ISSN 2350-1049

International Journal of Recent Research in Interdisciplinary Sciences (IJRRIS)
Vol. 13, Issue 2, pp: (1-10), Month: April - June 2026, Available at: www.paperpublications.org

Model Selection and Seasonal Volatility Dynamics in the Nigerian Stock Market: Evidence from Asymmetric GARCH Models

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DOI: https://doi.org/10.5281/zenodo.20505991

Published Date: 02-June-2026

Abstract: **This study investigates model selection and seasonal volatility dynamics in the Nigerian stock market using asymmetric Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. Daily returns of the Nigerian Stock Exchange (NSE) All Share Index from January 2016 to December 2025 are analyzed to capture key volatility characteristics across different market conditions. The study estimates and compares alternative volatility specifications, including GARCH (1,1), EGARCH, GJR GARCH, TGARCH, and QGARCH models, with primary emphasis on in-sample model performance. Preliminary diagnostic tests confirm that the return series is stationary and exhibits significant ARCH effects, indicating time varying volatility and justifying the use of GARCH-type models. The empirical results reveal strong volatility persistence and clear evidence of asymmetric responses to market shocks, consistent with the leverage effect observed in financial markets. Model selection based on log-likelihood values and information criteria (Akaike Information Criterion and Bayesian Information Criterion) indicates that the EGARCH model provides the best in sample fit among the competing specifications. This suggests that accounting for asymmetry significantly improves model performance in the Nigerian context. To examine seasonal volatility dynamics, calendar based dummy variables are incorporated into the variance equation. The results show no statistically significant day-of-the-week effects, while modest reductions in volatility are observed during the mid-year months, particularly from April to June. However, these seasonal effects are relatively weak compared to the dominant influence of volatility persistence. Overall, the findings highlight the superiority of asymmetric GARCH models for capturing volatility dynamics and provide useful insights for risk modelling and financial market analysis in emerging economies**

Keywords: **Stock Market Volatility; Model Selection; Asymmetric GARCH; EGARCH; Seasonality; Nigerian Stock Market.**

1. INTRODUCTION

Stock market volatility remains a central concern in financial economics due to its direct implications for risk management, asset pricing, portfolio allocation, and financial stability. In emerging markets, volatility is often more pronounced and persistent, reflecting structural inefficiencies, macroeconomic instability, and heightened sensitivity to external shocks (Atoi, 2014; Olowe, 2009). The Nigerian stock market, represented by the Nigerian Stock Exchange (NSE) All Share Index, exhibits these characteristics, making volatility modelling a critical area of empirical investigation.

A fundamental feature of financial return series is that volatility is time-varying, clustered, and persistent. Large price changes tend to be followed by further large changes, while periods of relative calm are similarly sustained (Mandelbrot, 1963). In addition, volatility often responds asymmetrically to market shocks, with negative shocks exerting a stronger impact than positive shocks of similar magnitude. This phenomenon, widely referred to as the leverage effect, challenges the assumptions of constant variance underlying traditional linear time series models (Black, 1976; Nelson, 1991).

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The introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle (1982) and its generalization into the GARCH model by Bollerslev (1986) marked a significant advancement in modelling time-varying volatility. Subsequent extensions of the GARCH framework, including the Exponential GARCH (EGARCH) model (Nelson, 1991), GJR-GARCH (Glosten et al., 1993), Threshold GARCH (TGARCH) (Zakoian, 1994), and Quadratic GARCH (QGARCH) (Sentana, 1995), have been developed to capture asymmetry and nonlinear volatility dynamics. Empirical evidence suggests that these asymmetric models often provide superior performance, particularly in emerging markets where negative shocks tend to have amplified effects on volatility (Omolade & Ngalawa, 2021).

Despite the extensive application of GARCH-type models in the literature, a key challenge remains the selection of the most appropriate model for a given financial time series. Many existing studies in the Nigerian context focus on single-model estimation or emphasize forecast performance, with limited attention to systematic in-sample model comparison using consistent evaluation criteria (Adegbite, 2020; Ogundipe & Olayemi, 2022). This creates uncertainty regarding the optimal specification for accurately capturing volatility dynamics. Moreover, while asymmetric behavior has been widely acknowledged, there is still a need for comprehensive comparative analysis across multiple GARCH variants within a unified framework.

