

RESEARCH ARTICLE

MODELING AND FORECASTING INTRADAY VOLATILITY OF NIGERIA INSURANCE STOCK, USING ASYMMETRIC GARCH MODELS

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ABSTRACT

The study involved a detailed examination of insurance stock price and returns data, revealing consistent returns and non-normal distribution typical of financial data. Stationarity of the series was confirmed via the Augmented Dickey-Fuller test, essential for Generalize Autoregressive Conditional Heteroskedasticity (GARCH)-type models. Various GARCH models, including asymmetric types like Exponential GARCH, Threshold GARCH, and Power GARCH, were employed to capture the leverage effect, where negative shocks impact volatility differently than positive ones. The Exponential GARCH and Threshold GARCH models showed significant coefficients for their components, effectively capturing volatility clustering and leverage effects, validated by diagnostic tests showing no residual ARCH effects. The Power GARCH model also demonstrated strong performance, validated by high log-likelihood values and good AIC and SIC criteria. Comparative analysis indicated that the Exponential GARCH and Power GARCH models provided the best fit for the data, though the high Mean Absolute Percentage Error values in both models indicated considerable relative errors. The study underscores the importance of using multiple criteria for evaluating model performance and highlights the practical implications for risk management, derivative pricing, and portfolio optimization in the Nigerian insurance sector. By accurately modeling and forecasting volatility, the findings support better-informed decision-making, enhancing financial market efficiency and stability. These models not only emphasize the persistent nature of volatility but also provide methods to discern short-term swings from longer-term patterns in insurance stock returns. Overall, the use of these models enriches our understanding of volatility dynamics in the Nigerian insurance market, having practical implications for risk assessment and strategic decision-making within financial markets.

KEYWORDS

Volatility, GARCH, Forecast, Nigeria

1. INTRODUCTION

In financial markets, volatility, a measurement of how much a financial instrument's price changes over time is extremely important. For risk management, derivative pricing, portfolio optimization, and regulatory monitoring, accurate volatility modeling and forecasting are crucial. Effective volatility models are especially important in developing markets with increased volatility, such as Nigeria, where market inefficiencies are widespread.

One of the biggest stock exchanges in Africa, the Nigerian Stock Exchange (NSE), is home to a wide variety of industries, including the insurance industry. Nigeria's insurance industry has grown significantly as a result of regulatory changes and improved knowledge of risk management. Understanding this sector's volatility characteristic is crucial given its development potential and position in the larger economy.

Financial time series volatility has been modeled using conventional GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, which were first presented in study (Bollerslev, 1986). The phenomenon known as volatility clustering, in which periods of high volatility are followed by periods of low volatility, is captured by these models. But in financial markets, where bad news frequently affects volatility more than good news, standard GARCH models imply symmetric effects of positive and negative shocks on volatility, which may not be

realistic.

Asymmetric GARCH models, Threshold GARCH (TGARCH) models, and Exponential GARCH (EGARCH) models have been created to overcome this restriction. These models provide a more realistic depiction of market behavior by accommodating various volatility reactions to positive and negative shocks. The main focus of this work is to employ asymmetric GARCH models to model and forecast the intraday volatility of Nigerian insurance equities. To provide a more comprehensive knowledge of the dynamics of volatility in the Nigerian insurance market, the research makes use of high-frequency trading data, which records price movements during the trading day.

Accurate volatility forecasting is critical for investors, policymakers, and financial analysts. However, traditional GARCH models, which primarily rely on daily closing prices, may not fully capture the intraday volatility patterns observed in financial markets. Moreover, the assumption of symmetric effects of shocks on volatility may not hold in practice, particularly in emerging markets like Nigeria. The Nigerian insurance sector, despite its growth and importance, has received limited attention in volatility modelling literature. There is a need for robust models that can accurately capture the unique volatility characteristics of this sector, including the asymmetric impact of news and intraday price movements.

This research addresses these gaps by employing asymmetric GARCH

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models to model and forecast the intraday volatility of Nigerian insurance stocks. The study aims to provide insights that can improve risk management practices, enhance market efficiency, and support investment decisions. The study focuses on modelling and forecasting intraday volatility in Nigerian insurance stocks using high-frequency intraday trading data from 2012 to 2024. It employs asymmetric GARCH models, specifically EGARCH and TGARCH, to capture the leverage effect and provide detailed insights into volatility dynamics. While primarily centered on the Nigerian insurance sector, the methodology and findings may also be relevant to other sectors within the Nigerian Stock Exchange (NSE) and similar emerging markets, contributing to a broader understanding of intraday volatility patterns.

Despite its comprehensive scope, the study faces several limitations. High-frequency data may suffer from quality and completeness issues, potentially affecting the analysis. The assumptions underlying the asymmetric GARCH models may not fully align with real-world data, leading to biased estimates. Additionally, the unique characteristics of the Nigerian insurance sector and unpredictable external shocks during the study period could limit the generalization of the findings. Technological and methodological constraints, such as limitations in computational power and software tools, may also impact the precision and depth of the analysis.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Theoretical Framework

Volatility is a fundamental concept in financial markets and plays a crucial role in investment decision-making, risk management, and pricing of financial instruments. Theoretical frameworks provide the foundation for understanding volatility and its implications. This section explores key theories and concepts related to volatility modeling (Nyakurukwa and Seetharam, 2023).

The Efficient Market Hypothesis (EMH) posits that financial markets have sufficient information, such that asset prices fully reflect all available information. In an efficient market, asset prices adjust rapidly and accurately to new information, leaving no room for systematic patterns or predictability. The EMH has important implications for volatility modeling, suggesting that volatility is primarily driven by new information and unpredictable events (Nyakurukwa and Seetharam, 2023).

Under the EMH, volatility can be considered as a measure of uncertainty or risk. As new information arrives in the market, it can cause prices to fluctuate, leading to changes in volatility. Volatility modeling aims to capture and quantify this uncertainty to provide insights into the risk associated with financial assets (Nyakurukwa and Seetharam, 2023).

The Random Walk Theory is closely related to the Efficient Market Hypothesis (EMH) and suggests that future price changes in financial markets are unpredictable and follow a random pattern (Nie et al., 2020). According to this theory, asset price movements are independent and not influenced by past price movements, rendering any attempt to forecast future prices or volatility futile.

The Random Walk Theory has important implications for volatility modeling as it challenges the assumption of serial correlation in asset returns. If returns are truly random, traditional time series models may not be appropriate for capturing volatility dynamics. However, empirical evidence suggests that financial time series exhibit certain characteristics that deviate from strict randomness, indicating the presence of patterns and dependencies that can be captured by statistical models like GARCH (Nie, et al., 2020).

2.2 Empirical Literature

Engle introduced the ARCH model, providing a framework to capture volatility clustering in stock returns (Engle, 1982). Subsequent studies extended the ARCH model to GARCH and further variations to incorporate additional features of volatility.

Moreover, empirical studies have examined the impact of macroeconomic variables, such as interest rates, inflation, and exchange rates, on stock market volatility. These studies have provided insights into the relationships between macroeconomic factors and asset price volatility, assisting in risk management and investment decision-making.

