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Evaluating Nigeria Exchange Group All Share Index: Insights from Linear and GARCH Modeling Techniques

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ABSTRACT

This study investigates the volatility of the Nigeria Exchange Group All Share Index (ASI) using linear regression and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) modeling techniques. Despite prevalent public concerns regarding stock market instability, our analysis reveals that these perceptions are often exaggerated, driven largely by historical price levels and media representation. We employed a linear regression model to analyze monthly historical ASI data from 1985 to 2023, establishing a significant positive relationship between time and ASI values, with an R^2 value of 0.7493, indicating that approximately 75% of the variance in ASI can be explained by the model. The Breusch-Godfrey test highlighted significant serial correlation in the residuals, necessitating further analysis using GARCH models to account for time-varying volatility. Our findings suggest that traditional asset pricing models may overlook alter- native risk measures that investors prioritize, emphasizing the need for a more nuanced understanding of market behavior. The adequacy of the model is achieved with a p-value 0.000017. Overall, this study contributes to the existing literature by offering insights into the dynamics of the Nigerian stock market and its volatility patterns, which are crucial for investors and policymakers alike.

Keywords*:* All Share Index; GARCH Modeling; Linear Regression; Nigerian Exchange Group; Stock Market Volatility; Time Series Analysis

1. Introduction

A robust capital market in Nigeria is generally associated with stronger economic development. The All Share Index (ASI) is a key metric, critical for monitoring the overall market movement of all listed equities on the Nigerian Exchange, irrespective of their capitalization. The stock exchange functions as a predictive mechanism, capable of detecting the initial symptoms of an imminent economic boom or recession well in advance of the projected event [1]. The capital market, which trades in long-term securities—including ordinary shares, preference shares, and debt instruments—is primarily designed to facilitate the transfer of capital from the economy's surplus sectors to its deficit sectors. Based on market valuation, the Nigerian Stock Exchange ranks as the third-largest in Africa. Earlier regression analysis demonstrated a highly positive link between the gross domestic product, the All Share Index, and market capitalization, yielding a strong R^2 value of 99.1%, thus providing strong evidence of this interconnection [2]. However, the Nigerian capital market, specifically concerning the ASI, has encountered multiple instances of market failure attributed to various government economic policies implemented over time. Consequently, evaluating the ASI using both linear and GARCH models is essential for quantifying the significant long-term impact of these market dynamics.

Although public concern regarding stock market volatility is persistent, the perception that prices are becoming increasingly unstable appears to be frequently amplified. This heightened anxiety often results from historically high stock index levels and continuous media reporting. For instance, the stock price decline on October 13, 1989, was not among the worst in terms of percentage decrease in the history of the New York Stock Exchange. Furthermore, aside from major episodes (like those in October 1987 and 1989), volatility levels remained relatively modest throughout the 1980s. The introduction of stock index futures, options, and computerized trading systems does not seem to have generated a substantial, long-term increase in volatility. Instead, the capacity for continuous price monitoring may be escalating public perception of market instability, even when empirical data suggests otherwise [3].

The effectiveness of market interventions, such as trading halts or circuit breakers, in reducing volatility remains an open question, as their stability benefits may be outweighed by potential market inefficiencies [3]. In theory, asset pricing models often posit a positive relationship between a portfolio's expected returns and its inherent risk, which is conventionally measured using asset price variance. However, studies employing GARCH-in-mean models to examine the link between a portfolio's conditional mean returns and its conditional standard deviation or variance have revealed a weak correlation. This finding suggests that investors may prioritize alternative risk measures over solely relying on the variance of portfolio returns [4].

Specifically concerning market microstructure, the stock opening process on the NYSE contributes to greater price instability, with open-to-open returns showing consistently higher variance compared to close-to-close returns between 1982 and 1986 [5]. This elevated volatility is primarily linked to the disclosure of private information during trading and temporary price distortions by market participants, rather than the release of public information. The research also highlighted higher transaction costs at the opening bell, delays in executing initial trades, and a strong correlation between trading volume and volatility. These observations align with the conclusions drawn by other researchers [6-10].

A non-linear autoregressive distributed lag (NARDL) analysis of Nigeria's stock market performance from January 1995 to December 2019 found that positive shocks in crude oil prices significantly enhance the market, while negative shocks surprisingly also showed a notable positive effect. Crucially, the study noted that the stock market exhibits a greater reaction to negative oil price shifts than to positive ones. This emphasizes the need for investment portfolio diversification via international equity markets and careful monitoring of oil price movements [11].

