the Maximum Likelihood Estimation (MLE) and the optimal model was selected using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan-Quinn Information Criterion (HQIC). The Information Criteria were estimated respectively as follows:

$$AIC = 2k + n\ln(RSS) \quad (9)$$

$$BIC = k\ln(n) + n\ln(RSS) \quad (10)$$

$$HQIC = 2k\ln(\ln n) + n\ln(RSS) \quad (11)$$

where k is the numbers of parameters, n is the numbers of observations, RSS is the residual sum of square.

The value at risk (VaR) was estimated using the historical VaR, parametric VaR and Monte Carlo VaR. The historical VaR was estimated as follows: sort the historical value of the asset in ascending order; obtain the value corresponding to the quantile of the desired levels of confidence; the estimated value is the minimum VaR at the confidence level. The parametric VaR was estimated as:

$$VaR = \mu - \sigma z \quad (12)$$

where μ is the mean price of the asset in the time horizon, σ is the standard deviation of the asset, z is the z-value at the level of confidence. The Monte Carlo VaR simulation using a GARCH model are as follows: fit the desired GARCH model using the logarithmic return from the stock's historical daily closing price; use the fitted GARCH model to simulate future returns; sort the future returns in ascending order; obtain the returns that corresponds to the quantile of the desired levels of confidence; use the returns to calculate its stock values; the estimated value is the minimum VaR at the confidence level.

C. Result

The daily prices of the Banking index and its returns were plotted over time to determine stationarity; the results are displayed in the figures below.

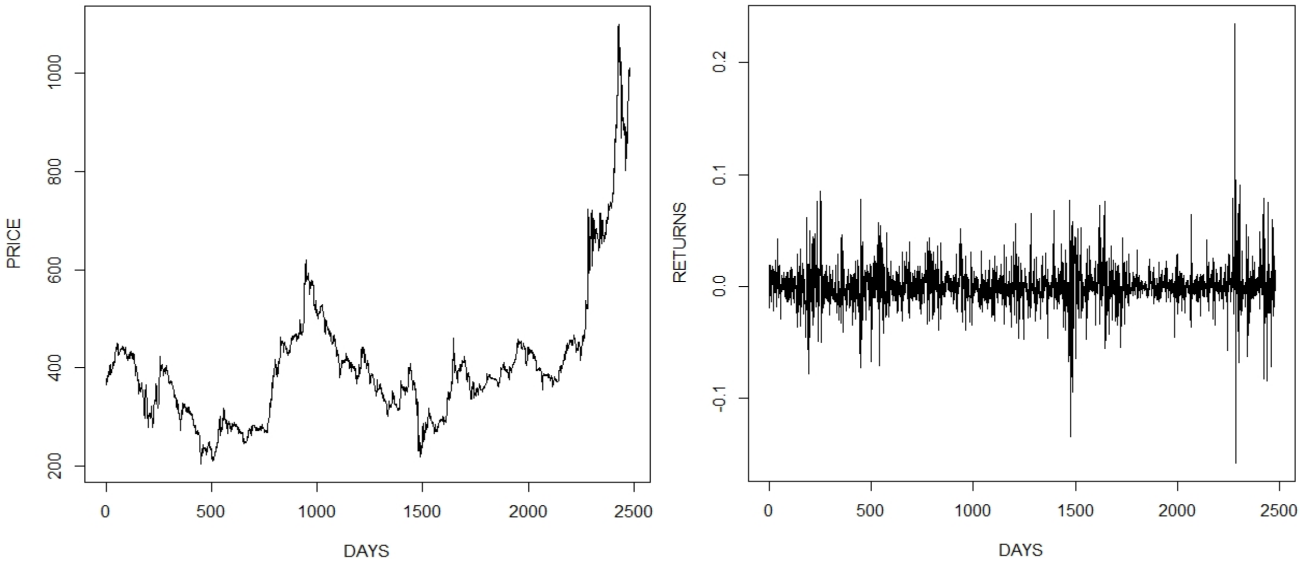

Fig 1: Time plot of NGX-BANK Price and returns

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The visual presentation shows that the statistical properties of the prices of the Nigeria Stock Exchange Banking Index (NGX-BANK) were not constant over time. Hence the prices were not stationary. Meanwhile, the return time plot suggested stationarity in the series.