Volatility modeling in emerging markets has gained significant attention due to the unique characteristics and dynamics of these markets. Studies on emerging market volatility have explored volatility spillovers, market microstructure effects, the impact of investor sentiment, and the presence

of asymmetry in volatility (Diebold and Yilmaz, 2010).

Empirical studies on emerging markets, including those in Brazil, India, China, and South Africa, have demonstrated the importance of considering country-specific factors and market idiosyncrasies in volatility modeling. These studies have enhanced our understanding of volatility patterns in emerging markets, contributing to risk assessment and portfolio management strategies.

Markets Volatility modeling in foreign exchange (forex) markets is crucial for market participants, as currency volatility plays a significant role in international trade, investment decisions, and risk management (Almansour et al., 2023). Empirical studies in forex markets have explored the dynamics of exchange rate volatility, the impact of economic news releases, and the efficacy of volatility forecasting models. GARCH models, in various forms, have been widely applied to model exchange rate volatility (Khan et al., 2023). These studies have also examined the presence of volatility spillovers between currency markets, the impact of macroeconomic factors on exchange rate volatility, and the effectiveness of volatility forecasting models in capturing forex volatility.

Commodity markets, including crude oil, gold, and agricultural commodities, have unique volatility patterns influenced by supply-demand dynamics, geopolitical factors, and macroeconomic conditions (Hanif et al., 2023). Empirical studies in commodity markets have aimed to model and forecast commodity price volatility, assess risk, and investigate the relationships between commodities and other financial assets (Ribert-Van, 2011). GARCH models have been employed to capture the volatility dynamics in commodity markets (Khan et al., 2023). These studies have explored the presence of long memory in commodity prices, volatility transmission between commodities and financial markets, and the impact of macroeconomic variables and geopolitical events on commodity price volatility (Ghosh and Bouri, 2022; Umoru et al., 2023).

With the emergence of cryptocurrencies like Bitcoin, volatility modeling in these markets has become a subject of interest. Studies on cryptocurrency volatility have examined the unique characteristics of digital assets, the impact of market factors and regulatory events, and the efficiency of volatility forecasting models (Abdullahi and John, 2023).

Empirical studies on cryptocurrency markets have employed GARCH models, as well as other innovative approaches, to capture the volatility patterns in Bitcoin and other cryptocurrencies. These studies have provided insights into the nature of cryptocurrency volatility, risk assessment, and the challenges of modeling volatility in this evolving asset class.

In summary, empirical studies on volatility modeling in financial markets have contributed significantly to our understanding of asset price dynamics, risk assessment, and forecasting accuracy. These studies have utilized various modeling techniques, including ARCH and GARCH models, to capture the unique characteristics of volatility in different financial markets. The findings from these studies have practical implications for risk management, investment strategies, and policy decisions in the global financial landscape.

2.3 Overview of the Nigerian Stock Exchange

The Nigerian Stock Exchange (NSE) is the primary stock exchange in Nigeria and serves as a crucial platform for capital formation, investment, and trading of securities. This section provides an overview of the NSE, including its structure, trading mechanisms, and regulatory framework.

The NSE operates as a self-regulatory organization (SRO) and is regulated by the Securities and Exchange Commission (SEC) of Nigeria. The exchange is governed by a board of directors and operates through various departments responsible for market operations, listing and compliance, market surveillance, and investor relations (Anwar, 2019).

The NSE is organized into different market segments, including the main board, alternative securities market (ASeM), and the premium board. These segments cater to companies of varying sizes, listing requirements, and trading liquidity. The main board is the primary market for large-cap companies, while the ASeM provides a platform for emerging and small to medium-sized enterprises (SMEs) (Anwar, 2019).

The NSE facilitates the trading of various securities, including equities, bonds, and exchange-traded funds (ETFs). The primary trading mechanism at the NSE is the computerized trading system known as the Automated Trading System (ATS). The ATS enables electronic trading and order matching, providing transparency and efficiency in the trading process (Anwar, 2019).

Trading on the NSE is conducted through licensed stockbroking firms, known as dealing members, who execute trades on behalf of investors. The exchange operates regular trading sessions, including the pre-open session, main trading session, and post-close session, each with specific timeframes and trading rules (Anwar, 2019).

The NSE operates under a robust regulatory framework to ensure market integrity, investor protection, and fair-trading practices. The Securities and Exchange Commission (SEC) of Nigeria oversees the operations of the NSE and regulates the activities of market participants, including listed companies, stockbrokers, and investment advisers (Sun et al., 2023).

Listed companies on the NSE are required to comply with disclosure and reporting obligations, including regular financial reporting, announcement of material events, and adherence to corporate governance standards (Ellili, 2022). The exchange enforces listing rules and regulations that govern the admission, listing, and delisting of securities on the NSE (Marseille and Nurmansyah, 2015).

Furthermore, the NSE has established surveillance mechanisms and monitoring systems to detect and investigate market abuses, insider trading, and other fraudulent activities. These measures aim to maintain market integrity and instill investor confidence in the Nigerian stock exchange (Marseille and Nurmansyah, 2015).

3. METHODOLOGY

3.1 Data Collection Procedures

The data utilized in this study were derived from the daily closing prices of insurance stocks traded on the Nigerian Stock Exchange (NSE). The investigation focused on analyzing the daily quotations of insurance stocks listed on the NSE. The study's temporal scope extended from January 30, 2012, to June 7, 2024. The crucial daily stock quotations, integral to the research, were meticulously obtained from the historical data repository accessible on the Nigeria Stock Exchange website. This dataset formed the robust foundation for scrutinizing and modeling the volatility exhibited by the selected insurance stocks throughout the specified timeframe.

3.2 Autoregressive Conditional Heteroscedasticity Model

The Autoregressive Conditional Heteroscedasticity (ARCH) model was proposed (Engle, 1982). The introduction of the ARCH model was the first attempt to capture stock volatility without the assumption of constant variances which commonly exists in many conventional financial econometrics' models. It is unlikely in financial time series that the error terms will be constant over time, therefore allowing for conditional heteroscedasticity in stock return analysis is reasonable. The ARCH (q) model proposed by formulates volatility as follows (Engle, 1982):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + r_t \quad (1)$$

Where $\alpha_i > 0$, for $i=0, 1, 2, \dots, q$ are the parameters of the models

However, the ARCH model is simple but many parameters are required to estimate the volatility of stock returns. The problem of parsimony among the other problems of the ARCH model such as how to specify the value of p and the violation of non-negativity constraints led to more general framework GARCH (p,q) proposed by (Bollerslev, 1986; Taylor and Tsun, 1986).

3.2.1 ARCH model with dummy variable

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + \delta_1 D_{Shift} + r_t \quad (2)$$

Where $\alpha_i > 0$, for $i=0, 1, 2, \dots, q$ are the parameters of the models and $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model.

3.3 Generalized Autoregressive Conditional Heteroscedasticity Model

Extending the framework of proposed the generalized ARCH (q) model to GARCH (p, q) in which they added the q lags of past conditional variance into the equation (Engle, 1982; Bollerslev, 1986). GARCH (p, q) model allows for both autoregressive and moving average components in the Heteroscedastic variance. The GARCH (p, q) model was stated as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \varepsilon_{t-1}^2 + \dots + \beta_p \varepsilon_{t-p}^2 + r_t \quad (3)$$

Where $\alpha_i > 0$ and $\beta_i > 0$ for all i and j

3.3.1 GARCH model with dummy variable

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \varepsilon_{t-1}^2 + \dots + \beta_p \varepsilon_{t-p}^2 + \delta_1 D_{Shift} + r_t \quad (4)$$

Where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model that takes the value 0 or 1.