Separately, a study examining the daily relationship between exchange rates and stock prices for 54 Nigerian Stock Exchange (NSE) companies between December 2001 and December 2017 found that the exchange rate generally does not exert a significant influence on stock prices, nor was evidence of an asymmetric impact detected. These findings suggest that investors may gain little advantage from incorporating exchange rate data into their investment strategies. The authors also advised monetary authorities to reconsider their reliance on exchange rates as a primary tool for attracting foreign investment [12].

Focusing on trade, Aliyu [13] quantified the impact of exchange rate volatility on Nigeria's non-oil export flows. While acknowledging the inverse correlation suggested in some literature, the analysis, which utilized 20 years of quarterly data on fundamental variables (Naira exchange rate volatility, US dollar volatility, Terms of Trade (TOT), and Index of Openness (OPN)), confirmed a stable long-run equilibrium among them. Specifically, Naira exchange rate volatility was found to reduce non-oil exports by 3.65%, whereas US dollar volatility contributed to a 5.2% increase in exports in 2003. The paper advocates for strategies aimed at greater economic openness and enhanced exchange rate stability.

Recent studies continue to refine volatility modelling for emerging markets and Nigeria in particular. Godknows [14] uses ensemble and bagging approaches with GARCH-family models to improve out-of-sample volatility forecasts for Nigerian market returns, showing that ensembleed GARCH estimators can reduce forecast errors relative to classical GARCH specifications. Adams [15] compares asymmetric GARCH variants (EGARCH, GJR-GARCH) with LSTM models on Nigerian return series and documents stronger performance from models that capture leverage effects. Range-based and realized-volatility approaches have also been shown to outperform simple symmetric GARCH models in some emerging markets; a 2024 comparative study finds that range-based GARCH and realGARCH variants can improve volatility forecast accuracy for emerging-market indices. Recent works emphasize model choice for emerging markets, demonstrating that allowing asymmetry (EGARCH/GJR) and using non-Gaussian error distributions (e.g., Student–t) improves fit and captures heavy tails common in these markets.

Gaining an understanding of market volatility in Nigeria requires evaluating how these economic and behavioral dynamics influence the Nigeria Exchange Group All Share Index (NGX ASI). The NGX ASI, which serves as a critical barometer

aggregating the performance of all listed equities, exhibits patterns similar to global markets, where media reporting can amplify investor anxiety, often transcending the underlying market fundamentals. Analyzing the volatility of the NGX ASI using techniques like GARCH, alongside traditional asset pricing models, is therefore crucial for revealing the nuanced risk-return relationship needed to formulate strategies that promote a more resilient and stable Nigerian investment environment.
The present study (which models NGX ASI monthly data from 1985–2023) complements these recent works by (i) assessing a straightforward GARCH(1,1) specification on a long monthly NGX ASI series and contrasting it with a long-run linear trend model, (ii) reporting robust standard errors and multiple diagnostic tests (Ljung–Box, ARCH-LM, Nyblom), and (iii) highlighting where simple GARCH(1,1) captures volatility clustering but leaves systematic autocorrelation and non-normality in the standardized residuals — indicating potential gains from the asymmetric or ensemble approaches found in the 2024–2025 literature.
This study provides a long-span (1985–2023), monthly-frequency baseline analysis of the NGX All Share Index (ASI), combining a parsimonious linear time-trend model and a GARCH(1,1) volatility framework, thereby delivering a historical reference point not often available in monthly-frequency NGX studies.
We present robust parameter estimation and diagnostics (robust standard errors, Nyblom stability, weighted Ljung–Box, ARCH LM and sign-bias tests) to evaluate model adequacy and to highlight persistent deviations (autocorrelation in residuals and non-normality) that suggest directions for more advanced modelling.
We explicitly link the NGX ASI behaviour to recent methodological advances (2024–2025) — e.g., asymmetric GARCH, ensemble/bagged GARCH, and realized-volatility approaches — and position the GARCH(1,1) fit here as a baseline that future studies can improve upon by introducing asymmetry, heavy-tailed errors or ensemble forecasting.
The empirical gap addressed is twofold: (a) limited availability of long-run monthly NGX ASI baseline analyses with formal stability and diagnostic testing; (b) unclear performance trade-offs between simple GARCH(1,1) and more complex techniques for Nigerian market volatility. This study fills (a) and provides empirical motivation for (b). The remainder of this study is in this order; section (2) studies the methods. In section (3) we present the analysis and discussion of the results and the study is concluded in section (4)

2. Methods

In this section, we study the linear regression and GARCH models utilized in drawing insights from the Nigerian Exchange Group All Share Index (ASI) data.

