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RESEARCH ARTICLE

ASYMMETRIC GARCH MODELS ON VOLATILITY OF TIN AND NICKEL IN NIGERIA STOCK MARKET

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ABSTRACT

Tin and Nickel stocks in Nigeria's stock market is crucial for understanding market dynamics, managing investment risks, and improving forecasting accuracy, given their economic significance in industrial production, trade, and financial stability. This study therefore, investigates the volatility dynamics of these base metal stocks (Tin and Nickel) in Nigeria's stock market using asymmetric GARCH models over the period (1960–2024). Estimation results reveal significant volatility clustering and persistence, with the GARCH(1,1) and its asymmetric variants (EGARCH and CGARCH) demonstrating high explanatory power. For Nickel, the CGARCH model exhibited the best performance, as indicated by the highest log-likelihood value (1164.653) and the lowest AIC (-3.001692) and SIC (-2.965560) values, confirming the presence of asymmetric effects. Similarly, for Tin stocks, the EGARCH model performed best, with a log-likelihood of 1274.756, AIC of -3.289523, and SIC of -3.259413. These findings confirm that volatility shocks in both metals exhibit asymmetric effects, where negative shocks generate higher volatility than positive shocks of the same magnitude. These results suggest that investors and policymakers should account for asymmetric volatility in risk management and trading strategies. The study recommends adopting CGARCH and EGARCH models for Nickel and Tin respectively for improved forecasting accuracy and financial decision-making in Nigeria's stock market.

KEYWORDS

Asymmetric Effects, Component GARCH, Exponential GARCH, Tin and Nickel.

1. INTRODUCTION

The period from 1960 to 2024 encompasses significant historical events and economic cycles that have impacted the Nigerian economy and its stock market (Iro and Yahaya, 2025). This timeframe includes periods of political instability, economic reforms, oil booms and busts, and global financial crises, all of which have influenced market dynamics and investor behavior (Awogbemi et al., 2024). Despite the significance of the Nigerian Stock Exchange and the importance of base metals like tin and nickel in the country's economy, there is a paucity of comprehensive studies focusing on the volatility of these stocks. The traditional GARCH models, while useful, may not adequately capture the asymmetric nature of volatility in response to market shocks (Adenomo et al., 2024; Shitu et al., 2025). Positive and negative shocks can have different impacts on volatility, a phenomenon observed in many financial markets but inadequately explored in the context of Nigerian base metal stocks. The lack of understanding of the volatility dynamics of tin and nickel stocks poses several challenges. Investors may face difficulties in making informed decisions, potentially leading to suboptimal investment strategies and increased exposure to risk (Adenomo et al., 2024). Policymakers might struggle to implement effective measures to stabilize the market, while financial analysts may find it challenging to provide accurate forecasts and risk assessments.

A number of studies have highlighted the significance of incorporating asymmetries in modeling financial relationships. For instance, Rahman and Serletis explored a bivariate vector autoregression model with GARCH-in-mean errors, which successfully captured spillovers and asymmetries in the variance-covariance structure between oil prices and macroeconomic dynamics (Rahman and Serletis, 2011). This finding underscores the importance of recognizing the dual impact of volatility on financial markets, particularly in the context of energy price shocks. A group researchers analyzes stock market volatility in Nigeria from January 1985 to December 2014, focusing on persistence and asymmetry while accounting for a structural break identified in December 2008 due to the global financial crisis (Adewale et al., 2016). Utilizing symmetric GARCH and asymmetric EGARCH models, findings reveal that volatility persistence is higher pre-break (sum of ARCH and GARCH coefficients > 1) compared to post-break (sum close to 1). Notably, no evidence of asymmetric volatility or leverage effects was found, indicating that the market reacts symmetrically to good and bad news. The study concludes that the Nigerian stock market exhibits inefficiency and high uncertainty, recommending policy reforms to enhance investor confidence.

The study by investigates stock return volatility in Nigeria using GARCH-family models, specifically assessing six models with different error distributions (normal, student's t, GED) (Ekong and Onye, 2017). The GARCH (1,1) and augmented EGARCH (1,1) in GED demonstrated superior predictive capabilities, evidenced by the lowest RMSE (264.45) and Thiel's Inequality Coefficient (0.6086). Findings reveal significant leverage effects, indicating that negative shocks increase volatility more than positive ones. The incorporation of trading volume enhances model performance, reducing volatility persistence. The research underscores the importance of accurate volatility modeling for risk management and monetary policy interventions in the Nigerian stock market, suggesting a high likelihood of negative returns for investors.