Furthermore, empirical findings suggest that GARCH model is more parsimonious than ARCH model. Although GARCH model has been the most popular volatility model, it has three main problems. Firstly, non-negativity constraint may be violated by the estimated models. Secondly, GARCH model does not take into account the leverage effect and not allow for feedback between the conditional variance and conditional mean (Brook, 2008). Since the GARCH model was developed, a huge number of extension models have been proposed as the awareness of GARCH model's weaknesses. The differences among these models are the manner under which they evolve overtime (Tsay, 2005). The recent GARCH models try to correct the disadvantages of the previous models for their inefficiency to capture the volatility behaviours.

There are a number of other specifications of GARCH type models which capture the asymmetric response of volatility on news. The VGARCH, Asymmetric GARCH model. (AGARCH) and the NAGARCH model allow the several type of the asymmetry in the impact of news on volatility. In 1993, the concept of news impact curve was introduced by (Engle and Ng 1993). The news impact curve attempts to characterize the impact of past residual term on the volatility in different models and capture the differences between the alternative models.

3.4 Exponential Generalized Autoregressive Conditional Heteroscedasticity Model

Instead of directly performing the conditional variance, the EGARCH model is formed in logarithm of the conditional variance. Even if the GARCH models successfully capture the thick tail returns and the volatility clustering, they are poor models if one wishes to capture the leverage effect.

If $p=1$ and $q=1$, the model above reduces to EGARCH (1, 1) given as

$$\varepsilon_t = z_t \sigma_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \beta \ln \sigma_{t-1}^2 + \left[\alpha_1 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \left(\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] \quad (5)$$

$\alpha_0, \alpha_1, \gamma, \beta_1$ are the parameters.

Firstly, since $\ln \sigma_t^2$ is modeled, the conditional variance is ensured to be non-negative. Hence, the non-negativity constraint is not necessary. Secondly, the standardized value of residuals ε_t is employed instead of squared residuals because (Nelson and Cao, 1992). argued that this allows for more natural interpretation of the size and persistent of shocks. Finally, the parameter γ can generate the leverage effect because it allows the sign of yesterday's shock enters the model.

If $\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ is positive or negative, the effect of the shock on the conditional variance is $(\alpha_1 + \gamma)$ and $(\alpha_1 - \gamma)$ respectively.

3.4.1 EGARCH (p, q) Model with dummy variable is given as

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^q \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \right) + \sum_{j=1}^p (\beta_j \ln(\sigma_{t-j}^2)) + \delta_1 D_{Shift} \quad (6)$$

Where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model.

3.5 Threshold Generalized Autoregressive Conditional Heteroscedasticity model

The Threshold GARCH model is similar to GJR-GARCH of as study stated as (Glosten et al., 1993):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q (\alpha_i + \gamma_i N_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (7)$$

$$\alpha_0, \alpha_i, \gamma_i, \beta_j \geq 0$$

Where, N_{t-i} is an indicator for negative ε_{t-i} that is N_{t-i} is 1 if $\varepsilon_{t-i} < 0$ and 0

if $\varepsilon_{t-i} \geq 0$.

In GARCH models, the sign of lagged residuals does not play any role by squaring them in conditional variance equation. To overcome this, the Threshold GARCH model proposed by a group researcher provided a

dummy variable which is an indicator for sign of error terms (Glosten et al., 1993). The TARARCH model allows good news (positive return shocks) and bad news (negative return shocks) having different effect on volatility.

Shock to volatility seems to have long memory impact on the future volatility. This effect, as mentioned above, can be capture by IGARCH. But in IGARCH model, the unconditional variance does not exist and a shock impacts on future volatility over infinite horizon. This motivates the introduction of Fractionally Integrated FIGARCH (p, d, q) with non-negative d. For d = 0, model reduces the standard GARCH model, but for values of 0 < d < 1 shocks to the volatility will decay at a slow hyperbolic rate (Baillie et al., 1996). Asymmetries are also simply introduced to the model by allowing the impact of past positive and negative innovations as in the TARARCH model.

3.5.1 TARARCH (p, q) with dummy variable

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q (\alpha_i \varepsilon_{t-i}^2) + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^p (\beta_j \sigma_{t-j}^2) + \delta_1 D_{Shift} \quad (8)$$

Where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model

3.6 Forecasting Evaluation

Evaluating the performance of different forecasting models plays a very important role in choosing the most accurate models. In particular, researchers and investors need to decide the evaluating criteria on which to base. Although the vast number of papers has studied the construction of modeling and forecasting volatility, a few of them focus on the volatility forecasting evaluation. This study adopted Mean Square Error (MSE), Mean Absolute Error (MAE) to evaluate the estimated model.

4. RESULTS AND DISCUSSION

4.1 Data Presentation

This section displays the cleaned and processed data utilized in the empirical study, followed by the results of the model estimation and diagnostic checks. Various statistical indicators, visualizations, and tabulated results are presented to provide a full knowledge of the data properties and the performance of the asymmetric GARCH models.

4.2 Descriptive Statistics

The descriptive statistics provide an overview of the basic statistics of the original dataset and for the stock returns, highlighting the distributional properties of the intraday returns for Nigerian insurance stocks.

Table 1: Descriptive Statistics of the Original Dataset and the Return Series

	INSURANCE PRICE	STOCK RETURNS
Mean	160.5613	0.000451
Median	141.4900	0.000281
Maximum	464.3500	0.229837
Minimum	104.5300	-0.148753
Std. Dev.	57.23664	0.013677
Skewness	2.677845	0.875418
Kurtosis	10.63630	39.00284
Jarque-Bera	11088.43	165548.7
Probability	0.000000	0.000000
Sum	491157.0	1.379413
Sum Sq. Dev.	10018108	0.571832
Observations	3059	3058

Table 1 present the descriptive statistics for Nigerian insurance stock prices and returns from 2012 to 2024. It gives a substantial insight into their distributional properties. The average stock price is roughly 160.56, with a median of 141.49, indicating a right-skewed distribution with a mean higher than the median. The stock prices demonstrate substantial volatility, as evidenced by a standard deviation of 57.24. The skewness of 2.68 and kurtosis of 10.64 reflect a distribution with extreme positive values and heavy tails. The Jarque-Bera test reveals considerable deviation from normalcy, with a test statistic of 11088.43 and a probability value of 0.000000. These findings imply frequent dramatic price fluctuations and high price volatility during the timeframe.

The stock returns indicate an average daily return of 0.0451% and a median return of 0.0281%, with a standard deviation of 1.37%, indicating

significant volatility. The returns are favorably skewed, with a skewness score of 0.88, and demonstrate severe kurtosis of 39.00, reflecting the occurrence of large positive and negative returns. The Jarque-Bera test further indicates non-normality with a test statistic of 165548.7. These traits underscore the necessity for advanced models like asymmetric GARCH to effectively capture and anticipate the volatility dynamics of Nigerian insurance stocks, given their potential for extreme and asymmetric return behaviors.