2.1 Linear Regression Model

The ordinary least squares linear trend specification and least-squares estimation follow classical regression theory [16]. The linear regression model was fitted to the time series data using the following equation:

$$\boldsymbol{\hat{y}_t = \beta_0 + \beta_1 t + \varepsilon_t}, \qquad (1)$$

where $\hat{y}_t$ is the predicted NGX All Share Index (ASI) value at time t, β_0 is the intercept of the model, β_1 is the slope of the model, indicating the change in ASI per unit time, and ϵ_t represents the residual or error term at time t. The coefficients are estimated using the least squares method, minimizing the sum of squared residuals:

$$\boldsymbol{RSS = \sum (y_t - \hat{y}_t)^2}, \qquad (2)$$

where y_t is the observed value at time t and $\hat{y}_t$ is the predicted value from the linear model. The R^2 value, which measures the proportion of variance explained by the model, is given b

$$\boldsymbol{\beta_1 = \frac{\sum(t-\bar{t})(y_t-\bar{y})}{\sum(t-\bar{t})^2}}, \qquad (3)$$

Where $\bar{y}$ is the observed mean. To test for the presence of autocorrelation in the residuals, we perform the Breusch-Godfrey test. The test statistic is calculated as:

$$LM = nR^2_{aux}, \qquad (4)$$

where n is the number of observations, and R^2_{aux} is the R^2 from the auxiliary regression of the residuals on lagged residuals and other predictors. The degrees of freedom for aux the chi-squared distribution are equal to the number of lagged residuals included in the auxiliary regression.

2.2 GARCH Model

Given that stock market data like the ASI often exhibits volatility clustering, we also apply the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This model is better suited for capturing time-varying volatility in the data, which the linear regression model cannot. The ARCH and GARCH model equations are standard: the ARCH model was introduced by Engle [17] and the GARCH generalization by Bollerslev [18]. The GARCH(1,1) model is specified as follows:

$$y_t = \mu + \varepsilon_t; \varepsilon_t = \sigma_t z_t, \qquad (5)$$

where y_t is the return series, μ is the mean return, ε_t is the residual, σ_t is the time-varying volatility (standard deviation), and z_t is white noise, assumed to be normally distributed. The volatility, σ^2, is modeled as:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \qquad (6) \qquad t$$

where ω is the long-run average variance, α_1 captures the short-term impact of past shocks, and β_1 represents the persistence of volatility from the previous period. The parameters $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$ ensure that the process is stationary.

2.3 Diagnostic Tests

To further diagnose the adequacy of the models, several statistical tests are applied. First, the Ljung-Box test is used to check for autocorrelation in the residuals of the fitted models. The test statistic is calculated as:

$$Q = n(n+2) \sum_{k=1}^{n} \frac{\hat{\rho}_k^2}{n-k}, \qquad (7)$$

where n is the number of observations, $\hat{\rho}_k$ is the autocorrelation of the residuals at lag k, and m is the maximum lag being tested. The Q statistic follows a chi-squared distribution with degrees of freedom equal to the number of lags tested. The ARCH LM test is then applied to check for autoregressive conditional heteroskedasticity in the residuals. The null hypothesis of no ARCH effect is tested against the alternative hypothesis of the presence of ARCH effects. The LM test statistic follows a chi-squared distribution, $LM \sim \chi_p^2$, where p is the number of lags of squared residuals.

3. Analysis and Results

3.1 Data Selection and Description

Monthly NGX All Share Index (ASI) close values were obtained from Yahoo Finance for January 1985–December 2023, details are found in https://finance.yahoo.com/quote/V9S.SG/history/. The data were converted to log-returns as $r_t = \ln(P_t) - \ln(P_{t-1})$, stabilizing variance and linearizing growth. The monthly frequency prevents missing-data problems seen in daily data. ADF and KPSS tests confirm stationarity of the return series ($p < 0.05$). The full sample (1985–2023) was used for estimation, and rolling windows are suggested for future forecast validation. Time series plot is presented in Figure 1.