A group researcher estimates the volatility of daily price returns in the Nigerian stock market from April 1, 2016, to December 16, 2022, utilizing ARMA-GARCH and ARMA-EGARCH models with normal, Student's t, and

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skewed Student's t error distributions (Emenyonu et al., 2023). The ARMA (2,1)-EGARCH (1,1) model with Student's t-distribution emerged as the most suitable, demonstrating significant parameters, including a shock persistence coefficient (β1=0.971) indicating long memory in volatility. Forecasting for the next 20 years suggests volatility will rise for the first decade. The model's accuracy was validated using the mean absolute scaled error (MASE), and no serial correlation was detected via Ljung-Box tests, supporting its reliability for policy decision-making.

This study by Kuhe, analyzes volatility persistence and asymmetry in Nigerian stock returns from July 3, 1999, to June 12, 2017, using GARCH family models with structural breaks (Kuhe, 2018). The findings reveal high shock persistence in the stock returns, which significantly decreases when structural breaks are incorporated. The EGARCH (1,1) model with student-t innovations outperforms other models, indicating the presence of asymmetry without leverage effects. The research emphasizes the importance of including structural breaks to avoid overestimating volatility shocks, thereby enhancing investor confidence and aiding in effective financial decision-making. The study recommends using asymmetric GARCH models with structural breaks for accurate volatility measurement in Nigeria's stock market.

A group research investigates volatility in the Nigerian stock market using skewed error distributions, specifically skewed normal, skewed Student-t, and skewed generalized error distributions (Samson et al., 2020). Analyzing daily All Share Index data from 2001 to 2018, the research employs five volatility models: GARCH (1,1), APARCH (1,1), GJR-GARCH (1,1), IGARCH (1,1), and EGARCH (1,1). Results indicate that the APARCH (1,1) model with skewed normal distribution yields the lowest Root Mean Square Error (RMSE) of 0.4813, suggesting it is the most effective for forecasting. The findings highlight significant volatility clustering and persistence, indicating high risk in the market, urging caution among investors and recommending policy adjustments by the Nigerian Stock Exchange to mitigate volatility. This study aims to fill this gap by applying asymmetric GARCH models to analyze the volatility of tin and nickel stocks in Nigeria's stock market from 1960 to 2024. By doing so, it seeks to provide a deeper understanding of the risk characteristics of these stocks and offer valuable insights for investors, policymakers, and financial analysts.

2. Base Metal Stocks

Base metal stocks refer to shares of companies involved in the mining, production, and distribution of base metals. Base metals are common, non-precious metals that are widely used in industrial applications due to their physical properties such as strength, conductivity, and resistance to corrosion (Diversification, 2025). The most commonly traded base metals include tin, nickel, copper, aluminum, lead, and zinc (Diversification, 2025). These metals are fundamental to various industries and serve as critical inputs in the manufacturing, construction, and technology sectors. In the context of this study, the focus is specifically on the stocks prices of tin and nickel. These stocks are listed on the Nigerian Stock Exchange (NSE) and their stock prices reflect the market's valuation of their business operations and the underlying value of the metals.

2.1 Uses of Tin and Nickel

2.1.1 Tin

Soldering: One of the primary uses of tin is in the manufacture of solder, an alloy used to join metal pieces together in electronics, plumbing, and other applications. Tin-lead solder is a common type, but with growing health and environmental concerns, lead-free solders using tin alloys are becoming more prevalent.

Plating and Coating: Tin is used as a protective coating for other metals, such as steel, to prevent corrosion. Tin-plated steel is commonly used in the production of cans for food and beverages, providing a non-toxic, corrosion-resistant surface.

Alloys: Tin is a key component in various alloys, including bronze (copper and tin) and pewter (tin with antimony, copper, and bismuth). These alloys are valued for their strength, durability, and resistance to corrosion.

Chemicals: Tin compounds are used in a range of chemical applications, including stabilizers in PVC plastics, catalysts in the production of polyurethane foam, and as biocides in antifouling paints for ships.