Another important yet underexplored aspect of volatility dynamics in the Nigerian stock market is seasonality. Calendar anomalies, such as day-of-the-week and month-of-the-year effects, have been documented in various financial markets and may influence trading behavior, liquidity patterns, and volatility distribution (Poon & Granger, 2003). Ignoring such seasonal patterns may lead to model misspecification and biased inference. However, empirical evidence on seasonal volatility effects in Nigeria remains limited and inconclusive (Olowe, 2009; Adegbite, 2020).

Motivated by these gaps, this study examines model selection and seasonal volatility dynamics in the Nigerian stock market using a range of symmetric and asymmetric GARCH-type models. Specifically, the study estimates GARCH (1,1), EGARCH, GJR-GARCH, TGARCH, and QGARCH models using daily returns of the NSE All Share Index over the period 2016 to 2025. Model selection is based on in-sample performance criteria, including log-likelihood values, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), allowing for a rigorous comparison of competing specifications.

In addition, the study incorporates seasonal effects into the volatility process through calendar-based dummy variables to assess the presence of day-of-the-week and monthly patterns. This dual focus on model selection and seasonality provides a more comprehensive understanding of volatility dynamics in the Nigerian stock market.

The contribution of this study is threefold. First, it provides a systematic comparative evaluation of both symmetric and asymmetric GARCH models within a unified empirical framework. Second, it emphasizes in-sample model selection, offering clarity on the most appropriate specification for capturing volatility dynamics in Nigeria. Third, it extends the analysis by incorporating seasonal effects, thereby addressing an important but underexplored dimension of volatility behavior in the Nigerian context.

The remainder of the paper is structured as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 contains the methodology which outlines the data, model specifications and estimation techniques. Section 4 presents and discusses the empirical results, while section 5 is the conclusion with key findings and implications.

2. LITERATURE REVIEW

2.1 Conceptual Issues in Stock Market Volatility

Stock market volatility refers to the degree of variation in asset prices or returns over time and is widely regarded as a key measure of financial risk and uncertainty (Poon & Granger, 2003). A fundamental characteristic of financial time series is that volatility is not constant but evolves over time. Empirical studies show that volatility exhibits clustering, whereby large changes in asset prices are followed by further large changes, and small changes tend to be followed by small changes (Mandelbrot, 1963). This behavior implies persistence in volatility, meaning that shocks to the market have long-lasting effects.

Another stylized fact of financial markets is volatility asymmetry. Negative shocks typically generate larger increases in volatility than positive shocks of the same magnitude, a phenomenon known as the leverage effect (Black, 1976). These characteristicsclustering, persistence, and asymmetry highlight the limitations of traditional constant-variance models and justify the use of more flexible econometric frameworks.

ISSN 2350-1049

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2.2 Theoretical Framework of Volatility Modelling

The modelling of time-varying volatility gained prominence with the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle (1982), which allows conditional variance to depend on past squared innovations. Bollerslev (1986) extended this framework to the Generalized ARCH (GARCH) model by incorporating lagged conditional variance terms, thereby capturing volatility persistence more effectively.

Despite its usefulness, the standard GARCH model assumes symmetric responses to shocks, which contradicts empirical evidence. To address this limitation, several asymmetric extensions have been developed. The Exponential GARCH (EGARCH) model (Nelson, 1991) captures asymmetry without imposing non-negativity constraints on parameters. The GJR-GARCH model (Glosten et al., 1993) and Threshold GARCH (TGARCH) model (Zakoian, 1994) introduce indicator functions to differentiate between positive and negative shocks. Similarly, the Quadratic GARCH (QGARCH) model (Sentana, 1995) allows for nonlinear effects in volatility dynamics. These models provide a more flexible framework for capturing the complex behavior of financial volatility.