TABLE 1: Descriptive Statistics

Statistic	Value	Statistic	Value
Observations	2477	Maximum	0.2352343
Mean	0.0003968255	Kurtosis	20.07389
Median	.0000	Skewness	0.5091155
Standard Deviation	0.01851229	Jarque-Bera	30194
Minimum	-0.1581235	p-value	2.2e-16

The number of returns from NGX-BANK for the period under consideration is 2477, the average return was 0.0003968255, which suggested that there were profits made across the period of the study. There were significant range between the maximum value (0.2352343) and the minimum value (-0.1581235) indicating the variation in the return of the asset. The kurtosis (20.07389) is larger than the kurtosis of the standard normal distribution (3) indicating a leptokurtic distribution signifying that the distribution has a wide tail. The skewness (0.5091155) indicated a positively skewed distribution which differs from the skewness of the standard normal distribution (0), this suggested that the distribution is asymmetric in nature. The Jarque-Bera test of normality was consistent with the inference from the skewness and the kurtosis, its low p-value ($2.2e^{-16}$) indicated that the returns does not follow a normal distribution.

TABLE 2: Unit Root Test

Test	Augmented Dickey Fuller (ADF)	Kwiatkowski-Phillips-Schmidt-Shin (KPSS)
Statistic	-13.015	0.30626
p-value	0.01	0.1

The null hypothesis of Augmented Dickey Fuller test tested if there exists a unit root in the returns of the asset, the null hypothesis was rejected given that the p-value (0.01) of the test is less than the level of significance (0.05). Hence, it was concluded that the presence of unit root in the returns is not significant. Furthermore, the null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin test tested if the returns are stationary, the null hypothesis was not rejected given that the p-value (0.1) of the test is not less than the level of significance (0.05). Hence, the returns are stationary. The Augmented Dickey Fuller test and the Kwiatkowski-Phillips-Schmidt-Shin test were consistent with the time plot of the returns which suggested that the returns were stationary. Hence, there are enough evidence to conclude that the statistical properties of the returns are constant over time.

To capture the linear dependencies and temporal patterns present in the returns of the series, the plot of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) were used to determine whether the return is better described by Autoregressive (AR), Moving Average (MA) or Autoregressive Integrated Moving Average(ARIMA) model.

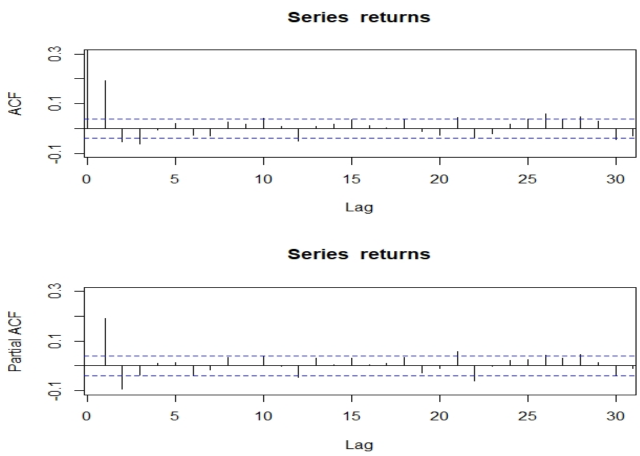

Fig 2: ACF and PACF of the return series

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Both ACF and PACF showed significant spikes at lag 1, with a sinusoidal pattern afterwards, signifying that the return is best described by an Autoregressive Integrated Moving Average (ARIMA) model. The R-function “auto.arima(returns)” which combines the unit root tests, minimization of the information criteria and maximum likelihood estimation to obtain the optimal ARIMA model selected ARIMA(2,0,1) model as the optimal mean model.

Several orders of GARCH(p,q), IGARCH(p,q), EGARCH(p,q), TGARCH(p,q) models were compared using the Information Criteria(IC), where p=1,2,3,4 and q=1,2,3,4.

ARIMA(2,0,1)-GARCH(1,2), ARIMA(2,0,1)- IGARCH(1,2), ARIMA(2,0,1)-EGARCH(4,4) and ARIMA(2,0,1)-TGARCH(1,1) were selected by the IC in each category.