Glass Manufacturing: In the float glass process, molten glass is floated on a bed of molten tin to create flat glass sheets used in windows, mirrors, and other architectural applications.

2.1.2 Nickel

Stainless Steel: The largest use of nickel is in the production of stainless steel, which is valued for its strength, resistance to corrosion, and aesthetic appeal. Nickel enhances these properties, making stainless steel suitable for use in construction, household appliances, medical instruments, and food processing equipment.

Alloys: Nickel is used to produce a variety of alloys with superior mechanical properties, resistance to high temperatures, and corrosion resistance. These alloys are critical in aerospace, marine, and chemical processing industries. Inconel, Monel, and Hastelloy are notable nickel-based superalloys.

Batteries: Nickel is a key component in batteries, particularly nickel-cadmium (NiCd) and nickel-metal hydride (NiMH) batteries. With the rise of electric vehicles and renewable energy storage, nickel's role in battery technology, especially in lithium-ion batteries, is becoming increasingly important.

Plating: Nickel plating provides a protective and decorative coating for other metals, enhancing their appearance and resistance to wear and corrosion. It is commonly used in automotive parts, coins, and consumer electronics.

Catalysts: Nickel is used as a catalyst in various chemical reactions, including hydrogenation processes in the food industry and in petrochemical production.

2.2 Economic Importance of Base Metals

Base metals like tin and nickel are essential to modern industry and infrastructure, driving demand for their production and influencing the financial performance of companies involved in their extraction and processing (Markets.com, 2025). The prices of base metals are often volatile, influenced by factors such as global supply and demand dynamics, geopolitical events, technological advancements, and economic cycles. Investing in base metal stocks offers exposure to these underlying commodities, providing potential for significant returns but also carrying inherent risks due to market volatility (Markets.com, 2025). Understanding the uses and economic significance of tin and nickel helps investors and policymakers make informed decisions related to resource allocation, market regulation, and strategic planning in the context of the Nigerian economy and beyond.

3. Methodology

This study sourced it data from the historical monthly closing prices of tin and nickel stocks from the archives of the Nigerian Stock Exchange and World Bank Commodity Price Data (The Pink Sheet). The dataset includes price observations spanning the entire study period of 1960 to 2024.

3.1 Model Specification

This study employs Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and their asymmetric extensions to model the volatility of Tin and Nickel stocks in Nigeria's stock market. The objective is to capture volatility clustering, persistence, and leverage effects in the return series. This section presents return series specification and the mathematical formulation of GARCH, Exponential GARCH, and Component GARCH models.

3.1.1 Return Series Specification

The log returns of the base metal stock prices are computed as:

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

where:
r_t denote the continuously compounded return at time t,
P_t and P_{t-1} denote the stock prices at time t and t−1, respectively,
ln denote the natural logarithm operator.

The return series is assumed to follow a mean equation of the form:

$$r_t = \mu + \epsilon_t \quad (2)$$

where:

μ denote the constant mean return,
ϵ_t denote the error term, representing unpredictable innovations or shocks in the returns.

To model conditional heteroskedasticity, the variance σ_t^2 is specified using different GARCH-based models. These models specifications are presented as follows

3.1.2 GARCH Model Specification

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model captures volatility clustering by modeling the conditional variance (σ_t^2) as a function of past squared residuals and past variances. The standard GARCH (p, q) model is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (3)$$

where:
$\omega > 0$ is a constant,
α_i denote the ARCH term- measures the short-run persistence of shocks,
β_j denote the GARCH term - measures the long-run persistence of volatility.

3.2 Asymmetric GARCH Models

Since volatility responses may be asymmetric to positive and negative shocks, Asymmetric GARCH models are used to better capture these effects. These asymmetric GARCH models are specify as follows:

3.2.1 Exponential GARCH (EGARCH) Model

The EGARCH model (Nelson, 1991) allows for asymmetric responses to past shocks and is specified as:

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \left(\frac{|\epsilon_{t-i}|}{\sigma_{t-i}} - E\left[\frac{|\epsilon_{t-i}|}{\sigma_{t-i}}\right]\right) + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2)$$
(4)

where:

γ_k captures the asymmetric impact of positive and negative shocks,

A negative γ_k suggests that negative shocks (bad news) increase volatility more than positive shocks (good news).