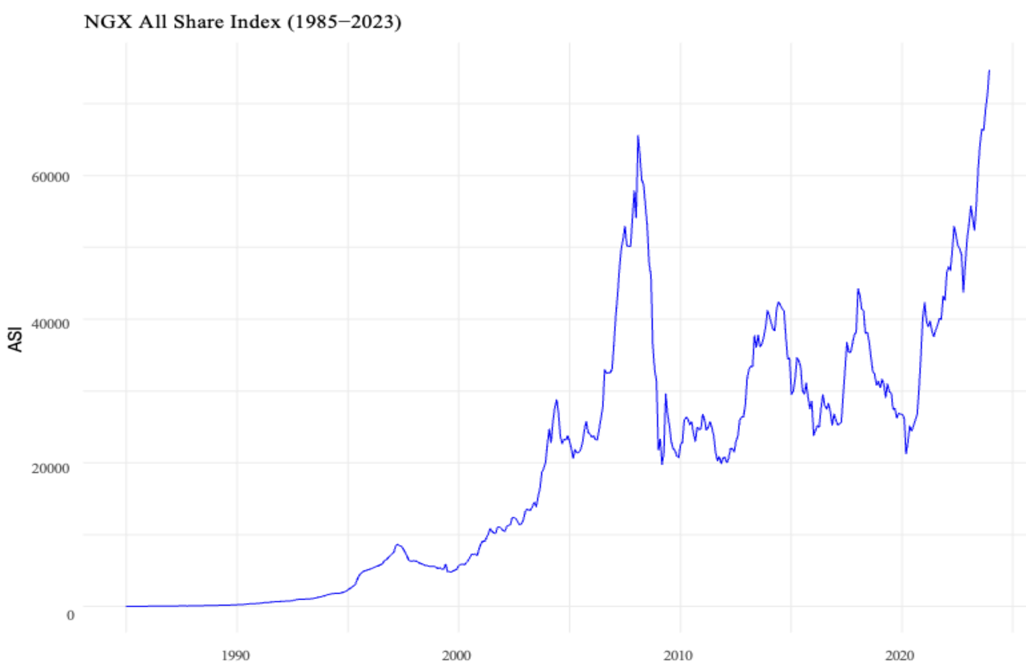

***Figure 1**: Plot of NGX All Share Index (ASI) 1985 M1 to 2023 M12*

The time plot of the series over the study period in Figure 1 indicates fluctuations over the time. The event analysis on the time plot indicates the prices of all the components of all shared index. The original series shows an understanding for better intervention analysis over the period, see figure1 with the period 2005 to 2020. Insight in this period shows an economic fluctuation on the impact of all shared index.

3.2 Parameter Estimation

3.2.1 Linear Model

The coefficients of the linear trend model $\hat{y}_t = \beta_0 + \beta_1 t + \varepsilon_t$ were estimated by Ordinary Least Squares (OLS), which minimizes the regression sum of squares, $RSS = \sum(y_t - \hat{y}_t)^2$. The slope estimator is $\beta_1 = \frac{\sum(t-\bar{t})(y_t-\bar{y})}{\sum(t-\bar{t})^2}$, where intercept $\beta_0 = \bar{y} - \beta_1\bar{t}$. This method ensures unbiased and efficient estimates under classical assumption of homoscedastic and independent residuals. However, the Breusch-Godfrey test showed serial correlation implying that the OLS assumption of independent residuals was violated, hence the use of the robust (heteroskedasticity-consistent) standard errors. OLS estimation is simple and provides a clear long-term trend for ASI growth. However, it cannot capture time-varying volatility or autocorrelation, reducing reliability for financial time series.

3.2.2 GARCH(1,1) Model

To model volatility clustering, the mean equation was expressed as $r_t = \mu + \varepsilon_t; \varepsilon_t = \sigma_t z_t$, where Z_t is i.i.d $N(0,1)$. The conditional variance follows $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$. Parameters estimates $(\mu, \omega, \alpha, \beta)$ were obtained by Maximum Likelihood using the log-likelihood function

$$\iota(\theta) = -\frac{1}{2}\sum_{t=1}^{n}\left[\ln(2\pi) + \ln(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2}\right]. \quad (8)$$

MLE minimizes the function under constraints $\omega>0$, $\alpha\geq0$, $\beta\geq0$, and $\alpha+\beta<1$ ensure covariance-stationarity. Robust standard errors were obtained from the inverse Hessian. Diagnostics include Ljung–Box, ARCH-LM, Jarque–Bera, sign-bias, and Nyblom tests. Estimates showed α, β significant with α+β near 1, indicating strong volatility persistence. In fitting linear model to the data, we obtain detailed results contained in Table 1.