TABLE 3: Parameter Estimates for the Mean Model and Symmetric GARCH Models

Mean Model+ GARCH Model	Parameter	Estimate	Std. Error	Pr(>|t|)	AIC	BIC	HQIC
ARIMA(2,0,1)+GARCH(1,2)	μ	-0.000070	0.000233	0.762513	-5.7271	-5.7060	-5.7194
	ϕ_1	0.488004	0.210264	0.020292			
	ϕ_2	-0.105445	0.036562	0.003926			
	θ_1	-0.316361	0.211408	0.134538			
	λ_0	0.000024	0.000005	0.000012			
	κ_1	0.356840	0.057436	0.000000			
	λ_1	0.457610	0.128402	0.000365			
	λ_2	0.184531	0.105863	0.081313			
ARIMA(2,0,1)+IGARCH(1,2)	μ	-0.000070	0.000233	0.762290	-5.7279	-5.7091	-5.7211
	ϕ_1	0.487970	0.210301	0.020322			
	ϕ_2	-0.105433	0.036564	0.003933			
	θ_1	-0.316330	0.211446	0.134646			
	λ_0	0.000024	0.000005	0.000011			
	κ_1	0.357892	0.045094	0.000000			
	λ_1	0.457810	0.128304	0.000359			
	λ_2	0.184298					

ARIMA-GARCH: The mean model - ARIMA(2,0,1) and the variance model - GARCH(1,2) models are given respectively as follows:

$$Y_t = -0.000070 + 0.488004\, Y_{t-1} - 0.105445\, Y_{t-2} - 0.316361\, \varepsilon_{t-1} \quad (13)$$

$$\sigma_t^2 = 0.000024 + 0.457610\, \varepsilon_{t-1}^2 + 0.184531\, \varepsilon_{t-2}^2 + 0.356840\, \sigma_{t-1}^2 \quad (14)$$

ARIMA-IGARCH: The mean model - ARIMA(2,0,1) and the variance model - IGARCH(1,2) models are given respectively as follows:

$$Y_t = -0.000070 + 0.487970\, Y_{t-1} - 0.105433 Y_{t-2} - 0.316330\, \varepsilon_{t-1} \quad (15)$$

$$\sigma_t^2 = 0.000024 + 0.457810\, \varepsilon_{t-1}^2 + 0.184298\, \varepsilon_{t-2}^2 + 0.357892\, \sigma_{t-1}^2 \quad (16)$$

TABLE 4: Parameter Estimates for the Mean Model and Asymmetric GARCH Models

Mean Model+ GARCH Model	Parameter	Estimate	Std. Error	Pr(>|t|)	AIC	BIC	HQIC
ARIMA(2,0,1)+ EGARCH(4,4)	μ	-0.000004	0.001147	0.996990	-5.7372	-5.6950	-5.7219
	ϕ_1	0.633796	0.002025	0.000000			
	ϕ_2	-0.108374	0.023218	0.000003			
	θ_1	-0.483920	0.013948	0.000000			
	λ_0	-0.199812	0.001333	0.00000			
	κ_1	0.050976	0.000420	0.00000			

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	κ_2	0.012246	0.000702	0.00000			
	κ_3	-0.041929	0.000439	0.00000			
	κ_4	-0.032393	0.000918	0.00000			
	λ_1	0.176713	0.000038	0.00000			
	λ_2	0.778154	0.000117	0.00000			
	λ_3	0.668382	0.000001	0.00000			
	λ_4	-0.647185	0.000255	0.00000			
	γ_1	0.564165	0.000182	0.00000			
	γ_2	0.327197	0.000103	0.00000			
	γ_3	-0.203052	0.000097	0.00000			
	γ_4	-0.438111	0.000017	0.00000			
ARIMA(2,0,1)+ TGARCH(1,1)	μ	-0.000075	0.000218	0.731600	-5.7259	-5.7048	-5.7183
	ϕ_1	0.495839	0.037211	0.000000			
	ϕ_2	-0.105710	0.017145	0.000000			
	θ_1	-0.336788	0.037257	0.000000			
	λ_0	0.001289	0.000289	0.000009			
	κ_1	0.275705	0.033250	0.000000			
	λ_1	0.740132	0.032715	0.000000			
	γ_1	0.019433	0.053255	0.715181			

