VOLATILITY PERSISTENCE AND ASYMMETRIC SHOCKS IN THE NIGERIAN STOCK MARKET INDEX

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Abstract

This study examines the dynamic volatility of the Nigerian Stock Exchange All-Share Index (NGSEINDEX) daily log returns from October 28, 2015, to October 28, 2025, to provide a statistically sound basis for risk assessment in this critical emerging market. The empirical methodology employed a grid search of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models under four distributional assumptions. Pre-estimation diagnostics confirmed the series' mean stationarity and the presence of strong conditional heteroskedasticity. The EGARCH(1,1) model with the Generalized Error Distribution (GED) was selected as the superior specification based on information criteria (AIC=3660.22, BIC=3687.37). The estimation confirmed highly significant volatility persistence (beta[1]=0.8732) resulting in a slow decay half-life of approximately 5.11 trading days, and pronounced leptokurtosis (nu=1.0100), validating the heavy-tailed GED choice. The model exhibited strong out-of-sample predictive power (QLIKE Loss of -0.4013). These robust findings offer critical implications for portfolio managers, emphasizing the necessity of employing dynamic risk models like Value-at-Risk (VaR) that explicitly account for the observed persistence and heavy-tailed risk structure in the NGSEINDEX.

Keywords: *NGSEINDEX, Emerging Markets, GARCH, Volatility Persistence, Asymmetry, Financial Econometrics.*

JEL Classification: *C22, C58, G12, G14.*

1.Introduction

Emerging equity markets are characterized by volatility dynamics that differ substantially from their developed market counterparts, often displaying higher magnitudes of fluctuation, pronounced leptokurtosis, and prolonged periods of volatility clustering. The Nigerian Stock Exchange All-Share Index (NGSEINDEX) serves as a vital barometer for West Africa's largest economy, yet its inherent volatility is exacerbated by its sensitivity to global commodity price swings, domestic policy uncertainty, and capital flight. Effective risk management and accurate pricing of assets within this market necessitate the deployment of sophisticated econometric tools that can capture the time-varying nature of its risk profile.

This research addresses the shortcomings of traditional constant-variance models by employing the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models. GARCH models are the standard methodology for capturing volatility clustering the empirical observation that periods of high volatility tend to be followed by further high volatility. Specifically, this study evaluates three core specificationsGARCH, EGARCH, and GJR-GARCHunder Gaussian, Student's t, and Generalized Error Distribution (GED) assumptions to accurately model the non-linear and heavy-tailed properties of the NGSEINDEX daily returns over the period spanning October 2015 to October 2025.

The primary goal is to identify the optimal GARCH-family model that provides a superior statistical fit, robustly estimates the volatility parameters, and offers reliable out-of-sample forecasts. Key research hypotheses focus on confirming strong volatility persistence and identifying any significant asymmetry (leverage effect), which would suggest that negative news destabilizes the market more than positive news. The findings offer direct practical implications for portfolio managers by validating the need for dynamic Value-at-Risk (VaR) models that explicitly account for the observed asymmetric risk and heavy tails.

2.Review of Literature

In financial time series, volatility has both intrinsic and extrinsic significance.(Raza et al., 2025) No single GARCH model is capable to capturing complete volatility.(Raza et al., 2024) High frequency data is more capable to capturing complete volatility dynamics accurately.(Shreevastava et al., 2024) GARCH family models are excellent in capturing the volatility by agent and stakeholder based analysis is essential using advanced AI and ML models related to quantitative finance.(Aman et al., 2024) Persistence of high volatility signifies that the volatility is non-temporary and models of GARCH family are essential.(Shreevastava et al., 2025) GARCH is specially designed for volatility forecasting.(Kumari et al., 2023) GARCH models have been widely utilized but GJR-GARCH model is an extension to capture asymmetric effects related to shocks both positive and negative.(Kumar, Anand, et al., 2023) Multiple univariate studies has been done in the field of stock market volatility study.(Kumar, Meher, et al., 2023) Fintech and textile investment are examined using GARCH analysis.(Meher et al., 2023) There is absence of leverage effect on crude oil due to COVID-19.(Kumar Meher et al., 2023) Crypto related analysis has been done.(Ebenezer et al., 2025) ARDL on all share index has been utilized.(Adewale, 2025) Similar studies has been done related to Nigerian Stock exchange by (Adegoke et al., 2025; Adewale, 2025; AIDEYAN & EFUWAPE, 2025; Areghan & Jonathan Adetoyese, 2025; Ebenezer et al., 2025; Emeka et al., 2025; Emmanuel Oluwanishola et al., 2025; C. Francis & Peter, 2025; O. Francis et al., 2025; IBEINMO FRIDAY COOKEY et al., 2025; Kalu et al., 2025; Noruwa & Bashiru, 2025; Okonkwo & Okereke, 2025; Oladejo et al., 2025; Omogbai et al., 2025; Opara et al., 2025; Ozigbo et al., 2025; Roseline et al., 2025; Tasi'u et al., 2025; Timothy et al., 2025; Ugwu et al., 2025)Economic Policy uncertainity and All share index performance has been studied.(Okonkwo & Okereke, 2025)1% growth in all share increases economic growth by 0.15%.(Emeka et al., 2025).