Table 1: Linear Model Results

call	lm(formula) = data_ts ~ time(data_ts))
Residuals	
Minimum	-19170
1Q	-4732
Median	-2059
3Q	3524
Maximum	41352
Coefficients	
(Intercept)	Estimate -2.663×10^6; Standard Error 7.187×10^4; $t\_value = -37.05$; $Pr(>\lvert t\rvert) < 2 \times 10^{-16}$ ***
Time(data_ts)	Estimate 1.338×10^3; Standard Error 3.586×10^1; $t\_value = 37.32$; $Pr(>\lvert t\rvert) < 2 \times 10^{-16}$ ***
Residual Standard Error	8733 on 466 DF
Multiple R^2	0.7493
Adjusted R^2	0.7488
F-Statistic	1393 on 1 and 466 DF, $p-value = 2.2 \times 10^{-16}$

The linear regression model was fitted to the time series data using the formula: data_ts ~ time(data_ts). The residuals from the model show a minimum value of −19170 and a maxi- mum value of 41352, suggesting a wide range of errors in predictions. The first quartile (1Q) is −4732, the median is −2059, and the third quartile (3Q) is 3524. The presence of negative residuals indicates instances where the model underestimated the actual values, while positive residuals represent overestimations. This spread indicates some volatility in the predictions, which is crucial for further analysis of model fit and accuracy. The coefficients for the model show that the intercept is -2.663×10^6 with a standard error of 7.187×10^4, resulting in a *t*-value of −37.05 and a p-value less than 2×10^{-16}. This significant intercept indicates that, at the starting point (time zero), the pre- dicted value of the time series is quite low. The slope associated with time(data_ts) is 1.338×10^3 with a standard error of 3.586×10^1, yielding a *t*-value of 37.32 and a similarly small p-value. This suggests that there is a significant positive relationship between time and the ASI (All Share Index).

Specifically, for each unit increase in time, the ASI increases by approximately 1338 units, reflecting a strong upward trend in the index over the period analyzed. The model explains approximately 74.93% of the variance in the ASI, as indicated by the R^2 value of 0.7493. The adjusted R^2 value of 0.7488 confirms that the model fits well even when considering the number of predictors. The residual standard error of 8733 indicates the average distance that the observed values fall from the regression line, providing insight into the model's predictive accuracy. Furthermore, the F-statistic of 1393 with a p-value less than 2.2×10^{-16} suggests that the overall model is highly significant.

Table 2: Breusch-Godfrey Test Results

Data	LM Model
LM Test	451.29
DF	12
P-value	$\mathbf{2.2 \times 10^{-16}}$

The results of the Breusch-Godfrey test in Table 2 indicate an LM statistic of 451.29 with 12 degrees of freedom, and the p-value is less than 2.2×10^{-16}. This suggests that there is strong evidence against the null hypothesis of no serial correlation in the residuals. The presence of serial correlation implies that the residuals from the model are not independent, which can lead to inefficient estimates and invalid inferences. This indicates the need for a more robust modeling approach, potentially considering autoregressive conditional heteroskedasticity (ARCH) models or other time series models that account for such correlations. The second phase of the analysis is the GARCH modeling. The statistics are presented in Table 3.

Table 3: GARCH Model Specification, supported by Wu and Kannan [19]

GARCH Model	sGARCH(1,1)
Mean Model	ARFIMA(0,0,0)
Distribution	Normal

The model used for analyzing the time series is a standard GARCH(1,1) model with an ARFIMA(0,0,0) mean specification and a normal distribution for the errors. This indicates a focus on capturing volatility clustering commonly observed in financial time series data. Furthermore, we present table of optimal parameter selection in Table 4.