2.3 Empirical Evidence on GARCH Type Models

A substantial body of empirical literature supports the superiority of GARCH type models in modelling financial market volatility. In emerging and African markets, Omolade and Ngalawa (2021) find that EGARCH models perform better due to their ability to capture leverage effects and asymmetry. Similarly, Ogundipe and Olayemi (2022) demonstrate that asymmetric GARCH models outperform symmetric specifications in explaining volatility persistence and shock responses.

In the Nigerian context, several studies have documented key stylized facts of volatility. Olowe (2009) reports strong volatility persistence during crisis periods, while Atoi (2014) confirms the presence of leverage effects and finds that advanced GARCH specifications improve model performance. Adegbite (2020) also highlights the importance of asymmetric modelling but focuses primarily on in-sample estimation without extensive model comparison. More recent studies, such as Adegboyo and Sarwar (2025), identify GJR-GARCH as a strong performer in forecasting volatility; however, their analysis does not incorporate seasonal effects or provide a unified comparative framework across multiple models.

Overall, the empirical literature suggests that asymmetric GARCH models are more suitable for capturing volatility dynamics, particularly in emerging markets characterized by structural instability and sensitivity to negative shocks.

2.4 Seasonal Volatility and Calendar Effects

Seasonality in stock market volatility refers to systematic variations in volatility across specific time intervals, such as days of the week or months of the year. Calendar anomalies have been widely documented in international financial markets and are often attributed to behavioral biases, institutional trading patterns, and the timing of information releases (Poon & Granger, 2003).

Despite its relevance, the empirical evidence on seasonal volatility in the Nigerian stock market remains limited. Many studies implicitly assume constant volatility over time and do not explicitly incorporate seasonal effects into the modeling framework (Olowe, 2009; Adegbite, 2020). This omission may result in model misspecification and biased inference, particularly if volatility exhibits systematic temporal patterns. To address these gaps and others specified in section 1.0, this study adopted a comprehensive in sample comparison of symmetric and asymmetric GARCH models, including GARCH, EGARCH, GJR-GARCH, TGARCH, and QGARCH. In addition, it incorporates seasonal effects through calendar dummy variables to capture potential temporal variations in volatility. By integrating model selection and seasonality within a unified framework, the study provides a more robust and comprehensive analysis of volatility dynamics in the Nigerian stock market.

3. METHODOLOGY

3.1 Data Description and Return Construction

This study utilizes daily closing prices of the Nigerian Stock Exchange (NSE) All Share Index covering the period from January 1, 2016 to December 31, 2025. This period captures different market conditions and provides sufficient observations for reliable volatility modelling.

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Stock returns are computed as continuously compounded (log) returns:

$$R_t = \ln(\frac{P_t}{P_{t-1}})$$

Where R_t denotes the return at time t, P_t is the closing price at time t, and P_{t-1} is the closing price at time t−1. Log returns are preferred due to their desirable statistical properties, including time additivity and approximate normality.

3.2 Preliminary Statistical Analysis

Prior to model estimation, standard diagnostic tests are conducted to validate the suitability of GARCH type models.

Stationarity of the return series is examined using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979). The presence of conditional heteroskedasticity is tested using the ARCH LM test (Engle, 1982). Rejection of the null hypothesis of no ARCH effects confirms time-varying volatility and justifies the application of GARCH models.

Descriptive statistics, including mean, standard deviation, skewness, and kurtosis, are also computed to examine the distributional characteristics of the return series.

3.3 Model Specification

To model conditional volatility, the study employs both symmetric and asymmetric GARCH type models. The general framework consists of a mean equation and a conditional variance equation.

3.3.1 GARCH (1,1) Model

The standard GARCH model (Bollerslev, 1986) is specified as:

The standard GARCH(1,1) specification is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (2)$$

where:

σ_t^2 is the conditional variance,

α_0 is the constant term,

α_1 captures the impact of past squared residuals (ARCH effect),

β_1 represents the lagged Conditional variance (GARCH effect).

The following are members of the GARCH family:

3.3.2 Exponential GARCH (EGARCH) Model

The EGARCH model accounts for asymmetry in volatility (Nelson, 1991):

$$In(\sigma_t^2) = \omega + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma(\left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| - E \left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right|) + \beta In(\sigma_{t-1}) \qquad (3)$$

where:

γ captures the asymmetric effect (leverage effect). If $\gamma < 0$, negative shocks have a stronger impact than positive shocks.

