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## MODELLING AND FORECASTING STOCK MARKET VOLATILITY USING GARCH MODELS

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### Abstract

This study empirically models and forecasts stock market volatility in Nigeria using the GARCH family of econometric models applied to twenty five years of monthly Nigerian Exchange Group All-Share Index data spanning January 2000 to December 2024. The work is motivated by the substantial structural shocks introduced by the 2023 macroeconomic policy reforms, specifically the removal of petroleum fuel subsidies and the unification of the foreign exchange windows, which fundamentally altered the volatility dynamics of the Nigerian equity market. Five model specifications were estimated: GARCH (1,1) with normal and Student-t innovations, EGARCH (1,1) with normal innovations, and GJR-GARCH (1,1) with normal and Student-t innovations. Prior to estimation, comprehensive diagnostic tests confirmed that the return series exhibits the canonical stylised facts of financial time series, namely significant excess kurtosis of 5.04, non-normality with a Jarque-Bera statistic of 317.67, stationarity of the log returns with an Augmented Dickey-Fuller statistic of negative 4.32, and strong conditional heteroskedasticity with an ARCH-LM statistic of 33.84. The GJR-GARCH model confirmed a statistically and economically significant leverage effect, with negative shocks raising conditional variance roughly two and a half times more than positive shocks of equal magnitude. On information criteria the GARCH (1,1) with Student-t innovations was preferred, while the GJR-GARCH with Student-t innovations produced the most accurate out-of-sample forecasts on the mean absolute error criterion. The study recommends the adoption of asymmetric specifications with fat-tailed innovations for risk management in the Nigerian market.

**Keywords:** GARCH, EGARCH, GJR-GARCH, stock market volatility, leverage effect, Nigerian Exchange Group

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## 1. Introduction

Stock market volatility, understood as the degree of price variation over time, ranks among the most consequential financial risks confronting investors in contemporary markets. Its measurement and prediction underpin a wide range of practices, including portfolio optimisation, derivative pricing, the estimation of Value-at-Risk, and the conduct of monetary policy by central banks (Aloui et al., 2023). As the global financial system has grown more unstable through geopolitical tension, post-pandemic adjustment, and abrupt shifts in monetary policy, the demand for econometric tools capable of reflecting these dynamics has risen sharply.

Stock returns display a set of statistically regular features commonly termed stylised facts. Among the most prominent are volatility clustering, in which large price changes tend to be followed by further large changes, and the leverage effect, in which negative news tends to raise volatility more than positive news of equal magnitude. Conventional linear models such as the autoregressive moving average framework assume constant variance and so cannot accommodate these features (Umar et al., 2023). This limitation led Engle (1982) to propose the autoregressive conditional heteroskedasticity model, later generalised by Bollerslev (1986) into the more parsimonious GARCH framework that remains a foundation of financial econometrics.

The Nigerian Exchange Group presents a particularly compelling case for volatility analysis. As a principal centre for capital mobilisation in sub-Saharan Africa, it has weathered considerable macroeconomic turbulence in recent years, including the removal of fuel subsidies, the unification of the foreign exchange window, surging inflation, and persistent foreign exchange scarcity (Musa and Ibrahim, 2023). Asymmetric extensions of the basic model address the leverage effect directly: the EGARCH model of Nelson (1991) specifies the logarithm of the conditional variance and so permits asymmetry without non-negativity restrictions, while the GJR-GARCH model of Glosten, Jagannathan, and Runkle (1993) introduces an indicator variable that amplifies the impact of negative shocks.