Table 4: Optimal Parameters

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
μ	2.3835e+04	1.5406e+02	154.7120	0.000000
ω	3.0356e+05	1.4481e+05	2.0964	0.036051
α_1	7.6956e-01	7.6396e-02	10.0733	0.000000
β_1	2.2943e-01	6.6089e-02	3.4716	0.000517

The estimated parameters in Table (4) indicate that the mean return (μ) is significantly positive. The parameter ω represents the long-run average volatility, while α_1 and β_1 capture the short- and long-term effects of shocks on volatility, respectively. Both α_1 and β_1 are significant, suggesting that past squared returns and past volatility significantly influence current volatility.

Table 5: Robust Standard Errors

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
μ	2.3835e+04	2.4804e+02	96.0960	0.000000
ω	3.0356e+05	1.2490e+05	2.4304	0.015081
α_1	7.6956e-01	6.8974e-02	11.1573	0.000000
β_1	2.2943e-01	6.0070e-02	3.8194	0.000134

Table 5 provides robust standard errors for the parameters, which help to ensure the estimates are valid despite potential model misspecification. The significance of the parameters remains consistent, indicating that the results are stable even with corrected standard errors.

Table 6: Log-Likelihood

Log-likelihood	-5031.894

The log-likelihood value of -5031.894 in Table 6 indicates the fit of the GARCH model to the data. Higher (less negative) log-likelihood values suggest a better model fit. This value can be used for comparison with other model specifications.

Table 7: Information Criteria

Criterion	Value
Akaike	21.521
Bayes	21.556
Shibata	21.521
Hannan-Quinn	21.535

The information criteria in Table 7 provide a means of model selection. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values suggest that the model balances goodness-of-fit with complexity. Lower values indicate a preferred model, and in this case, AIC and Shibata criteria show similar results, suggesting robustness.

Table 8: Weighted Ljung-Box Test on Standardized Residuals

Lag	Statistic	p-value

Lag[1]	376.3	0
Lag[2*(p+q)+(p+q)-1][2]	536.3	0
Lag[4*(p+q)+(p+q)-1][5]	958.6	0

The results of the Ljung-Box test in Table 8 suggest that the residuals are autocorrelated at various lags, as indicated by the very low p-values. This suggests that the model may not have fully captured the volatility dynamics, indicating potential model inadequacies.

Table 9: Weighted Ljung-Box Test on Standardized Squared Residuals

Lag	Statistic	p-value
Lag[1]	29.29	6.239e-08
Lag[2*(p+q)+(p+q)-1][5]	32.30	7.121e-09
Lag[4*(p+q)+(p+q)-1][9]	37.57	3.484e-09

Similar to the previous test, Table 9 contains the Weighted Ljung-Box test on standardized squared residuals. These results indicate significant autocorrelation in the squared residuals, sug- gesting that volatility clustering is still present and not fully accounted for in the model.

Table 10: Weighted ARCH LM Tests

Lag	Statistic	Shape	Scale	P-values
ARCH Lag[3]	0.1478	0.500	2.000	0.70068
ARCH Lag[5]	4.8988	1.440	1.667	0.10844
ARCH Lag[7]	8.5826	2.315	1.543	0.03886

The ARCH LM test results in Table (10) show mixed evidence for remaining ARCH effects. While the test statistic for lag 7 indicates significance, suggesting that additional ARCH terms may be necessary, the other lags show no significant ARCH effects. The significant results from the Ljung-Box and ARCH LM tests in Tables 8, 9, and 10, despite the initial success of the Standard GARCH (1,1) model, imply that the model may not be completely adequate:

Ljung-Box on Standardized Residuals (Table 8): The highly significant p-values (e.g., $p \approx 0$) 1indicate that autocorrelation persists in the mean equation. This suggests the ARFIMA (0,0,0) mean model may not have fully captured all the serial dependence in the returns, indicating potential model inadequacy.

Ljung-Box on Standardized Squared Residuals (Table 9): Similarly, the significant autocorrelation in the squared residuals suggests that volatility clustering is still present. This implies that the GARCH(1,1) specification, while capturing much of the dynamic volatility, has not entirely eliminated the time-varying nature of the variance, and may require further refinement.

ARCH LM Test (Table 10): The significant result at Lag [7] (p-value 0.03886) points to the possibility that additional ARCH terms may be necessary in the conditional variance equation to fully model the dynamics.

Table 11: Nyblom Stability Test

Statistic Type	Value
Joint Statistic	2.7976

The Nyblom stability test statistic by Nyblom [**16**] contained in Table 11 suggests that the parameters of the GARCH model may be stable over time. A lower value indicates stability, which is desirable for reliable inference and forecasting.