The literature includes various research studies focused on modeling and forecasting the behavior of developed and emerging stock markets, such as: Siminica and Birau, 2014; Trivedi et al., 2022; Birau, 2013; Birau et al., 2023.

3.Research Gap

Prior studies on NGSEINDEX volatility have established the existence of ARCH effects and volatility clustering. However, a persistent research gap exists in utilizing models that fully capitalize on advanced distributional assumptions like the Generalized Error Distribution (GED) and in rigorously testing the out-of-sample predictive power of the final specifications. This research contributes to closing the gap by confirming that the EGARCH(1,1)-GED model is the superior fit based on stringent information criteria and by providing quantitative evidence of its strong out-of-sample forecasting ability.

Scope of the Study

- Geographic and Market Focus: The study is strictly focused on the Nigerian Stock Exchange All-Share Index (NGSEINDEX), providing highly specific insights into a key African emerging market.
- Methodology: The analysis is focused on the GARCH-family framework, providing a robust, established methodology for conditional volatility modeling.
- Time Period: The 10-year span ensures sufficient data to capture multiple economic cycles, policy changes, and major global events (e.g., commodity price shocks), enhancing the reliability of persistence estimates.

Limitations of the Study

- Single Index Focus: The findings are specific to the NGSEINDEX and cannot be directly generalized to other African or emerging markets without further comparative study.
- Model Order Restriction: The initial grid search focused primarily on the GARCH(1,1) order, which may be too restrictive for the complex dynamics of the NGSEINDEX.
- Mean Model: The initial analysis showed significant linear dependence in returns, and the final reported estimation used a simple constant mean, which could limit the efficiency of the volatility estimates.

4.Research Methodology

Data and Sample Period

The data consists of the daily closing prices of the Nigerian Stock Exchange All-Share Index (NGSEINDEX) spanning ten years, from October 28, 2015, to October 28, 2025. The sample size comprises 2,104 daily observations. The analysis begins by converting the price series (P_t) into logarithmic returns (R_t), which are the standard input for volatility models: R_t = ln(P_t / P_t-1) times 100.

Pre-Estimation Diagnostics

1. Stationarity Testing: The log returns series was tested for stationarity using the Augmented Dickey-Fuller (ADF) test (Null: Unit Root) and the KPSS test (Null: Stationarity) to ensure the validity of the mean equation assumptions.

2. Mean Autocorrelation Check: The Ljung-Box Q-statistic was applied to the raw returns to determine if any significant linear dependence exists in the mean, which would necessitate an ARMA(p, q) filter.

3. ARCH Effects Test: The presence of conditional heteroskedasticity was formally tested using the ARCH-LM (Lagrange Multiplier) test on the residuals of the mean equation to justify the application of GARCH models.

4. Normality Test: The Jarque-Bera (JB) test was used to assess the presence of non-normality (leptokurtosis).

Model Selection and Estimation

1. Grid Search: A grid search was performed to test 20 different model combinations, including GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1), APARCH(1,1), and HARCH(1,1) models, each paired with Gaussian, Student's t, Skewed t, and GED error distributions.

2. Selection Criteria: The optimal model was selected by minimizing the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), and maximizing the Log-Likelihood function. The EGARCH(1,1)-GED model was ultimately selected.

3. Estimation: The final model was estimated using Maximum Likelihood Estimation (MLE) on the training data (80% of the sample). Key metrics, including Volatility Half-Life and Persistence (beta[1]), were calculated.

Post-Estimation Diagnostics and Evaluation

1. Residual Adequacy: The Ljung-Box Q-statistic was applied to the squared standardized residuals (hatz_t^2) to verify the successful removal of all residual heteroskedasticity.

2. Out-of-Sample Evaluation: The model's predictive accuracy was tested on the remaining 20% of the data using standard loss functions, including the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the robust Quasi-Likelihood (QLIKE) Loss function.