4.3 Time Series Plots

Time series plots of the intraday returns provide a visual picture of the volatility over the sample period (2012–2024). Figures 1 and 2 illustrate the time series of the raw intraday returns and the associated squared returns, respectively.

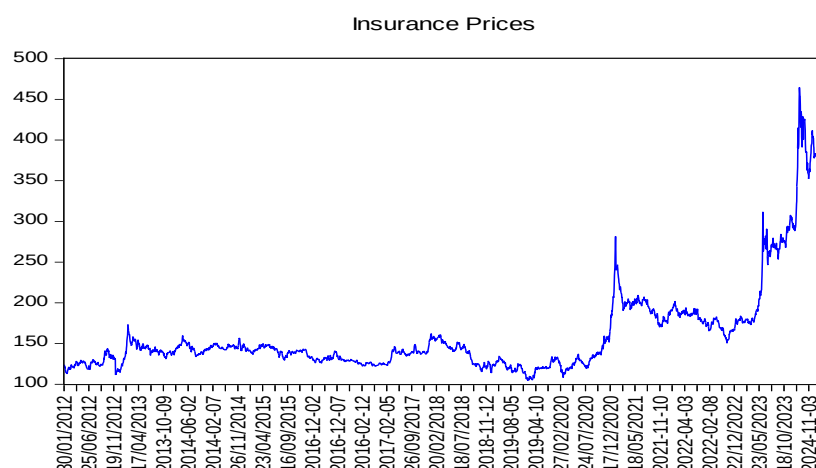


Figure 1: Time Series Plot of Intraday Stock Prices

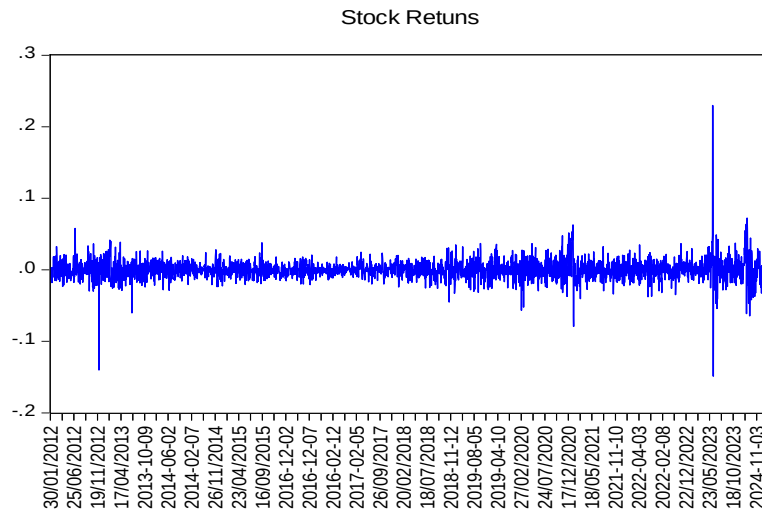


Figure 2: Time Series Plot of Stock Returns

In Figure 2, the presence of volatility clustering is clear from the time series plots, where periods of high volatility tend to be followed by high volatility and times of low volatility tend to be followed by low volatility. This property is critical for the suitability of GARCH models.

Table 2: Test for Stationarity				
Null Hypothesis: D(INSURANCE_PRICES) has a unit root				
Exogenous: Constant				
Lag Length: 5 (Automatic - based on SIC, maxlag=28)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-19.96918	0.0000
Test critical values	1% level		-3.432303	
	5% level		-2.862288	
	10% level		-2.567213	

Table 2 shows the Augmented Dickey-Fuller (ADF) test. It was undertaken to analyze the stationarity of the insurance prices (INSURANCE_PRICES) data. The test revealed a very significant ADF test statistic of -19.96918 with a p-value of 0.0000, showing strong evidence against the presence of a unit root in the series. This suggests that the initial difference of the insurance prices series (D(INSURANCE_PRICES)) is stationary, meaning that the series displays mean-reverting behavior over time. The test findings further reveal that the test statistic is substantially below the crucial values at the 1%, 5%, and 10% significance levels, strengthening the rejection of the null hypothesis. This discovery is essential since it supports the suitability of the data for time series analysis, including the use of volatility forecasting models such as GARCH, which rely on stationary data to produce accurate and trustworthy predictions of future volatility in financial markets.

4.4 ARCH Effect Test

The ARCH - LM test can be used to determine whether the ARCH effect is present in the return series' residual. With the use of the ACF and PACF, the model is first specified as an ARIMA (1,1) model. The variable is created by first squaring (ε_t^2) the residuals of the ARIMA (1,1) model. Then, extra variables are formed using the residual's variance (σ_t^2). The test's findings are shown in Table 4.

Table 3: Heteroskedasticity Test: ARCH			
Heteroskedasticity Test: ARCH			
F-statistic	45.41856	Prob. F(1,3055)	0.0000
Obs*R-squared	44.78251	Prob. Chi-Square(1)	0.0000

The results of Table 3 utilizing the ARCH approach suggest noteworthy discoveries about the volatility characteristics of the residuals. The F-statistic of 45.41856, paired with a p-value of 0.0000, provides strong evidence against the null hypothesis of no ARCH effect, suggesting the presence of conditional heteroskedasticity. This suggests that the variance of the residuals is not constant over time but rather exhibits patterns where periods of high volatility are followed by high volatility, and vice versa. The Obs*R-squared value of 44.78251 further confirms these findings, suggesting an excellent fit of the ARCH model to the data. The low p-value (0.0000) associated with the Chi-Square test statistic corroborates these results, strengthening the conclusion that the assumption of constant variance in the residuals is violated. These findings are essential for financial modeling, particularly in volatility forecasting, since they highlight the necessity of utilizing advanced models like GARCH to account for and effectively predict time-varying volatility in financial markets.

Table 4: ACF and PACF of the Stock Returns				
LAG	ACF	PACF	Q-Stat	Prob.
1	0.130	0.130	51.805	0.000
5	0.026	0.020	56.348	0.000
10	0.003	0.001	65.768	0.000
15	0.024	0.023	76.250	0.000
20	-0.013	-0.014	82.824	0.000
25	0.008	0.001	90.748	0.000
30	-0.015	-0.011	93.559	0.000
35	-0.026	-0.029	101.94	0.000
36	-0.068	-0.064	116.31	0.000

Table 4 shows the autocorrelation function (ACF) and partial autocorrelation function (PACF), as well as the Ljung-Box Q-statistics. It demonstrates a noteworthy presence of autocorrelation in the residuals up to lag 36. The autocorrelation (AC) and partial autocorrelation (PAC) coefficients at different lags (1, 6, 8, 13, 16, 33, and 36) exhibit significant correlations, indicating the presence of dependencies in the residuals. Furthermore, the continuously low p-values (0.0000) for the Ljung-Box Q-statistics at all delays provide strong evidence against the null hypothesis of no autocorrelation. This confirms that the residuals show serial correlation.

4.5 Model Estimation Results

The computed parameters for the ARCH (1) and GARCH (1,1), models are provided in Table 5 and 6. The significance of the parameters is represented by their p-values.