3.3.3 GJR-GARCH Model

The GJR-GARCH model (Glosten, Jagannathan, &Runkle, 1993) introduces an indicator function I_{t-1} to differentiate between positive and negative shocks:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma I_{t-1} \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (4)$$

where $I_{t-1} = 1 \; if \; \epsilon_{t-1} < 0, otherwise \; I_{t-1} = 0.$

The term γ measures the additional impact of negative shocks.

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3.3.4 Threshold GARCH (TGARCH) Model

The TGARCH model (Zakoian, 1994) is specified as:

$$\sigma_t = \sigma_0 + \sigma_1 \mid \epsilon_{t-1} \mid + \gamma I_{t-1} \mid \epsilon_{t-1} \mid + \beta_1 \sigma_{t-1} \qquad (5)$$

where:

γ captures the asymmetric response of volatility to negative shocks.

3.3.5 Quadratic GARCH (QGARCH) Model

The QGARCH model (Sentana, 1995) allows for a quadratic term to capture nonlinearity in volatility persistence:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (6)$$

where

γ captures nonlinear effects of past returns on volatility.

3.4 Model Estimation and Forecast Evaluation

All models are estimated using **Maximum Likelihood Estimation (MLE) technique**.

$$\hat{\theta} = \arg\max_{\theta \in \Theta} \ \ell(\theta) = \arg\max_{\theta \in \Theta} \sum_{t=1}^{T} \ln f(y_t \mid \mathcal{F}_{t-1}, \theta)$$

Where:

- y_t= observed return
- $f(\cdot)$ = conditional density (e.g., normal, Student-t)
- $\mathcal{F}_{t-1}$= information set at time $t-1$
- θ = vector of model parameters
- T= sample size

3.5 In-Sample Evaluation

- Akaike Information Criterion (AIC)

$$\text{AIC} = -2\ell(\hat{\theta}) + 2k$$

Where:

- $\ell(\hat{\theta})$= maximized log-likelihood
- k = number of estimated parameters
- Bayesian Information Criterion (BIC)

$$\text{BIC} = -2\ell(\hat{\theta}) + k\ln(T)$$

Where:

- T = sample size
- k= number of parameters

Model selection rule: choose the model with the **smallest BIC**.

3.6 Modelling Seasonal Volatility Effects

To examine seasonal patterns in volatility, calendar based dummy variables are incorporated into the variance equation. These include day of the week and month of the year effects.

ISSN 2350-1049

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The extended variance equation for the EGARCH model is specified as:

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \alpha(\frac{|\ \varepsilon_{t-1}\ |}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}) + \gamma(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}) + \sum_{i=1}^{4}\delta_i D_{i,t} + \sum_{j=1}^{11}\phi_j M_{j,t}$$

where $D_{i,t}M_{j,t}$ represent weekday and monthly dummy variables, respectively. One category from each group is omitted to avoid multicollinearity.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1 Introduction

Daily returns of the Nigerian Exchange All Share Index (2016 - 2025) are analyzed to examine volatility dynamics. The analysis begins with descriptive statistics and preliminary tests, followed by estimation of symmetric and asymmetric GARCH models.

4.2 Descriptive Statistics of NGX ASI Return

Table 1: Descriptive Statistics of NGX ASI Daily Returns

Statistic	Value	Explanation
Mean	-0.00069	Average return is ≈ 0, indicating no consistent daily gain or loss
Std. Deviation	0.00907	This shows moderate volatility (≈ 0.9% daily fluctuation).
Skewness	-0.218	Slight left skewness, negative shock occur slightly more often.
Kurtosis	8.33	Highly leptokurtic, presence of fat tails and extreme returns

The NGX ASI return series exhibits non normal characteristics, it has heavy tails and mild asymmetry, which is typical of financial markets and supports the suitability of GARCH type volatility models.