ARIMA-EGARCH: The mean model - ARIMA(2,0,1) and the variance model - EGARCH(4,4) models are given respectively as follows:

$$Y_t = -0.000004 + 0.633796\, Y_{t-1} - 0.108374\, Y_{t-2} - 0.483920\, \varepsilon_{t-1} \quad (17)$$

$$log\sigma_t^2 = -0.199812 + 0.176713 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.778154 \left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| + 0.668382 \left|\frac{\varepsilon_{t-3}}{\sigma_{t-3}}\right| - 0.647185 \left|\frac{\varepsilon_{t-4}}{\sigma_{t-4}}\right| + 0.564165 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 0.327197 \frac{\varepsilon_{t-2}}{\sigma_{t-2}} - 0.203052 \frac{\varepsilon_{t-3}}{\sigma_{t-3}} - 0.438111 \frac{\varepsilon_{t-4}}{\sigma_{t-4}} + 0.050976\, log\sigma_{t-1}^2 + 0.012246\, log\sigma_{t-2}^2 - 0.041929\, log\sigma_{t-3}^2 - 0.032393\, log\sigma_{t-4}^2 \quad (18)$$

ARIMA-TGARCH: The mean model - ARIMA(2,0,1) and the variance model - TGARCH(1,1) models are given respectively as follows:

$$Y_t = -0.000075 + 0.495839\, Y_{t-1} - 0.105710\, Y_{t-2} - 0.336788\, \varepsilon_{t-1} \quad (19)$$

$$\sigma_t^2 = 0.001289 + 0.740132\, \varepsilon_{t-i}^2 + 0.019433\, I_{t-i}\varepsilon_{t-i}^2 + 0.275705\, \sigma_{t-1}^2 \quad (20)$$

Comparing the estimate of these models, all the estimates of ARIMA(2,0,1)-EGARCH(4,4) were statistically significant, indicating that each of the parameters has meaningful effect on the model. Similarly, comparing the Information Criteria of the GARCH models, ARIMA(2,0,1)-EGARCH(4,4) is the model with the least Information Criteria. Hence, the model that best capture the linear dependencies, temporal patterns and the time varying volatility of the NGX-Banking index is the ARIMA(2,0,1)-EGARCH(4,4) model. The AR(1) coefficient of 0.633796 indicated a positive correlation between the current value and the value preceding it. This shows that an increase in the preceding value will result in an increase in the current value. The AR(2) coefficient -0.108374 indicated a negative correlation between the current value and the value in two periods ago. This shows that an increase in the value two periods ago will result in a decrease in the current value. The MA(1) coefficient of -0.483920 indicated that a positive error in the previous period will lead to a decrease in the current value. Furthermore, the coefficients of the lag values of volatility (0.050976, 0.012246, -0.041929, -0.032393) compared with the coefficients of the new shocks (0.176713, 0.778154, 0.668382, -0.647185) of the EGARCH(4,4) model showed that volatility is more sensitive to new shock than to its lagged values. The magnitude of the coefficient of gamma (γ_1, γ_2, γ_3, γ_4) shows the leverage effect. The first lagged leverage effect (0.564165) suggested that a negative shock in the previous period increases volatility in the current period and the magnitude of the effect is relatively strong. The second lagged leverage effect (0.327197) suggested that a negative shock two periods ago still has a significant impact on increasing volatility in the current period, although the effect is weaker than the one period lag. The third and fourth lagged leverage effect (-0. 203052, -0.438111) indicated that a positive shock three and four periods ago actually decrease volatility in the current period. These could be perceived as the calming effect.

The Ljung-Box test was conducted on the residual of the model to investigate the presence of autocorrelation in the residuals, the ARCH LM test was conducted to investigate the presence of heteroscedasticity in the residuals, and the Pearson Goodness of fit test to test the goodness of fit.

TABLE 5: Residual Test

		Statistic	p-value
Ljung-Box Test	Lag[1]	0.1307	0.7177
	Lag[23]	7.7053	0.8661
	Lag[39]	15.3179	0.8144
ARCH LM Test	ARCH Lag[9]	5.022	0.25020
	ARCH Lag11]	5.167	0.12847
	ARCH Lag[13]	5.648	0.24661
Adjusted Pearson Goodness of Fit Tests	Group 20	17.51	0.5554
	Group 30	17.84	0.9474
	Group 40	38.06	0.5127
	Group 50	44.09	0.6719

The p-values of the Ljung-box test higher than the level of significance (0.05) suggested that the residuals are uncorrelated; indicating that the EGARCH(4,4) model will adequately capture the time series dynamics. Similarly, the high p-values of the ARCH LM test signified that the presence of residual heteroscedasticity is not significant in the residual, indicating that the EGARCH (4,4) will adequately capture the volatility clustering. Furthermore, the goodness of fit test examine how well the EGARCH model fits the asset under consideration. The p-values are higher than the level of significance suggesting a good fit of the EGARCH model.