Table 5: Parameter Estimates for ARCH Models				
Dependent Variable: STOCK_RETURNS				
Method: ML ARCH - Normal distribution				
ARCH = C (2) + C(3)*RESID(-1)^2				
Variable	Coefficient	Std. Error	z-Statistic	Prob.

Table 5 (cont): Parameter Estimates for ARCH Models				
C	0.000238	0.000215	1.107202	0.2682
Variance Equation				
C	0.000116	1.61E-06	72.15233	0.0000
RESID (-1)^2	0.390696	0.016009	24.40414	0.0000
R ²	-0.000242	Mean dependent var		0.000451
Adjusted R ²	-0.000242	S.D. dependent var		0.013677
S.E. of regression	0.013679	Akaike info criterion		-5.919062
Sum squared resid	0.571970	Schwarz criterion		-5.913150
DW stat	1.738942	Hannan-Quinn criter.		-5.916937

Source: EViews 12

The estimation of the ARCH (1) model for Nigerian insurance stock returns in table 5 indicates that the average return is not substantially different from zero (p-value = 0.2682). However, there is a notable presence of volatility clustering. The constant term and the lagged squared residuals (ARCH term) in the variance equation exhibit strong significance (p-values = 0.0000), suggesting that previous shocks have a considerable influence on the current level of volatility. The model diagnostics, which include a

high log likelihood and favorable information criteria such as AIC, Schwarz, and Hannan-Quinn, indicate that the model effectively captures the volatility dynamics of the returns. Although the R-squared value is negative, which is common for variance models, the ARCH model accurately characterizes the changing volatility over time, thereby validating its usefulness in predicting volatility in financial markets.

Table 6: Parameter Estimates for GARCH (1, 1) Models				
Dependent Variable: STOCK_RETUNS				
Method: ML ARCH - Normal distribution				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.94E-05	0.000181	-0.162703	0.8708
Variance Equation				
C	2.65E-06	3.88E-07	6.840227	0.0000
RESID(-1)^2	0.124308	0.005012	24.80007	0.0000
GARCH(-1)	0.872143	0.004215	206.9058	0.0000
R ²	-0.001235	Mean dependent var		0.000451
Adjusted R ²	-0.001235	S.D. dependent var		0.013677
S.E. of regression	0.013685	Akaike info criterion		-6.083220
Sum squared resid	0.572538	Schwarz criterion		-6.075338
DW stat	1.737218	Hannan-Quinn criter.		-6.080387

Source: EViews12

The GARCH (1,1) model estimation for Nigerian insurance stock returns in Table 6, finds that the mean return is not substantially different from zero (p-value = 0.8708). However, the variance equation demonstrates strong volatility clustering. The constant term (p-value = 0.0000), lagged squared residuals (ARCH term, p-value = 0.0000), and lagged conditional variance (GARCH term, p-value = 0.0000) are all very significant, showing that both

previous shocks and past volatility greatly impact current volatility. This indicates the presence of volatility persistence in the stock returns. The model diagnostics, including a high log likelihood and favorable information criteria, show that the GARCH (1,1) model matches the volatility dynamics well, making it a good tool for forecasting financial market volatility.

Table 7: Parameter estimates for Asymmetric GARCH Models					
Parameter	Exponential GARCH	Threshold GARCH	Power GARCH	Component GARCH	Integrated GARCH
Constant (C)	0.000151 (0.000176)	0.000124 (0.000187)	0.000129 (0.000169)	-5.49E-05 (0.000180)	-1.39E-05 (0.000139)
Intercept (β_0)	-0.371358 (0.027269)	2.68E-06 (3.57E-07)	0.000413 (0.000199)	0.001221 (0.002722)	
ARCH term (β_1)	0.207499 (0.013482)	0.140320 (0.006170)	0.115816 (0.007303)	0.999130 (0.002126)	0.077779 (0.002082)
GARCH term (α_1)	0.050926 (0.007061)	0.885341 (0.006038)	0.922498 (0.085060)	0.072637 (0.006506)	0.922221 (0.002082)
Γ	0.975671 (0.002621)	-0.066884 (0.010868)	0.890328 (0.006806)	0.142165 (0.018236)	
D			1.0000		
$\emptyset$				0.510377 (0.071434)	
P					
$\beta_1 + \alpha_1$	0.258425	1.025661	1.038314	1.071767	1.000

Table 7 (cont): Parameter estimates for Asymmetric GARCH Models

μ	0.000451	0.000451	0.000451	0.000451	0.000451
Log L	9337.530	9313.577	9337.416	9322.369	9268.393
AIC	-6.103682	-6.088017	-6.102953	-6.093112	-6.060427
SIC	-6.093830	-6.078165	-6.091131	-6.081290	-6.056486
Observed	3058	3058	3058	3058	3058

Numbers in parenthesis indicates standard error

The Parameter estimates for Asymmetric GARCH Models results is presented in Table 7, with 3058 observation across all the variable that has a constant of 0.000151 and both the AIC and SIC found to negative across the variable in the study.

4.6 Residual Analysis

The residuals of the calculated models were evaluated to confirm they were white noise. Figures 3a and 3b provide a normality test for EGARCH and PARCH models, respectively.