4.3 Preliminary Test

4.3.1 Augmented Dickey Fuller (ADF) Unit Root Test

Table 4.2: Augmented Dickey Fuller (ADF) Unit root Test

Statistic	**Value**
ADF Statistic	-10.557
Lag Length	13
Intercept	Included
Trend	Not Included
P value	$\prec$ 0.01
Decision	Reject H_o

Interpretation

The ADF statistic is highly negative with p value below 1%, which implies that NGX ASI return series is stationary. This satisfies the Stationary requirement for GARCH type.

4.3.2 ARCH LM Test for Heteroskedasticity

Table 4.3: ARCH LM Test

Statistic	**Value**
Chi Square	281.13
Degree of Freedom	12
Lags Used	12
P value	$\prec$ 0.001
Decision	Reject H_o

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Interpretation

The highly small p value supports strong ARCH effects in the NSE return series, indicating time varying volatility. This supports volatility estimate using GARCH family models.

4.4 Model Estimation and Diagnostic Framework

In order to account for financial return series' leptokurtic and heavy-tailed nature, Maximum Likelihood Estimation (MLE) is used to estimate all competing volatility models, including Standard GARCH, EGARCH, TGARCH ,GJR-GARCH, and QGARCH,
Comprehensive diagnostics assess model adequacy and robustness:

4.4.1 Model Comparison (In Sample Fit)

Table 4.4: Information Criteria Comparison

Model	Loglikelihood	AIC	BIC
GARCH	8458.86	−6.8350	−6.8256
EGARCH	8467.94	−6.8415	−6.8298
GJR GARCH	8459.23	−6.8345	−6.8227
TGARCH	8459.19	−6.8344	−6.8227
QGARCH	8404.35	−6.7909	−6.7815

Interpretation

EGARCH(1,1) has the highest log likelihood and lowest AIC and BIC values among all competing specifications. EGARCH has the best sample fit to the NGX ASI return series.

The superiority of the EGARCH model implies that volatility responds asymmetrically to positive and negative shocks, validating market leverage effects. In sample volatility model EGARCH is preferred.

4.5 Seasonal Volatility Effects

To examine whether volatility in the Nigerian Stock Exchange (NSE) exhibits calendar based patterns, seasonal dummy variables were incorporated into the **variance equation** of the EGARCH(1,1) model.

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}) + \gamma(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}) + \sum_{i=1}^{4} \delta_i D_{i,t} + \sum_{j=1}^{11} \phi_j M_{j,t}$$

Two types of seasonality were tested:

1. **Day-of-Week Effects** (Tuesday–Friday; Monday as base)

Monday is the **base category**, so we include 4 dummies:

- $D_{1,t}$ = Tuesday, $D_{2,t}$ = Wednesday, $D_{3,t}$ = Thursday, $D_{4,t}$ = Friday
- Each $D_{i,t} = 1$ if the return at time t falls on that day, otherwise 0.
- δ_iMeasures excess volatility relative to Monday.

2. **Monthly Effects** (February–December; January as base)

- $M_{1,t}$ = February, $M_{2,t}$ = March, ..., $M_{11,t}$ = December
- $Each\ M_{j,t}$ = 1if observation ttt occurs in that month, otherwise 0.
- ϕ_j Measures excess volatility relative to January.

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The objective was to determine whether volatility differs systematically across trading days or months.

4.5.1 Hypotheses

Day-of-Week Seasonality

H_0: No weekday volatility effect

$$\beta_{Tue} = \beta_{Wed} = \beta_{Thu} = \beta_{Fri} = 0$$

H_1: At least one weekday has a significant volatility effect.

Monthly Seasonality

H_0: No monthly volatility effect

$$\beta_{Feb} = \beta_{Mar} = \cdots = \beta_{Dec} = 0$$

H_1: At least one month has a significant volatility effect.

Decision Rule:

Reject H_0 if **p-value < 0.05** (robust standard errors used).

4.5.2 Day of Week Volatility Effects

(Base Category = Monday)

Table 4.5: Weekday Variance Effects

Day	Coefficient Sign	Robust p-value	Decision	Interpretation
Tuesday	Negative	0.759	Not Significant	No difference from Monday
Wednesday	Negative	0.718	Not Significant	No difference
Thursday	Positive	0.496	Not Significant	No effect
Friday	Negative	0.993	Not Significant	No effect

Conclusion:

There is no statistically significant day-of-the-week volatility pattern in NSE returns. Volatility behaviour from Tuesday to Friday does not differ meaningfully from Monday.