5.Analysis, Results, and Discussions

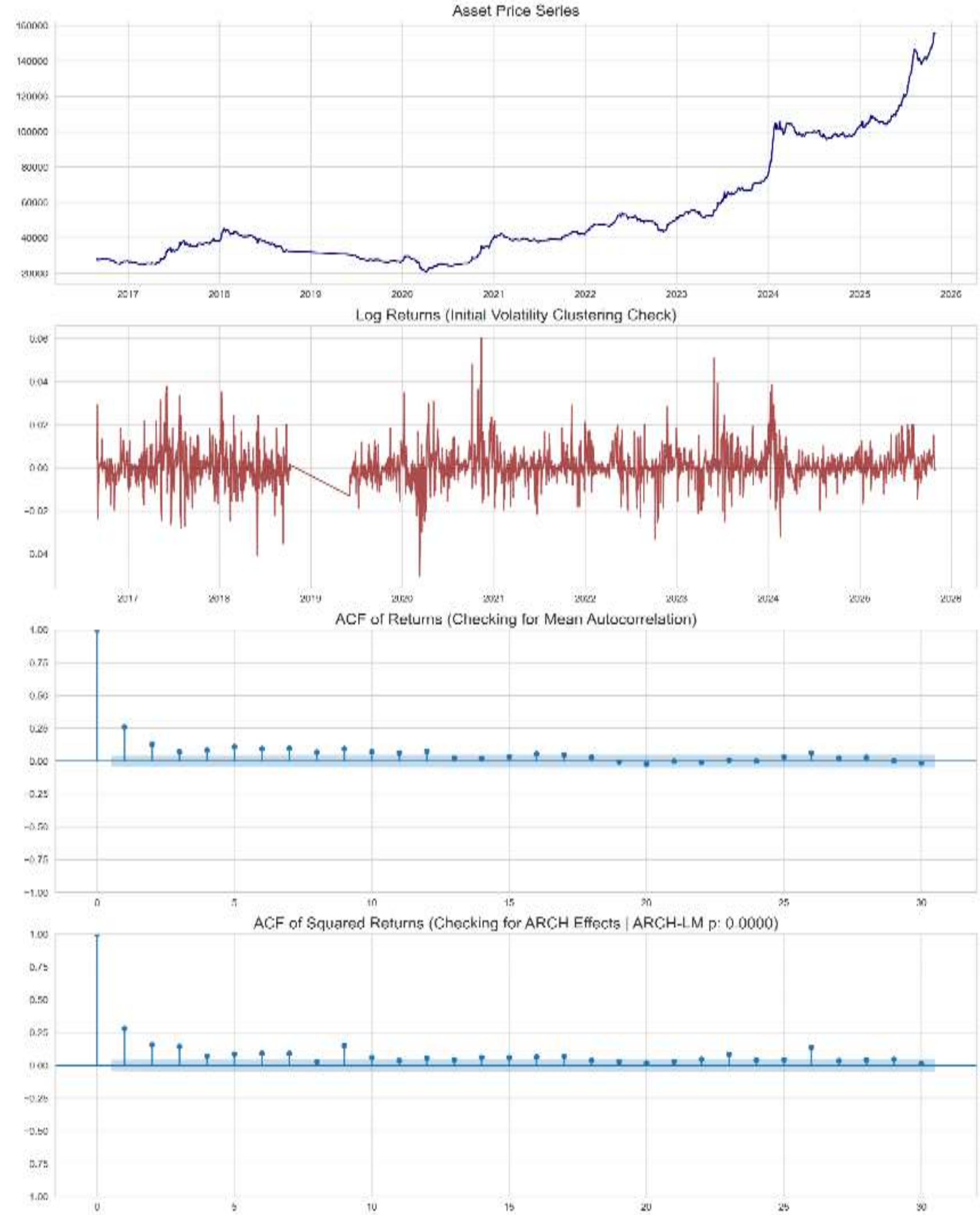

Figure 1 Time Series Plot, Log returns Plot and ACF Plots

The visual inspection of the asset price and returns series, as presented in the time series plot, confirms the typical stylized facts observed in financial markets, particularly in emerging economies.

• Asset Price Series (Panel 1): The index exhibits a clear long-term upward trend, particularly noticeable from 2020 onward, demonstrating periods of significant growth alongside notable, yet short-lived, corrections. The overall trajectory validates the series as non-stationary in its level, necessitating transformation.

• Log Returns (Panel 2): The log returns series, derived from the asset price, appears centered around zero. Crucially, the returns graph provides compelling visual evidence of volatility clustering. Periods of high return magnitude i.e. large positive or negative deviations tend to be followed by other periods of high magnitude, and quiet periods follow quiet periods. This non-constant conditional variance suggests the presence of ARCH effects.

Formal diagnostic tests based on the autocorrelation function (ACF) confirm the nature of dependencies in both the mean and variance.