The empirical literature consistently favours asymmetric specifications. Adegboyo and Sarwar (2025) analysed daily All-Share Index data and found a significant leverage effect, with the GJR-GARCH model under Student-t innovations providing both the best fit and the best forecasts. Ahmed et al. (2025) reported that heavy-tailed error distributions best explained extreme movements in Nigerian market capitalisation returns, and Wanjuki et al. (2024) identified the GJR-GARCH model as the most suitable specification for the Nairobi Securities Exchange. Mahajan et al. (2022) found that asymmetric GARCH models outperformed both symmetric variants and recurrent neural networks in out-of-sample prediction for the NIFTY 50, while firm level heterogeneity in Nigeria was documented by Mohammed et al. (2022). Despite this body of work, rigorous comparison of in-sample fit and out-of-sample forecasting using post-2023 Nigerian data remains scarce (Okafor and Egbunike, 2025), and it is this gap the present study addresses.

The study pursues four objectives: to test for volatility clustering, non-normality, and heteroskedasticity in the All-Share Index series; to estimate the basic GARCH (1,1) and gauge shock persistence; to compare the asymmetric EGARCH and GJR-GARCH models in order to establish whether negative news affects volatility more than positive news; and to evaluate forecasting accuracy across specifications using standard loss functions so as to identify the most effective predictive tool for the Nigerian market.

## 2. Methodology

### 2.1 Data and Pre-processing

The study adopts a quantitative, ex post facto and longitudinal design appropriate to historical time series that cannot be manipulated directly (Okafor and Egbunike, 2025). The primary variable is the monthly All-Share Index of the Nigerian Exchange Group, drawn from the official database of the Central Bank of Nigeria. Monthly observations were chosen to secure a consistent twenty five year series from January 2000 to December 2024 and to align with comparable long-horizon studies, with the acknowledgement that monthly returns smooth intra-month dynamics and may understate the leverage effect relative to daily frequency. The raw index is transformed into a stationary series of logarithmic returns through Equation 1,

$$r_t = \ln(P_t / P_{t-1}) \times 100 \quad (1)$$

where  $P_t$  is the index level at time  $t$ . The logarithmic transformation is preferred to simple percentage returns because it stabilises the variance and brings the distribution closer to normality (Wen et al., 2024). Descriptive statistics, the Augmented Dickey-Fuller and Phillips-Perron unit root tests, and the Engle Lagrange multiplier test for conditional heteroskedasticity were applied before model estimation.

### 2.2 The ARCH and GARCH Models

Engle (1982) proposed that the conditional variance of the error term depends on the magnitude of past errors. With the innovation written as the product of the conditional standard deviation and a standardised disturbance in Equation 2, the ARCH process of order  $q$  is given by Equation 3,

$$\begin{aligned} \varepsilon_t &= \sigma_t z_t \quad (2) \\ \sigma_t^2 &= \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \quad (3) \end{aligned}$$

Bollerslev (1986) generalised this by allowing the conditional variance to depend on its own lagged values, giving the GARCH ( $p$ ,  $q$ ) variance equation in Equation 4,

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (4)$$

The sum of the ARCH and GARCH coefficients measures the persistence of volatility shocks. A value near unity implies that shocks dissipate slowly, and a sum equal to one corresponds to the integrated GARCH case in which a shock has a permanent effect. The unconditional variance is finite and positive only when this sum is strictly less than one, as expressed in Equation 5,

$$\sigma^2 = \omega / (1 - (\alpha_1 + \beta_1)), \alpha_1 + \beta_1 < 1 \quad (5)$$

2.3 Asymmetric Specifications

The EGARCH model of Nelson (1991) specifies the logarithm of the conditional variance, as in Equation 6, so that the variance is positive for any parameter values and the non-negativity constraints of the standard model are removed,

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^p \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^q [\alpha_i (\varepsilon_{t-i} / \sigma_{t-i}) + \gamma_i (\varepsilon_{t-i} / \sigma_{t-i})^2] \quad (6)$$

The GJR-GARCH model of Glosten, Jagannathan, and Runkle (1993) instead augments the variance equation with an indicator that switches on for negative shocks, as in Equation 7, where the indicator defined in Equation 8 equals one for bad news and zero otherwise,

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 \quad (7)$$

$$I_{t-1} = 1 \text{ if } \varepsilon_{t-1} < 0, \quad 0 \text{ if } \varepsilon_{t-1} \geq 0 \quad (8)$$

A positive asymmetry coefficient confirms the leverage effect, since the contribution of a negative shock to conditional variance then exceeds that of a positive shock of equal size. Five specifications were estimated by maximum likelihood: GARCH (1,1) under normal and Student-t innovations, EGARCH (1,1) under normal innovations, and GJR-GARCH (1,1) under normal and Student-t innovations. Forecast accuracy was assessed using the root mean square error and the mean absolute error.