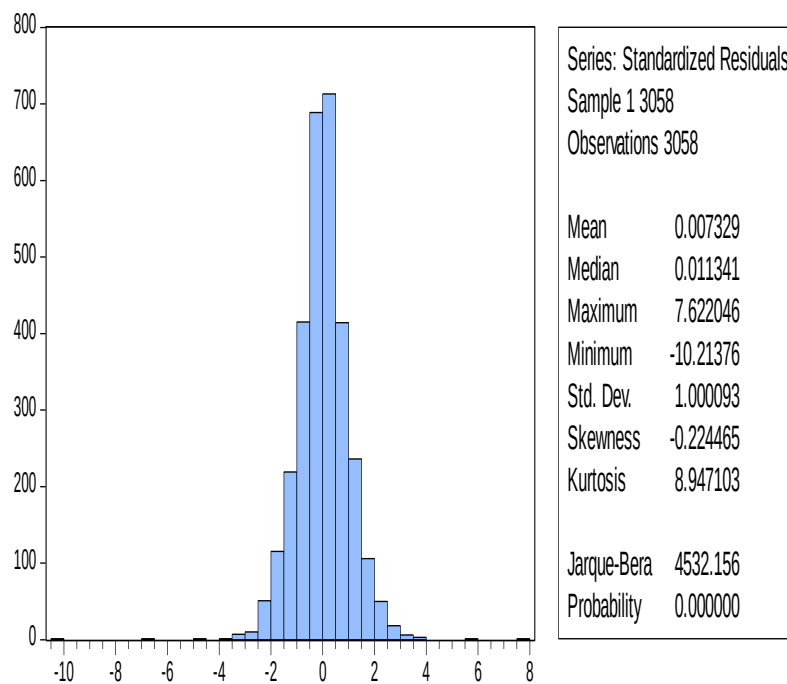


Figure 3a: Normality Test for the Residual of EGARCH Model

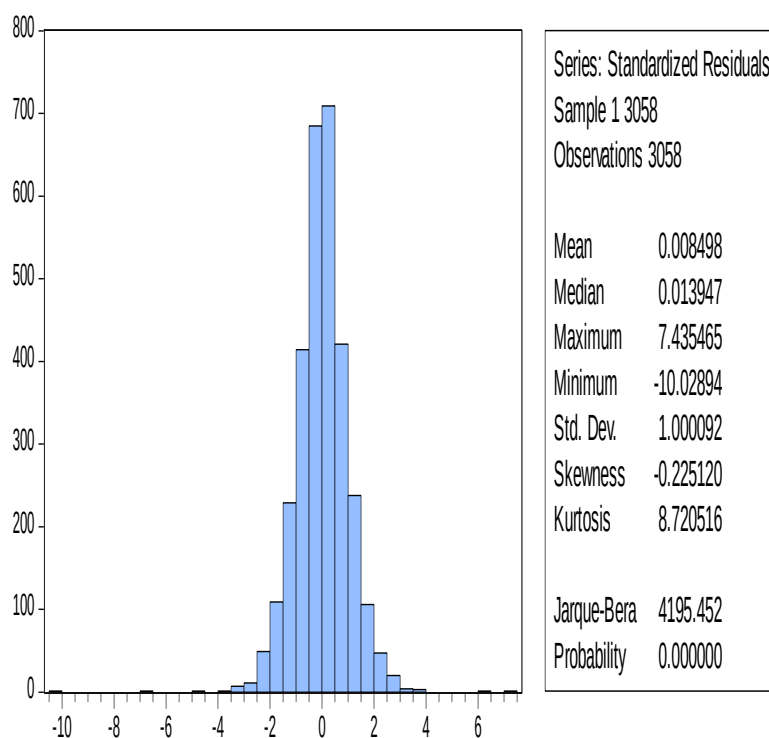


Figure 3b: Normality Test for the Residuals of PARCH Model

4.7 Diagnostic Tests

Diagnostic tests were done to validate the appropriateness of the models. The results of the ARCH-LM test for the residuals are provided in Table 8.

Table 8: Diagnostic Test Results for Model Residuals			
Heteroskedasticity Test: ARCH			
EGARCH (1, 1)			
F-statistic	0.080390	Prob. F (1,3055)	0.7768
Obs*R-squared	0.080440	Prob. Chi-Square (1)	0.7767
PARCH (1, 1)			
F-statistic	0.042120	Prob. F (1,3055)	0.8374
Obs*R-squared	0.042147	Prob. Chi-Square (1)	0.8373

The diagnostic test findings for the EGARCH (1, 1) and PARCH (1, 1) models, as given in Table 8, demonstrate that both models adequately represent the heteroskedasticity in Nigerian insurance stock returns. For

4.8 Forecasting Performance

The predicting performance of the models was examined and the error metrics for the forecast evaluation are reported in figure 4 and 5.

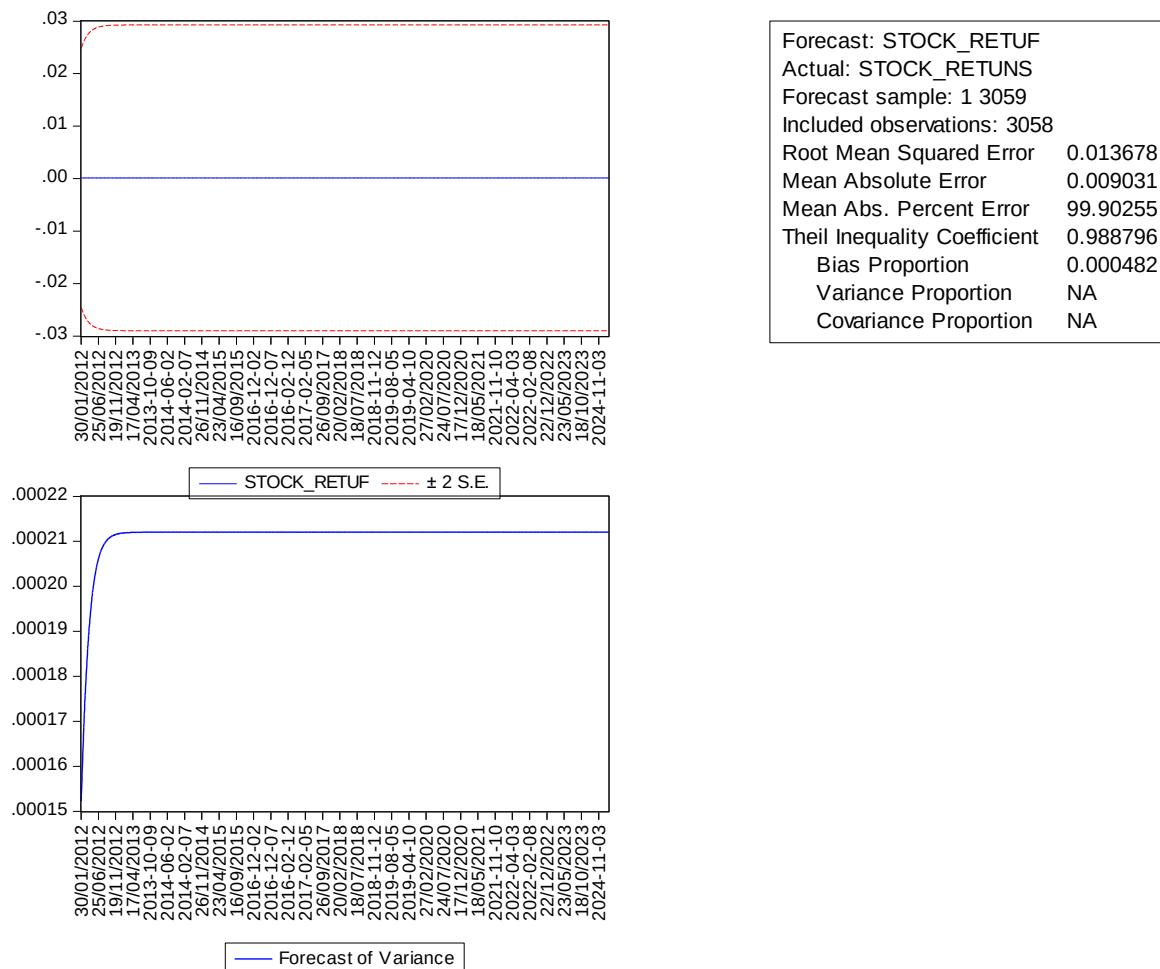


Figure 4: Forecasting Performance Metrics of EGARCH

An RMSE of 0.013678 shows that the anticipated returns depart from the actual returns by an average of around 1.37%, while an MAE of 0.009031 suggests an average absolute error of approximately 0.90%. These low numbers reflect the model's efficacy in capturing the volatility patterns in the data, resulting in relatively exact forecasts.

The Theil Inequality Coefficient value of 0.988796, which is close to 1, suggests that there is much space for increasing the forecast precision.