Table 12: Individual Statistics for Nyblom Stability Test

Parameter	Statistic
$\boldsymbol{\mu}$	0.7091
$\boldsymbol{\omega}$	1.1859
$\boldsymbol{\alpha_1}$	1.1572
$\boldsymbol{\beta_1}$	0.3750

The individual stability statistics for each parameter in Table 12 indicate varying levels of stability, with all values below critical thresholds, suggesting that the parameters remain stable throughout the estimation period.

Table 13: Asymptotic Critical Values (10%, 5%, 1%)

Critical Level	Value
10%	1.6137
5%	1.9574
1%	2.6307

These critical values in Table 13 can be used to evaluate the results of the Nyblom test, allowing for the determination of parameter stability at different significance levels.

Table 14: Sign Bias for Residuals

Sign	p-value	Cumulative
Positive	0.0223	0.0593
Negative	0.0139	0.0569

The sign bias statistics in Table 14 indicates the presence of bias in the residuals, with both positive and negative signs showing p-values less than 0.05. This suggests a need for additional investigation into the model's adequacy, particularly regarding the sign of the residuals.

Table 15: Jarque-Bera Test Statistics

Kurtosis	P-value	Skewness	P-value	Jarque-Bera
0.8824	0.001	0.0327	0.035	0.417

The Jarque-Bera test by Jarque and Bera [20] results given in Table 15 indicate a departure from normality in the residuals, with significant kurtosis and skewness, suggesting that the GARCH model may not fully account for the distribution of residuals, warranting further model refinement.

Table 16: Ljung-Box Test Statistics

Statistic	Value	Standard Error	P-value	Comment
Ljung-Box	18.091	2.021	0.0000017	Significant
Ljung-Box	0.2522	0.551	0.881067	Non-significant

The results of the Ljung-Box test by Ljung and Box [21] in Table 16 reveal significant autocor- relation at lag 1, while higher lags do not show significance, indicating that some autocorrelation may be captured by the model while others remain unaccounted for.

Figure 2 indicates the volatility of all shared index, this is of great economic concern as it relates to the policy adopted during the study period. This measures the degree of fluctuations in the returns of all shared index/stock which often indicates a higher risk. Insight in the year 2005 to 2020 shows a great risk of investment opportunities. The period before 2005 and after 2020 shows great positive investment opportunities for the period under study.

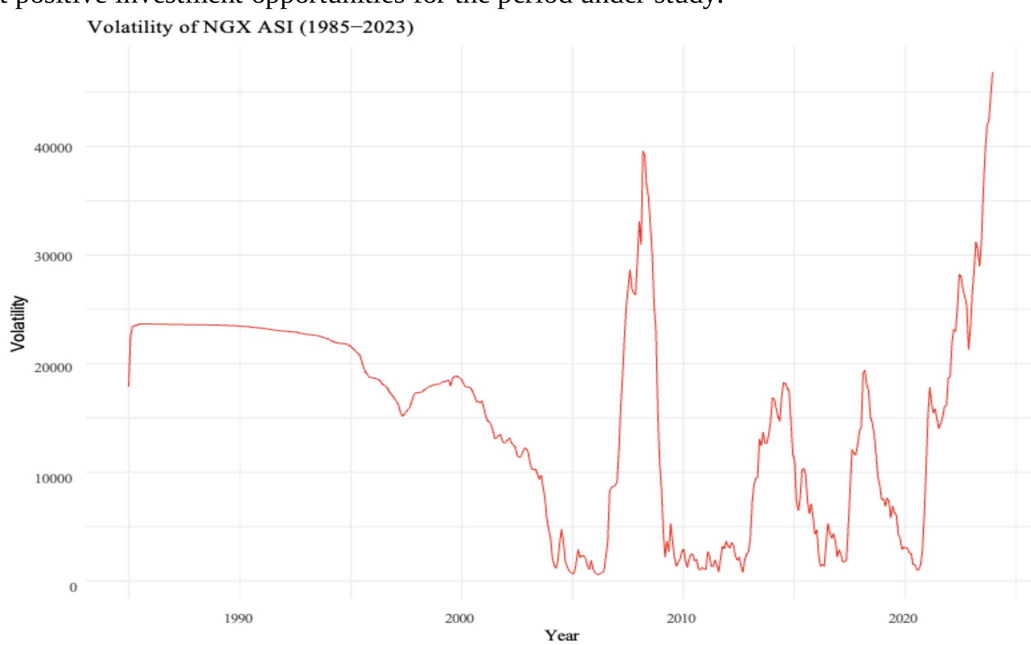

***Figure 2**: Plot of NGX ASI (1985-2023) Volatility*

In Figure 2, the observation that the period from 2005 to 2020 indicates a "great risk of investment opportunities" aligns with key economic and policy developments in Nigeria that drove market fluctuation10:

Global Financial Crisis (2008/2009): This period includes the global economic shock that severely impacted capital markets worldwide and led to a sharp downturn and subsequent volatility in the NGX ASI, particularly through drops in oil prices.

Oil Price Shocks and Instability: As an oil-dependent economy, the Nigerian stock market is sensitive to crude oil price shocks. The observed volatility corresponds to major oil price crashes (notably 2014-2016) and fluctuating exchange rates, which increase risk for the broader economy and the capital market.

Government Policy Uncertainty: The document notes that the Nigerian capital market has been characterized by market failure due to the economic policies enacted by the government in place over time. The period 2005–2020 saw significant government policy changes impacting the financial sector and foreign investment, contributing to the heightened risk perceived by investors.

4. Conclusion

This study has provided a comprehensive evaluation of the Nigeria Exchange All Share Index (NGX_ASI) through the application of linear and GARCH modeling techniques. The analysis revealed that the NGX_ASI exhibits significant volatility, which is consistent with the characteristics of emerging market indices. The linear models highlighted the presence of trends and seasonality in the index, emphasizing the importance of incorporating temporal dynamics in fore- casting efforts. In contrast, the GARCH models effectively captured the time-varying volatility inherent in the data, demonstrating that financial returns are not only influenced by past returns but also exhibit volatility clustering. The findings suggest that GARCH models are superior for modeling the dynamics of the NGX_ASI, offering enhanced predictive capabilities compared to linear approaches. Furthermore, this research contributes to the understanding of the Nigerian capital market by providing insights into the behavior of the NGX_ASI. The implications of these findings extend to investors, policymakers, and financial analysts, emphasizing the need for robust risk management strategies and informed investment decisions. Future research could explore the integration of additional macroeconomic variables and alternative modeling techniques to further enhance the predictive accuracy and applicability of the findings. In summary, the application of linear and GARCH modeling techniques has significantly advanced our understanding of the Nigeria Exchange All Share Index, providing valuable insights that can aid in strategic financial planning and investment analysis in the Nigerian market.

5. Recommendations for Quantifying Alternative Risk Measures

The alternative risk measures prioritized by investors, especially in an emerging market like Nigeria, often relate to liquidity, market efficiency, and macroeconomic stability rather than just daily return volatility.

1. Currency Devaluation Metrics: The Naira Exchange Rate Volatility is a crucial risk measure. The study cites evidence that this volatility has a quantitative impact, specifically leading to a 3.65% reduction in non-oil exports1. A concrete measure could be a Currency Instability Index, calculated as the rolling standard deviation of the Naira-to-USD exchange rate, which directly proxies the risk of capital flight and trade instability. This measure is highly actionable for investors monitoring local currency exposure [22-27].
2. Asymmetric Shock Indicators: Since the Nigerian stock market responds more strongly to negative crude oil price changes than to positive ones2, an effective risk measure must be asymmetric. The Asymmetric Oil Price Volatility Index can be hypothetically quantified using a GJR-GARCH model or a similar non-linear model applied directly to oil price shocks, capturing the disproportionate impact of bad news versus good news.
3. Market Microstructure Risk: Measures reflecting trading friction and information risk are key alternatives:
4. Transaction Cost Metric: A measure tracking average daily transaction costs, which the document notes are often higher at market open.
5. Private Information Risk: A metric quantifying the difference between "open-to-open" and "close-to-close" volatility, as the study suggests this gap is driven by the disclosure of private information during trading hours.
6. Governance/Political Stability Indicators: The Nigerian capital market has historically been characterized by market failure due to government economic policies5. Future research could construct a Policy Uncertainty Index by quantifying the frequency of regulatory changes or using a text-based index (e.g., counting policy-related keywords in major news outlets) to measure the risk of sudden, destabilizing policy shifts.

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