3. Data Analysis and Discussion

3.1 Data Presentation

Figure 1 presents the monthly closing level of the All-Share Index together with the computed monthly logarithmic returns. The index opened near 5,752 points in January 2000, rose through the bull market of the 2000s, collapsed from a peak near 66,000 points during the global financial crisis of 2008, recovered over the following decade, and absorbed a further shock during the pandemic disruption of March 2020. The most pronounced structural shift in the entire history follows the 2023 reforms, when the index surged past 100,000 points and closed the year near 102,926. The lower panel reveals visible clusters of large returns interspersed with calmer intervals, the signature of time-varying volatility that motivates the GARCH approach.

Figure 1: NGX All-Share Index – Price Level and Monthly Log Returns (January 2000 – December 2024)

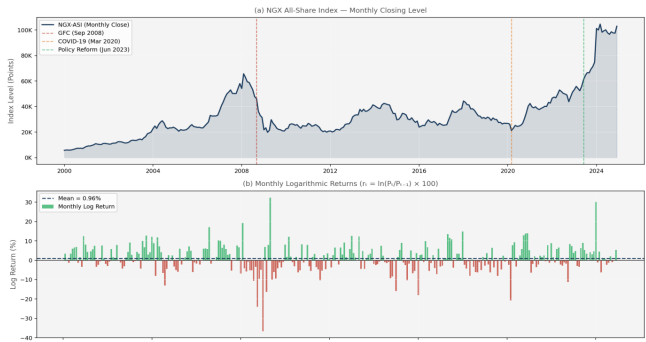


Figure 1. NGX All-Share Index monthly closing level and monthly logarithmic returns, January 2000 to December 2024. Source: Authors' computation from CBN data.

Table 1 reports the descriptive statistics for the 299 monthly returns. The mean monthly return of 0.96 percent confirms long-run appreciation, yet the standard deviation of 6.91 percent

signals a high-risk environment. The excess kurtosis of 5.04 establishes leptokurtosis, and the Jarque-Bera statistic of 317.67 decisively rejects normality at every conventional level.

Table 1. Descriptive statistics of NGX monthly log returns (January 2000 to December 2024).

| Statistic        | Value    | Interpretation            |
|------------------|----------|---------------------------|
| Observations (N) | 299      | Monthly, 25 years         |
| Mean return      | 0.9647%  | Long-run appreciation     |
| Median return    | 0.4556%  | Right-skewed by outliers  |
| Std. deviation   | 6.9107%  | High monthly volatility   |
| Minimum return   | −36.59%  | Extreme loss (2008)       |
| Maximum return   | +32.35%  | Extreme gain (2023)       |
| Skewness         | −0.1879  | Slight negative skew      |
| Excess kurtosis  | 5.0356   | Heavy tails (leptokurtic) |
| Jarque-Bera      | 317.67   | Rejects normality         |
| JB p-value       | < 0.0001 | Non-normal confirmed      |

Source: Authors' computation.

Figure 2 examines the distributional properties more closely. The fitted Student-t density with about seven degrees of freedom describes the observed returns far better than the normal curve, the quantile plot confirms heavy tails at both extremes, and the squared returns display the clustering that a constant variance model cannot capture.