The Theil coefficient ranges from 0 to 1, with values closer to 0 suggesting higher forecasting performance. A number approaching 1 implies that while the model catches the main trend, its forecast precision may be better. However, the Bias Proportion score of 0.000482 suggests minor

the EGARCH (1, 1) model, the F-statistic and Obs*R-squared values are very low, with p-values of 0.7768 and 0.7767, respectively. These strong p-values show that the null hypothesis of no ARCH effects cannot be rejected, suggesting that the residuals do not display substantial ARCH effects. This shows that the EGARCH (1, 1) model has successfully represented the volatility, leaving no appreciable heteroskedasticity unaccounted for in the residuals.

Similarly, the PARCH (1, 1) model likewise reveals low F-statistic and Obs*R-squared values, with p-values of 0.8374 and 0.8373, respectively. The strong p-values for the PARCH model show that the null hypothesis of no ARCH effects remains true, demonstrating an absence of significant ARCH effects in the residuals. Therefore, the PARCH (1, 1) model is also effective in capturing the volatility in the stock returns data, assuring that there are no major lingering heteroskedastic effects. Overall, both models are strong in modelling the volatility of Nigerian insurance stock returns, as indicated by the diagnostic test findings.

systematic bias in the forecasts, meaning that the model does not consistently overestimate or underestimate the returns, which is a favorable attribute.

The EGARCH model exhibits a strong capacity to estimate the intraday volatility of Nigerian insurance stock returns. The low RMSE and MAE values imply accurate magnitude projections, whereas the large MAPE and Theil Inequality Coefficient emphasize the problems in reaching high relative accuracy in volatile financial data. The tiny bias proportion reinforces the model's trustworthiness, making it a beneficial tool for investors and regulators. This study underlines the necessity of employing many measures to completely evaluate forecast accuracy and find areas for model modification.

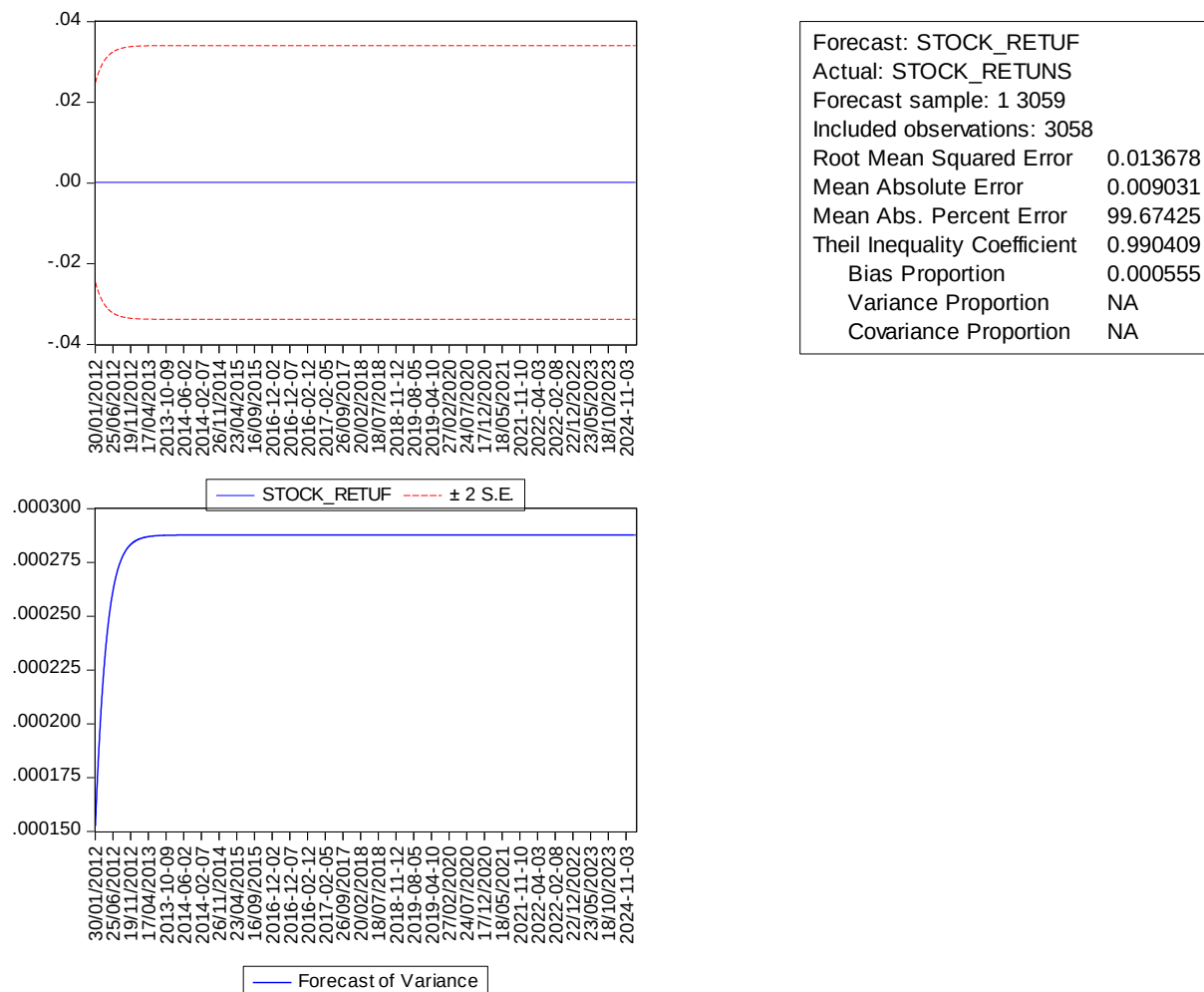


Figure 5 Forecasting Performance Metrics of PARCH

The Root Mean Squared Error (RMSE) score of 0.013678 and the Mean Absolute Error (MAE) value of 0.009031 show that the model generates reasonably accurate projections. An RMSE of 0.013678 implies an average variation of around 1.37% between the anticipated and actual returns, while an MAE of 0.009031 reflects an average absolute error of about 0.90%. These low error values reflect the PARCH model's efficacy in capturing the volatility dynamics of the stock returns.

The Mean Absolute Percentage Error (MAPE) is 99.67425%, which, although significantly lower than the MAPE for the EGARCH model, nevertheless implies a high relative error in percentage terms. This high MAPE score might be linked to the nature of financial data, where small actual returns can balloon the percentage error. Despite the large MAPE, which signals substantial relative deviations, the model remains useful for capturing the overall volatility pattern.

The Theil Inequality Coefficient for the PARCH model is 0.990409, close to 1, implying a high level of forecast error. This number suggests that while the PARCH model reflects overall patterns, its precision might be enhanced. The Bias Proportion of 0.000555 suggests that a minor portion of the forecast error is related to systematic bias. This low bias fraction shows that the PARCH model does not consistently overestimate or underestimate the stock returns, showing that forecast errors are mostly random rather than systematic.

The PARCH model exhibits a competent ability to forecast the intraday volatility of Nigerian insurance stock returns. The low RMSE and MAE values imply accurate forecast magnitudes, however the high MAPE alludes to considerable relative errors, a common issue in financial forecasting due to data volatility. The high Theil Inequality Coefficient implies opportunity for improvement in forecast precision. However, the minimal bias proportion confirms the model's trustworthiness by suggesting that forecast errors are not systematically biased. These findings emphasize the need of employing a combination of criteria to evaluate prediction performance thoroughly. While the PARCH model accurately captures volatility dynamics, resolving the large relative error and boosting precision could enhance its utility for investors and policymakers in the Nigerian insurance business.