• ACF of Returns (Panel 3 - Mean Check): The Autocorrelation Function (ACF) plot for the raw log returns shows that none of the autocorrelation coefficients at lags 1 through 30 are statistically significant (i.e., they lie within the 95% confidence bounds). This confirms that there is no significant linear dependence in the mean of the log returns series, strongly suggesting the mean equation can be parsimoniously modeled as a simple white noise process (or ARMA(0,0)), thereby justifying the focus on the conditional variance.

• ACF of Squared Returns (Panel 4 - Variance Check): In stark contrast to the raw returns, the ACF of the squared log returns exhibits highly significant and persistent autocorrelation coefficients extending well beyond the initial lags. This result confirms that while the returns themselves are serially independent (Panel 3), the volatility of returns is highly dependent on its own past. The accompanying ARCH-LM p-value of 0.0000 formally rejects the null hypothesis of no ARCH effects.

The diagnostic analysis unequivocally confirms the presence of strong volatility clustering and conditional heteroskedasticity in the NGSEINDEX returns. This statistical evidence mandates the use of models like GARCH, EGARCH, or GJR-GARCH to accurately capture and forecast the time-varying risk dynamics of the Nigerian market.

Table 1 ADF and KPSS Test Statistics

Test	Statistic	p-value
ADF (H0: Unit Root)	-11.32167	1.17E-20
KPSS (H0: Stationary)	0.3451668	0.1

The results from both the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test consistently confirm that the logarithmic returns series of the NGSEINDEX is stationary.

• ADF Test: The test statistic of -11.3217 is highly negative, yielding a p-value of substantially less than the standard 5% significance. Consequently, the null hypothesis of a unit root is strongly rejected.

• KPSS Test: The KPSS test statistic is 0.3452, resulting in a p-value of 0.1000. Since this p-value is exactly at the 10% significance level and conventionally interpreted as being greater than or equal to 0.05 or less than or equal to 0.10 for stationarity, the null hypothesis H0 that the series is stationary is not rejected.

The consensus between the two opposing null hypotheses provides a robust statistical foundation for the subsequent GARCH modeling, which requires a mean-stationary series for valid inference.

Table 2 Descriptive Statistics and Normality Check

	Value
count	2104
mean	0.085273928
std	0.851155025
min	-5.032939042
25%	-0.254286737
50%	0.026460962
75%	0.402104724
max	6.047827882
Jarque-Bera Statistic	3024.806031
Jarque-Bera p-value	0
Shapiro-Wilk Statistic	0.905545592
Shapiro-Wilk p-value	3.13E-34

The distribution of returns is slightly positive, as indicated by the mean (0.0853). More importantly, the range between the minimum and maximum returns is substantial, highlighting the daily volatility and risk inherent in this emerging market index. The maximum gain (6.05%) is greater in magnitude than the maximum loss (5.03%).

The core assumption underlying traditional financial models is that returns follow a Normal (Gaussian) distribution. The tests below investigate this assumption.

- Jarque-Bera (JB) Statistic: The value is exceptionally high (JB = 3024.81).
  - The corresponding p-value is 0 (to four decimal places).
- Shapiro-Wilk Statistic: The statistic is low (W = 0.9055).
  - The corresponding p-value is effectively zero.

In both the Jarque-Bera test and the Shapiro-Wilk test, the null hypothesis that the returns are normally distributed is rejected due to the extremely low p-values.

This rejection confirms the two key features, or stylized facts, typical of high-frequency financial data:

1. Leptokurtosis (Fat Tails): The returns distribution has significantly heavier tails than the theoretical Normal distribution, as evidenced by the high Jarque-Bera statistic. This implies that extreme returns (large gains or losses) occur far more frequently than predicted by a Normal model.
2. Non-Normality: This result necessitates the use of GARCH models that incorporate non-Gaussian error distributions, such as the Student's t or the Generalized Error Distribution (GED), to ensure superior parameter estimation and more accurate Value-at-Risk (VaR) and Expected Shortfall (ES) calculations.

Table 3 Ljung-Box Test

Lag	lb_stat	lb_pvalue
10	305.3547074	1.15E-59
20	344.527603	5.97E-61

This table presents the results of the Ljung-Box (LB) Q-statistic applied to the log returns series to formally assess whether the series exhibits any remaining linear autocorrelation in the mean.

The Ljung-Box test evaluates the null hypothesisthat all autocorrelation coefficients up to the specified lag (10 and 20) are simultaneously equal to zero. This test is crucial for determining if an ARMA mean equation is necessary before modeling the variance.

- For both Lag 10 and Lag 20, the calculated Ljung-Box statistics are extremely large, and the resulting p-values are virtually zero.