Figure 2: Distributional Properties of NGX Monthly Log Returns

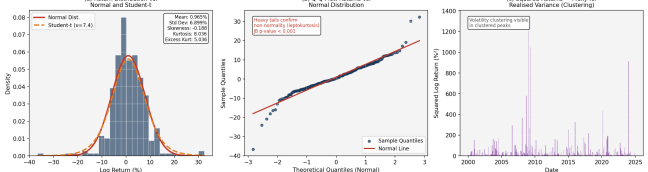


Figure 2. Distributional properties: histogram with fitted densities, quantile plot, and squared returns. Source: Authors' computation.

3.2 Stationarity and ARCH Effects

Table 2 reports the Augmented Dickey-Fuller test. The price level is non-stationary, with a statistic of negative 0.54 that fails to reject the unit root null, whereas the log returns are stationary with a statistic of negative 4.32 that exceeds the one percent critical value in absolute terms. The returns are therefore integrated of order zero and suitable for volatility modelling.

Table 2. Augmented Dickey-Fuller unit root test results.

| Series      | ADF stat. | CV 1% | CV 5% | Decision       |
|-------------|-----------|-------|-------|----------------|
| ASI level   | −0.5356   | −3.51 | −2.89 | Non-stationary |
| Log returns | −4.3174** | −3.51 | −2.89 | Stationary     |

Note: \*\* denotes rejection of the unit root null at the 1 percent level. Source: Authors' computation.

Table 3 confirms the presence of conditional heteroskedasticity. The ARCH-LM statistic of 33.84 with a probability of 0.0007 decisively rejects the null of constant variance, justifying the GARCH framework.

Table 3. ARCH-LM test results (12 lags).

| Test              | Statistic | p-value | Conclusion             |
|-------------------|-----------|---------|------------------------|
| ARCH-LM (12 lags) | 33.8375   | 0.0007  | ARCH effects confirmed |

Source: Authors' computation.

### 3.3 GARCH Estimation Results

Table 4 presents the maximum likelihood estimates and information criteria for all five specifications. In the symmetric GARCH (1,1) the persistence measure reaches 0.9998, confirming that shocks decay slowly and the process is near-integrated. The GARCH (1,1) with Student-t innovations attains the lowest AIC and BIC, making it the preferred model on information criteria. The central result emerges from the GJR-GARCH model, whose asymmetry coefficient of 0.1425 under normal innovations is positive and economically meaningful: a negative shock contributes the sum of the ARCH and asymmetry coefficients, about 0.2365, to subsequent variance, against only 0.0940 for a positive shock, so that bad news raises volatility roughly two and a half times more than equivalent good news. The estimates are stable when Student-t innovations are introduced, confirming the robustness of the leverage effect.

**Table 4. GARCH family model estimation results.**

| Parameter   | GARCH-N | GARCH-t | EGARCH-N | GJR-N   | GJR-t   |
|-------------|---------|---------|----------|---------|---------|
| $\omega$    | 0.3556  | 0.3515  | ~0.000   | 0.2613  | 0.2611  |
| $\alpha$    | 0.1573  | 0.1587  | 0.1051   | 0.0940  | 0.0930  |
| $\gamma$    | —       | —       | ~0.000   | 0.1425  | 0.1420  |
| $\beta$     | 0.8425  | 0.8384  | 1.0000   | 0.8346  | 0.8355  |
| $\nu$       | —       | 7.44    | —        | —       | 7.03    |
| Persistence | 0.9998  | 0.9971  | 1.0000   | 0.9999  | 0.9996  |
| Log-Lik.    | -1012.1 | -997.5  | -1003.4  | -1025.0 | -1009.0 |
| AIC         | 2030.2  | 2002.98 | 2014.8   | 2058.1  | 2027.96 |
| BIC         | 2041.3  | 2017.77 | 2029.6   | 2072.9  | 2046.4  |

Source: Authors' estimation. Lowest AIC and BIC identify the preferred model.