Value at Risk

TABLE 6: Value at Risk at 99%, 95% and 90% level of significance in 10 days' horizon

VaR	Confidence Level	Value at Risk
Historical	99%	880.7046
	95%	897.6030
	90%	918.7260
Variance-Covariance	99%	860.0681
	95%	885.0701
	90%	897.8552
Monte Carlo	99%	954.8640
	95%	983.8151
	90%	992.3696

For a 10-day period, the historical VaR implied that a loss that is more than 918.73 is likely to be incurred on the NGX-Banking index with 10% probability, 5% probability that the loss will be more than 897.60 and 1% probability that the loss will be more than 880.70; the variance-covariance VaR suggested that there is 10% probability that NGX-Banking index will experience a loss more than 897.86, 5% probability that the loss will be more than 885.07 and 1% probability that the loss will be more than 860.07 and the Monte carlo VaR implied that there is 10% probability that NGX-Banking index will experience a loss more than 992.37, 5% probability that the loss will be more than 983.82 and 1% probability that the loss will be more than 954.86.

After obtaining the optimal model – ARIMA(2,0,1)+EGARCH(4,4), the GARCH fit was then use to forecast the volatility of 10- periods ahead. The 10-periods future volatility are as follows: 0.02188181, 0.02086944, 0.02351677, 0.02039852, 0.02196043, 0.02224388, 0.01987327, 0.02266489, 0.02043350, 0.02044057

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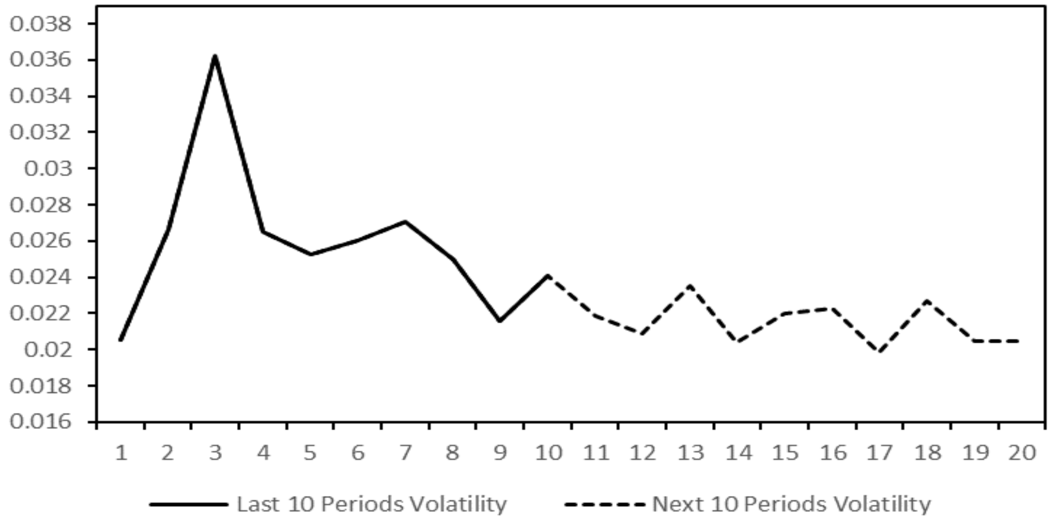

Fig 3: Forecasted Time plot

III. CONCLUSION

This study aims to define an effective volatility model that can both forecast and reflect the accepted structured attributes regarding conditional volatility. Structured attributes like volatility persistence and the asymmetric impact of return shocks. The capacity of models belonging to the GARCH family to capture these attributes, were illustrated using ten years of daily data on the Nigeria Stock Exchange Banking Index. It became apparent that the Nigeria Stock Exchange Banking Index's conditional volatility was quite persistent. The returns from the daily price were stationary but not normally distributed showing the asymmetric nature of the returns. It was established that ARIMA(2,0,1)+EGARCH(4,4) was a good model that can forecast volatility and capture the structured attributes regarding conditional mean and volatility. There was no indication of heteroscedasticity or autocorrelation in the ARIMA-EGARCH model's residual. Meanwhile, there is a 1% chance that the loss from the asset will exceed 860.07 in 10 days.

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