4.5.3 Monthly Volatility Effects

(Base Category = January)

Table 4.6: Monthly Variance Effects

Month	Sign	Robust p-value	Decision	Interpretation
February	–	0.163	Not Significant	No effect
March	–	0.554	Not Significant	No effect
April	–	**0.002**	**Significant**	Lower volatility
May	–	**0.046**	**Significant**	Lower volatility
June	–	**0.005**	**Significant**	Lower volatility
July	+	0.553	Not Significant	No effect
August	–	0.070	Marginal	Weak evidence
September	–	0.096	Marginal	Weak evidence
October	–	0.477	Not Significant	No effect
November	–	0.314	Not Significant	No effect
December	–	0.078	Marginal	Weak evidence

4.5.4 Interpretation Of Seasonal Findings

Weekday Pattern

- Statistically insignificant across all weekdays.
- NSE volatility is not driven by trading day effects.
- Suggests market efficiency with respect to short term calendar anomalies.

Monthly Pattern

- Clear mid year volatility reduction **(**April **-** June).
- Possible explanations:
  - Lower trading intensity
  - Reduced macroeconomic announcements
  - Portfolio rebalancing cycles
- Marginal evidence in August, September, and December, but not strong enough for firm conclusions.

4.5.5 Interpretation with Volatility Persistence

Despite the presence of some monthly seasonality, theβ (persistence) parameter remains dominantin magnitude and significance. This implies:

- Volatility is primarily shock driven and persistent, not calendar-driven.
- Seasonal factors play only a secondary role**.**

Interpretation

The empirical evidence indicates weak seasonal volatility effects in the NSE. While a modest mid year reduction in volatility is observed, weekday effects are absent, and most monthly coefficients are statistically insignificant. Consequently, NSE volatility dynamics are better explained by **persistence and leverage mechanisms** rather than calendar abnormality, reinforcing the robustness of the EGARCH framework used in this study.

5. CONCLUSION AND CONTRIBUTION TO KNOWLEDGE

5.1 Conclusion

This study investigates model selection and seasonal volatility dynamics in the Nigerian stock market using symmetric and asymmetric GARCH-type models, based on daily returns of the NSE All Share Index from 2016 to 2025. The results confirm key stylized facts of financial time series, including volatility clustering, persistence, and non-normality. Diagnostic tests indicate that the series is stationary and exhibits significant ARCH effects, supporting the application of GARCH models.

Model selection using log-likelihood, AIC, and BIC consistently identifies the EGARCH model as the best-performing specification. This underscores the importance of accounting for asymmetry in volatility, as negative shocks are found to have stronger effects than positive shocks. While other models capture persistence, they show weaker performance and limited ability to model asymmetry.

Seasonal analysis reveals no significant day-of-the-week effects, though slight reductions in volatility are observed between April and June. Overall, volatility is driven more by persistent shocks than seasonal patterns, and the EGARCH model provides the most robust framework for modelling stock market volatility in Nigeria.

5.2 Contribution to Knowledge

This study makes key contributions to financial econometrics and volatility modelling in Nigeria. First, it provides a unified comparison of symmetric and asymmetric GARCH type models (GARCH, EGARCH, GJR-GARCH, TGARCH, and QGARCH) within a consistent framework, offering clearer evidence for model selection.

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Second, it emphasizes in sample model selection using AIC and BIC, focusing on identifying the model that best captures the data-generating process rather than relying mainly on forecasting performance.

Third, it presents strong empirical evidence supporting asymmetric models particularly EGARCH as the most suitable for capturing volatility dynamics and leverage effects in the Nigerian stock market.

Fourth, it incorporates seasonal analysis using calendar effects, showing that while some monthly patterns exist, they are weak relative to volatility persistence.

Overall, the study integrates model selection and seasonality into a single framework, providing a more robust and practical approach to volatility modelling in emerging markets

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