Figure 3 plots the estimated conditional volatility from three of the models across the full sample, showing pronounced spikes during the 2008 crisis, the 2020 disruption, and the post-2023 reform period, alongside the broad agreement of the specifications in tranquil intervals.

**Figure 3: Estimated Conditional Volatility (Standard Deviation) from GARCH Family Models — NGX All-Share Index (2009-2024)**

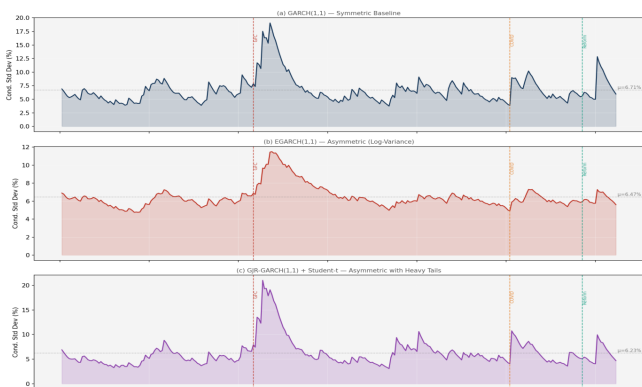


Figure 3. Estimated conditional volatility from GARCH family models, 2000 to 2024.

Source: Authors' computation.

Figure 4 displays the autocorrelation functions of the returns and their transforms. Raw returns show no significant autocorrelation, consistent with weak-form efficiency, whereas squared and absolute returns display significant, slowly decaying

autocorrelation, the hallmark of volatility clustering.

**Figure 4: Autocorrelation Functions — Returns, Squared Returns, and Absolute Returns**

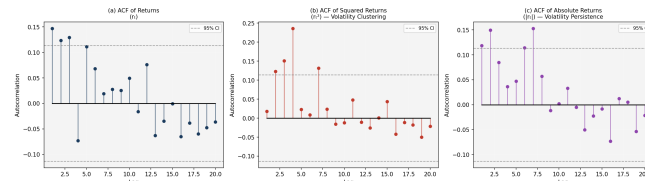


Figure 4. Autocorrelation functions of returns, squared returns, and absolute returns.

Source: Authors' computation.

The news impact curve in Figure 5 makes the asymmetry explicit. The GJR-GARCH curve lies above the symmetric GARCH curve for all negative shocks and below it for all positive shocks, and at a shock of ten percent the conditional variance following a negative shock is about two and a half times that following a positive shock of equal magnitude. Introducing Student-t innovations preserves this asymmetry while improving the fit of the tails.

**Figure 5: News Impact Curves — Illustrating the Leverage Effect in GARCH vs. GJR-GARCH Models**

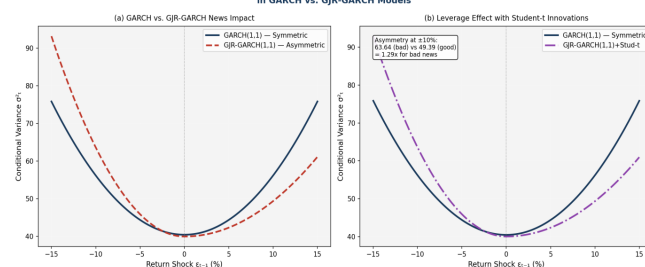


Figure 5. News impact curves for the symmetric GARCH and asymmetric GJR-GARCH models.

Source: Authors' computation.

### 3.4 Volatility Forecasting

Table 5 reports the out-of-sample forecasting accuracy over the twelve month hold-out period of 2024, with each model estimated on the in-sample period to December 2023. On the root mean square error criterion the EGARCH model performs marginally best, but the differences across models are small and may not be statistically distinguishable. On the mean absolute error criterion the GJR-GARCH model under Student-t innovations is clearly superior, improving on the symmetric GARCH by 3.8 percent and on the EGARCH by 5.9 percent. The asymmetric, fat-tailed specification thus provides the most reliable forecasts in the practically important sense of average absolute error.