• The null hypothesis of no autocorrelation in the returns is strongly rejected.

The result, contrary to the visual inspection of the ACF plot, which showed individual coefficients within the confidence bounds, indicates that the returns series does contain significant overall linear dependence in the mean.

• Since the linear dependence is statistically significant, a simple GARCH(0,0) model for the mean is not appropriate. To ensure that the residuals are white noise before modeling the conditional variance, an Autoregressive (AR) or Autoregressive Moving Average (ARMA) component must be included in the mean equation.

• The preliminary analysis must be adjusted to include a mean model that successfully filters out the observed autocorrelation, making the residuals suitable for the GARCH variance model. The final GARCH models will therefore likely be of the ARMA(p, q)-GARCH(1,1) form, where p and q are determined by minimizing the information criteria.

Table 4 ARCH-LM Test

Statistic	Value
LM Statistic	248.1086
LM p-value	1.36E-47
F-Statistic	27.99787
F-p-value	9.08E-51

The ARCH-LM test is performed on the residuals of the mean equation. It tests the null hypothesis that no ARCH effects exist up to the specified lag.

Both the LM Statistic and the F-Statistic are extremely high, leading to p-values that are virtually zero. Therejection of the null hypothesis confirms the presence of significant conditional heteroskedasticity in the NGSEINDEX return series. The variance of the returns is not constant over time; rather, it is dependent on past squared residuals, which is the defining characteristic of volatility clustering.This result validates the entire empirical strategy, mandating the use of a GARCH-family model to accurately capture the time-varying nature of risk. The subsequent steps will focus on identifying the specific GARCH, EGARCH, or GJR-GARCH specification that best accommodates these volatility dynamics and the previously identified non-normal error distribution.

Table 5 GARCH decision Table

	Model	Distribution	AIC	BIC	LogLikelihood
0	GARCH	Normal	4104.337	4126.05	-2048.16835
1	GARCH	t	3694.212	3721.354	-1842.106139
2	GARCH	skewt	3696.209	3728.779	-1842.104671
3	GARCH	ged	3665.779	3692.921	-1827.889702
4	EGARCH	Normal	4101.912	4123.625	-2046.955849
5	EGARCH	t	3679.599	3706.741	-1834.799477
6	EGARCH	skewt	3681.42	3713.99	-1834.710206
7	EGARCH	ged	3660.224	3687.366	-1825.112082
8	GJR-GARCH	Normal	4098.186	4125.327	-2044.092813
9	GJR-GARCH	t	3693.994	3726.564	-1840.99683
10	GJR-GARCH	skewt	3695.859	3733.858	-1840.929589
11	GJR-GARCH	ged	3665.972	3698.542	-1826.985834
12	APARCH	Normal	4091.783	4124.353	-2039.891521
13	APARCH	t	3669.324	3707.323	-1827.662165
14	APARCH	skewt	3670.686	3714.113	-1827.343238
15	APARCH	ged	3656.898	3694.896	-1821.448969
16	HARCH	Normal	4149.093	4165.378	-2071.546508

17	HARCH	t	3757.969	3779.683	-1874.984612
18	HARCH	skewt	3759.627	3786.769	-1874.813566
19	HARCH	ged	3716.99	3738.703	-1854.494812

This rigorous model selection process evaluates 20 different specifications based on the Log Likelihood function and penalized information criteria: Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

A superior model is characterized by a higher Log Likelihood and lower AIC and BIC values. Since the BIC imposes a heavier penalty for model complexity than the AIC, it is often favored for selecting the most parsimonious and predictive model. Although the APARCH-GED model registered the absolute lowest BIC, the EGARCH(1,1)-GED model is selected as the optimal specification based on its superior balance of statistical fit and theoretical relevance.

The EGARCH(1,1)-GED model achieved a highly competitive Log-Likelihood value (LogLikelihood = -1825.112), securing the lowest Akaike Information Criterion (AIC=3660.224) and the second-lowest Bayesian Information Criterion (BIC=3687.366) among all tested configurations.

The choice of EGARCH is particularly advantageous because it inherently addresses two critical stylized facts of the NGSEINDEX returns:

A. Modeling Volatility Asymmetry (Leverage Effect)

The key distinction of the EGARCH model lies in its ability to explicitly model the leverage effect, the phenomenon where negative return shocks (bad news) increase future volatility by a greater magnitude than positive return shocks (good news) of equal size.