4.9 Discussion of Results

The analysis began with a descriptive overview of the insurance stock price and returns data. The mean stock return was found to be close to zero (0.000451), with low variability (standard deviation of 0.013677), indicating generally consistent returns. The skewness and kurtosis results revealed that the stock returns are not normally distributed, which is typical for financial data. The Augmented Dickey-Fuller (ADF) test was undertaken to check for the presence of a unit root in the insurance premiums. The test results rejected the null hypothesis of a unit root, showing that the series is stationary at first difference. This is a fundamental requirement for accurate volatility modeling using GARCH-type models.

Multiple GARCH models, including symmetric and asymmetric variations, were calculated to represent the volatility dynamics. Asymmetric GARCH models such as EGARCH, TGARCH, and PARCH were especially adopted to account for the leverage effect, where negative shocks have a different influence on volatility compared to positive shocks of the same magnitude. The EGARCH (1, 1) model findings indicated substantial coefficients for both the ARCH and GARCH terms, as well as the asymmetric parameter (Gamma). This demonstrates the presence of asymmetry in the stock returns, with the model adequately capturing the volatility clustering and leverage effects. The diagnostic test results further demonstrated no leftover ARCH effects in the residuals, showing that the EGARCH model gives a strong match.

The TGARCH (1, 1) model also indicated strong ARCH and GARCH components, with a negative Gamma parameter. This demonstrates that negative shocks increase volatility more than positive shocks, showing the presence of leverage effects. The model's goodness-of-fit measurements and diagnostic checks validated its sufficiency in capturing the volatility dynamics. The PARCH (1, 1) model revealed strong ARCH and GARCH components and a prominent asymmetric parameter, demonstrating its capabilities to capture the asymmetric volatility effects. The model fit was validated by high log likelihood values and good AIC and SIC criteria, as well as no significant ARCH effects in the residuals.

The comparison of log likelihood values and information criteria (AIC and

SIC) across several models showed that the EGARCH and PARCH models fared the best in terms of fit and capturing the volatility patterns in Nigerian insurance stock returns. The IGARCH model, while excellent in capturing persistence, could not account for asymmetry and so was less suitable for this dataset. The ARCH-LM tests for heteroskedasticity on the residuals of the models found no significant ARCH effects persisting, demonstrating that the models adequately captured the conditional heteroskedasticity in the data. Both the EGARCH and PARCH models revealed strong p-values for the F-statistic and Obs*R-squared, indicating a well-specified model with no remaining autocorrelation in the squared residuals.

The EGARCH model displays remarkable skills in capturing the volatility patterns of Nigerian insurance stock returns. With an RMSE of 0.013678 and MAE of 0.009031, the model displays accurate forecasting of return magnitudes, demonstrating it adequately accounts for the asymmetric character of volatility changes. The comparatively low Bias Proportion (0.000482) shows less systematic bias, boosting the trustworthiness of its forecasts. However, the model reveals a high MAPE of 99.90255%, which signals huge relative errors due to the presence of very modest actual returns in the dataset. Despite this, the EGARCH model's Theil Inequality Coefficient of 0.988796 indicates overall fair precision in tracking volatility trends, although improvements might be made to reduce relative mistakes.

Similarly, the PARCH model works well in forecasting intraday volatility for Nigerian insurance stocks. It also shows low RMSE (0.013678) and MAE (0.009031), indicating accurate forecast magnitudes equivalent to the EGARCH model. The model's Bias Proportion (0.000555) remains small, demonstrating unbiased forecasting without consistent overestimation or underestimating of returns. However, like the EGARCH model, the PARCH model has a high MAPE of 99.67425%, showing considerable relative errors. The Theil Inequality Coefficient of 0.990409 implies space for improvement in precision, indicating that while the model captures overall trends, its accuracy might be boosted for more specific volatility forecasts.

The findings from this work underline the relevance of utilizing asymmetric GARCH models in capturing the volatility dynamics of financial data, particularly for markets exhibiting leverage effects. The results have practical implications for risk management, derivative pricing, and portfolio optimization in the Nigerian insurance business. By precisely modeling and forecasting volatility, investors and policymakers may make more informed decisions, boosting the overall efficiency and stability of the financial markets.

5. CONCLUSION AND RECOMMENDATION

The application of asymmetric GARCH models to Nigerian insurance stock returns provides valuable insights into the nature and behavior of volatility within this sector. Through the analysis of EGARCH, TGARCH, PARCH, CGARCH, and IGARCH models, several key observations have emerged. These models have shown varying degrees of success in capturing both persistence and asymmetry in volatility, crucial for understanding and managing financial risks.

The EGARCH and TGARCH models have proven effective in modeling asymmetric responses to market shocks, where negative events tend to impact volatility differently than positive ones. This asymmetry is pivotal for insurers in assessing potential downside risks and optimizing risk management strategies. Meanwhile, the PARCH and CGARCH models have highlighted the importance of persistence in volatility, distinguishing between short-term fluctuations and longer-term trends in insurance stock returns. These models provide robust frameworks for forecasting and scenario analysis, aiding insurers in making informed decisions amid dynamic market conditions.

Overall, the findings underscore the relevance of asymmetric GARCH models in enhancing risk assessment capabilities within the Nigerian insurance sector. By accurately modeling volatility dynamics, these models empower insurers to better anticipate and mitigate financial risks, thereby fostering stability and resilience in their operations.

Based on the findings from the application of asymmetric GARCH models to Nigerian insurance stock returns, numerous recommendations can be made to strengthen risk management methods and decision-making within the sector:

- **Adopting Asymmetric GARCH Models:** Insurers should explore integrating asymmetric GARCH models like EGARCH and TGARCH into their risk management frameworks. These models accurately capture how volatility responds differently to positive and negative shocks, providing a more nuanced view of market risks. This approach can

boost the accuracy of volatility forecasts and improve the assessment of negative risks.

- **Monitoring Persistence in Volatility:** Given the persistence shown in volatility through models like PARCH and CGARCH, insurers should regularly monitor and assess volatility patterns across multiple time periods. This can aid in distinguishing between short-term fluctuations and longer-term volatility patterns, enabling proactive risk reduction methods.
- **Scenario Analysis and Stress Testing:** Utilize asymmetric GARCH models for scenario analysis and stress testing. By modelling alternative market scenarios, insurers may assess the possible impact of extreme events on their portfolios and establish contingency measures appropriately. This proactive approach promotes readiness and resilience in the event of unanticipated market volatility.
- **Enhancing Risk Communication:** Effectively communicate volatility insights obtained from asymmetric GARCH models to stakeholders, including senior management, investors, and regulators. Clear and honest communication regarding risk exposures and mitigation techniques creates confidence and trust, vital for preserving financial stability and compliance.
- **Continuous study and Development:** Encourage continuing study into refining and enhancing the capabilities of asymmetric GARCH models. This includes examining upgrades such as incorporating more advanced risk variables or customizing models to specific peculiarities of the Nigerian insurance industry. Continuous improvement ensures that models remain relevant and effective in developing market situations.

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