**Table 5. Out-of-sample forecast error metrics (January to December 2024 hold-out).**

| Model                    | RMSE   | MAE    |
|--------------------------|--------|--------|
| GARCH(1,1)-Normal        | 257.25 | 92.49  |
| EGARCH(1,1)-Normal       | 255.82 | 94.57  |
| GJR-GARCH(1,1)-Student-t | 258.87 | 88.97* |

Note: \* best MAE performer. Source: Authors' computation.

Figure 6 illustrates the forecasting performance, tracing how closely each model follows the realised volatility of the hold-out period and confirming the ranking through the error metrics. Figure 7 summarises model selection by information criteria, where the GARCH model with Student-t innovations records the lowest AIC and BIC.

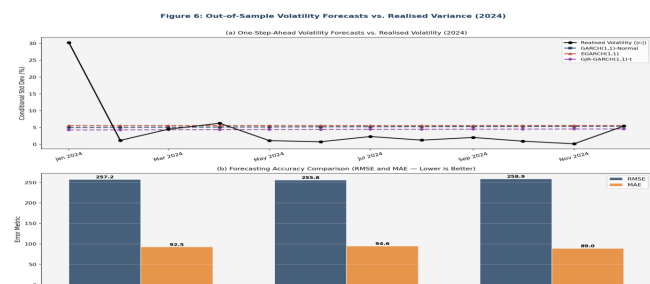


Figure 6. Forecasting performance over the 2024 hold-out period.

Source: Authors' computation.

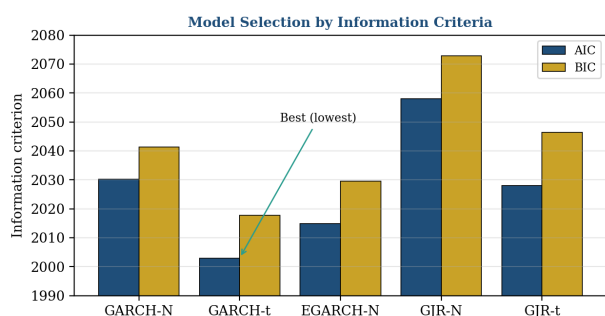


Figure 7. Model selection by Akaike and Bayesian information criteria across the five specifications.

Source: Authors' computation.

### 3.5 Discussion of Findings

Three conclusions follow from the evidence. The returns exhibit pronounced volatility clustering and conditional heteroskedasticity, confirmed jointly by the excess kurtosis, the autocorrelation of squared returns, and the ARCH-LM test, which together establish that a constant variance model is inadequate. The market responds asymmetrically to news, with the leverage effect estimated consistently across distributional assumptions and carrying direct implications for downside risk, since negative events generate disproportionately larger volatility surges. Finally, volatility is highly persistent, the near-integrated persistence measures indicating that shocks decay slowly and that elevated volatility regimes endure once established. The practical message is that risk management in the Nigerian market should rely on asymmetric specifications with fat-tailed innovations, which capture both the leverage effect and the heavy tails that govern extreme losses.

### 4. Conclusion and Recommendations

This study modelled and forecast the volatility of the Nigerian Exchange Group All-Share Index over twenty five years using the GARCH family of models. The returns were confirmed to be non-normal, stationary in log form, and strongly heteroskedastic. Among the five specifications, the GARCH (1,1) with Student-t innovations was preferred on information criteria, while the GJR-GARCH with Student-t innovations delivered the most accurate forecasts on the mean absolute error criterion and provided clear evidence of a leverage effect under which negative shocks raise volatility about two and a half times more than positive shocks. Volatility was found to be highly persistent throughout. It is recommended that investors and risk managers adopt asymmetric, fat-tailed specifications for Value-at-Risk estimation, stress testing, and hedging, that regulators monitor persistence as an indicator of systemic fragility, and that future work extend the analysis to daily data and to multivariate settings

capable of capturing volatility spillovers across markets.

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