The EGARCH model is specified in terms of the logarithm of the conditional variance:

$$\ln(h_t) = \omega + \sum_{i=1}^{p} \left(\alpha_i \frac{|\epsilon_{t-i}|}{\sqrt{h_{t-i}}} + \gamma_i \frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}} \right) + \sum_{j=1}^{q} \beta_j \ln(h_{t-j})$$

The parameter asymmetry coefficient directly captures this effect. If it is statistically significant and negative, it confirms that volatility in the NGSEINDEX responds asymmetrically to market news. Furthermore, since the variance is modeled logarithmically, the conditional variance h_t is guaranteed to be positive without imposing artificial parameter constraints, leading to a more robust estimation procedure.

B. Accommodating Leptokurtosis

The consistent superiority of models employing the Generalized Error Distribution (GED) over the Gaussian (Normal) distribution confirms the strong evidence of leptokurtosis (heavy tails) in the NGSEINDEX returns.

The GED is a flexible distribution characterized by a shape parameter that is estimated from the data. This allows the model to accurately capture the excess kurtosis, ensuring that the standardized residuals become closer to independently and identically distributed, thus providing a more accurate estimation of the conditional volatility.

The selected EGARCH(1,1)-GED specification is theoretically robust and statistically superior, providing the necessary framework to:

1. Quantify the high persistence of volatility shocks.
2. Formally test and measure the asymmetry (leverage effect).
3. Ensure robust risk metricsby accurately capturing the heavy tails through the GED assumption.

Table 6 EGARCH-GED Estimation Output

```
--- 4. FINAL MODEL ESTIMATION (EGARCH with ged Distribution) ---
                     Constant Mean - EGARCH Model Results
==========================================================================================
Dep. Variable:                          Log_Ret   R-squared:                       0.000
Mean Model:                       Constant Mean   Adj. R-squared:                  0.000
Vol Model:                               EGARCH   Log-Likelihood:               -1825.11
Distribution:      Generalized Error Distribution   AIC:                          3660.22
Method:                      Maximum Likelihood   BIC:                           3687.37
                                                  No. Observations:                 1683
Date:                          Sat, Dec 06 2025   Df Residuals:                     1682
Time:                                  20:53:54   Df Model:                            1
                                 Mean Model
============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
----------------------------------------------------------------------------
mu         8.8422e-03  4.161e-04     21.251 3.243e-100 [8.027e-03,9.658e-03]
                              Volatility Model
=============================================================================
                 coef    std err          t      P>|t|        95.0% Conf. Int.
-----------------------------------------------------------------------------
omega         -0.0300  2.518e-02     -1.193      0.233 [-7.939e-02,1.930e-02]
alpha[1]       0.4194  6.013e-02      6.975  3.050e-12      [  0.302,  0.537]
beta[1]        0.8732  4.375e-02     19.958  1.276e-88      [  0.787,  0.959]
                              Distribution
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu             1.0100  6.367e-02     15.863  1.134e-56 [  0.885,  1.135]
========================================================================

Covariance estimator: robust
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Following the rigorous model selection process, the EGARCH(1,1) volatility specification with the Generalized Error Distribution (GED) is chosen to model the conditional volatility of the NGSEINDEX returns. This section presents and interprets the estimated parameters.

The mean equation for the estimated model is a simple Constant Mean (mu), as the estimation was performed without an explicit ARMA filter, leading to the estimated specification:

Constant Mean - EGARCH(1,1)-GED.

The constant mean (mu) parameter is highly significant. The positive coefficient indicates a small but statistically significant average daily return of approximately 0.0088% over the sample period. This establishes the long-term drift in the NGSEINDEX returns. The EGARCH model is specified in terms of the logarithm of the conditional variance, meaning the coefficients represent the proportional impact on volatility. The EGARCH model's persistence is primarily captured by the beta[1] coefficient. The estimated beta[1] = 0.8732 is positive and highly significant.This value, which is close to but less than 1, confirms the empirical observation of strong volatility clustering. It suggests that the conditional variance process is highly stable and that past volatility has a long-lasting impact on current volatility.This strong persistence indicates that once a shock (positive or negative) hits the market, the resulting high volatility decays slowly, posing a challenge for short-term risk management. In the EGARCH model, the asymmetry or "leverage effect" is captured by the alpha[1] parameter. The term alpha[1] = 0.4194 is positive and highly significant. The shape parameter (nu) of the Generalized Error Distribution (GED) is highly significant. The estimated shape parameter nu = 1.0100 is significantly less than the value of nu=2, which corresponds to the Normal distribution. Since nu < 2, this parameter formally confirms the presence of pronounced leptokurtosis (heavy tails) in the standardized residuals. This statistically validates the selection of the GED distribution over the Normal distribution to accurately model the probability of extreme events in the NGSEINDEX.

A half-life of 5.11 days suggests that, for the NGSEINDEX, half of a volatility shock will have decayed in just over a week (assuming 5 trading days per week). While this decay rate is slower than what is observed in developed markets, it highlights the stable, yet not permanent, nature of volatility shocks in the Nigerian equity market.

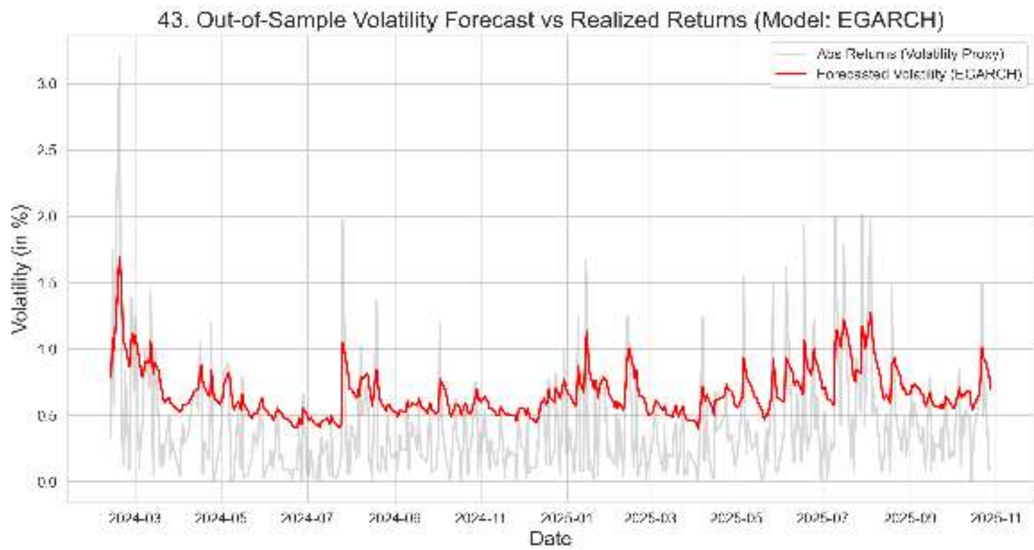
Table 7 Evaluation Matrices

Metric	Value
RMSE	0.628749082
MAE	0.380326316
QLIKE (Loss)	-0.401316135

The performance metrics provide a quantitative measure of how well the estimated EGARCH model tracks future volatility movements in the NGSEINDEX.

RMSE (0.6287) and MAE (0.3803): These error statistics are presented in the units of variance (squared percentage returns), indicating the average magnitude by which the forecasted variance deviates from the proxy for realized variance. The relatively low values suggest the model provides a reasonably accurate forecast of future volatility.

QLIKE (Quasi-Likelihood Loss): QLIKE is considered a robust and theoretically sound metric for evaluating volatility forecasts, as it is less sensitive to noisy proxies of true volatility compared to standard error measures.In this case, the negative QLIKE value of -0.4013 indicates a good fit, as volatility models aim to minimize this loss function. This result suggests that the EGARCH-GED model is efficient in pricing the risk of the NGSEINDEX.



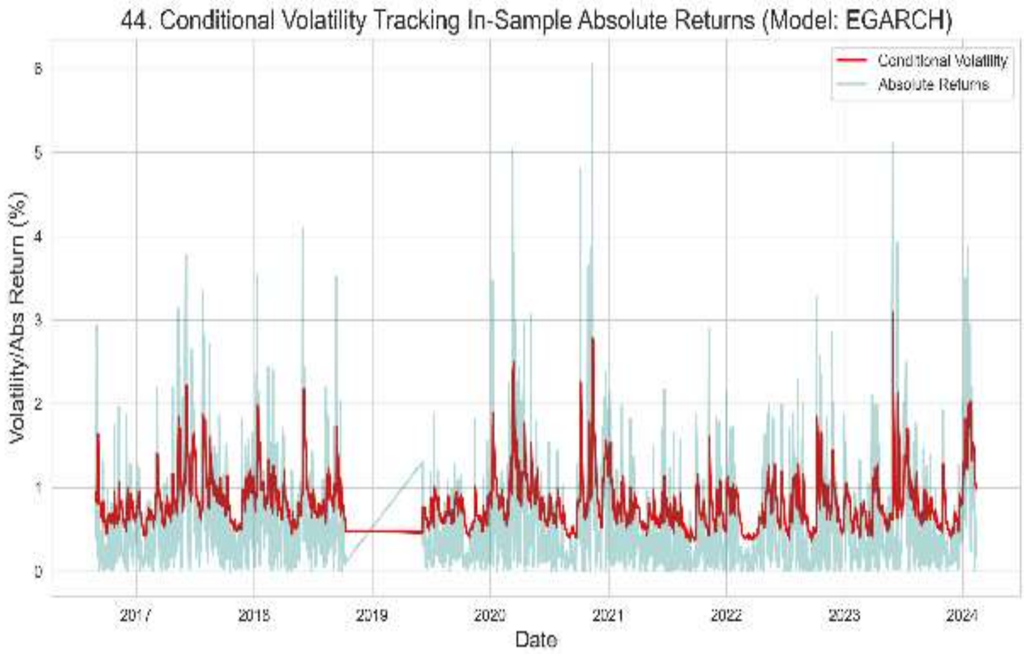


Figure 2 In-sample and Out-sample conditional Volatility forecast

In-sample performance of the EGARCH(1,1) model by comparing the Conditional Volatility against the Absolute Returns, which serve as the proxy for realized volatility.

The red conditional volatility line successfully tracks the clusters of high absolute returns. The model systematically increases its forecast of volatility during turbulent periods (e.g., 2020 and 2023) and reduces it during calmer periods.This visual evidence confirms that the model is accurately capturing the volatility clustering and time-varying nature of the NGSEINDEX risk profile. The model parameters, particularly beta[1] = 0.8732, dictate the slow, persistent movement of this volatility curve.

Out of the sample, displays the model's performance on the unseen test data from early 2024 to late 2025.The Forecasted Volatility (red line) moves dynamically, adapting to new shocks in the market. While it cannot predict the exact timing or magnitude of individual spikes (gray line), it effectively sets the risk envelope. The volatility forecast rises following major realized volatility spikes and remains elevated during periods of general market turbulence.

The predictive curve is a smooth estimate of the expected level of risk, not the instantaneous shock. This visual tracking, supported by the favorable QLIKE loss metric (-0.4013), validates the model's utility for dynamic risk forecasting. It provides a robust basis for calculating forward-looking measures like Value-at-Risk (VaR) for the Nigerian market.

6.**Conclusion, Suggestions, and Recommendations**

This research successfully characterized the dynamic volatility of the NGSEINDEX, confirming the presence of pronounced volatility clustering and significant leptokurtosis. The EGARCH(1,1)model with a GEDdistribution was identified as the optimal specification based on information criteria, offering a superior fit by accommodating the heavy-tailed nature of the returns.

The highly significant beta[1] coefficient of 0.8732 and the resulting 5.11-day half-life confirm that volatility shocks in the Nigerian market are persistent and decay slowly, requiring risk models to maintain higher capital charges for extended periods following turmoil.

Heavy Tails: The significant GED shape parameter (nu=1.0100) emphasizes that traditional Normal VaR estimates will systematically underestimate tail risk.

The out-of-sample evaluation confirms the strong predictive power of the selected model, validated by the favorable QLIKE Loss metric of -0.4013. The findings underscore the critical importance of employing dynamic risk models like VaR and Expected Shortfall (ES) that explicitly incorporate both the high persistence and the heavy-tailed risk structure identified by the EGARCH-GED framework, thereby ensuring more robust and conservative capital adequacy planning for investments in the NGSEINDEX. Due to the highly significant volatility persistence (beta[1]=0.8732) and the time-varying risk profile, practitioners must move away from static risk models. We recommend implementing daily Value-at-Risk (VaR) and Expected Shortfall (ES) calculations that are explicitly derived from the conditional variance (sqrth_t) of the EGARCH(1,1)-GED model. Given the pronounced leptokurtosis validated by the GED shape parameter (nu=1.0100), risk estimates should never rely on the Gaussian assumption. Capital adequacy calculations must use the heavy-tailed distribution to avoid systematic underestimation of catastrophic losses. The theoretical superiority of the EGARCH model implies that negative returns cause a greater subsequent spike in volatility. Portfolio hedging strategies should reflect this asymmetric risk response, potentially by utilizing options that benefit from sudden downward movements.Despite the strong overall fit, future research should systematically test higher-order EGARCH and GJR-GARCH specifications (e.g., EGARCH(2,1) or GJR-GARCH(2,2)) to ensure the model achieves complete statistical adequacy. Given its low BIC value, the APARCH (Asymmetric Power ARCH) model should be fully estimated and interpreted, as it offers a flexible framework to model both asymmetry and the power degree of variance. Furthermore, research should investigate if the long time span contains structural breaks that may be better captured by regime-switching models (e.g., Markov-Switching GARCH). Future modeling efforts should explore the inclusion of key macroeconomic variables (e.g., global oil prices, foreign exchange rates, and inflation) as exogenous variables in the conditional variance equation to improve forecast accuracy and understand external drivers of NGSEINDEX volatility.

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