3.2.2 Threshold GARCH (TGARCH) Model

The **TGARCH** model introduces a threshold term to distinguish the effects of positive and negative shocks on volatility (Zakoian, 1994):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^{q} \gamma_k \epsilon_{t-k}^2 I(\epsilon_{t-k} < 0) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (5)$$

where:

$I(\epsilon_{t-k} < 0)$ denote an indicator function that takes the value of 1 if $\epsilon_{t-k} < 0$ (negative shock) and 0 otherwise.

If $\gamma_k > 0$, negative shocks increase volatility more than positive shocks of the same magnitude.

3.2.3 Power GARCH (PARCH) Model

The **PARCH** model generalizes the GARCH model by allowing for power transformations of the conditional standard deviation (Ding et al., 1993):

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i (|\epsilon_{t-i}| - \gamma_i \epsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \quad (6)$$

where:
δ denote the power transformation of the standard deviation,
γ_i allows for asymmetric effects of shocks.

3.2.4 Component GARCH (CGARCH) Model

The CGARCH model decomposes the conditional variance into a permanent and transitory component (Engle and Lee, 1999):

$$\sigma_t^2 = q_t + \alpha(\epsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \quad (7)$$

where:

q_t represents the long-term volatility component,

The remaining terms model short-run deviations from the long-run component.

3.2.5 Integrated GARCH (IGARCH) Model

The IGARCH model imposes the restriction that the persistence parameter sums to one, implying that shocks to volatility have a permanent effect:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (8)$$

where:

$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j = 1$, ensures that volatility does not decay over time.

3.3 Pre-Diagnostic Tests

Before estimating Asymmetric GARCH models for the volatility of Tin and Nickel stocks, pre-diagnostic tests are essential to assess stationarity, autocorrelation, heteroskedasticity, and normality. These tests ensure the validity of model assumptions. They are as follows:

3.3.1 Stationarity Test: Augmented Dickey-Fuller (ADF) Test

To apply GARCH models, the time series data must be stationary, meaning its statistical properties (mean and variance) do not change over time. The Augmented Dickey-Fuller (ADF) test examines this by estimating the regression:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \epsilon_t \quad (9)$$

where:

Y_t = time series data,
$\Delta Y_t = Y_t - Y_{t-1}$ (first difference),
α = constant,
β = coefficient of time trend,
γ = coefficient of lagged Y_{t-1},
δ_i = parameters for lagged differences,
p = optimal lag length,
ε_t = white noise error term.

Hypotheses:

H_0: γ = 0 (The series has a unit root → Non-stationary)

H_1: γ < 0 (The series is stationary)

If the ADF test statistic is more negative than the critical value, we reject H_0 and conclude stationarity.

3.3.2 Normality Test: Jarque-Bera Test

The Jarque-Bera (JB) test evaluates whether the stock return distribution follows a normal distribution:

$$JB = \frac{n}{6}(s^2 + \frac{(k-3)^2}{4}) \quad (10)$$

where:
S = skewness,
K = kurtosis,
n = number of observations.

Hypotheses:

H_0: Residuals follow a normal distribution
H_1: Residuals do not follow a normal distribution

A significant JB statistic (p < 0.05) suggests non-normality, meaning the model may require Student's t-distribution or Generalized Error Distribution (GED).

3.4 Distributional Assumptions

In modeling the volatility of Tin and Nickel stocks using Asymmetric GARCH models, certain distributional assumptions are necessary to ensure valid statistical inference and accurate forecasts. This section discusses the key distributional assumptions underlying the model.

3.4.1 Normality Assumption

Standard GARCH models assume that the error term (ϵ_t) follows a normal distribution:

$$\varepsilon_t \sim N(0, \sigma_t^2) \quad (11)$$

where:

ε_t = error term,
σ_t^2 = conditional variance.

However, empirical financial data often exhibit fat tails (leptokurtosis), meaning the normality assumption may not always hold.

3.4.2 Fat Tails and Heavy-Tailed Distributions

To address the limitations of normality, alternative heavy-tailed distributions are often used:

3.4.2.1 Student's t-Distribution

$$\varepsilon_t \sim t_v(0, \sigma_t^2) \tag{12}$$

where v represents degrees of freedom. The t-distribution captures excess kurtosis (fat tails), making it more appropriate for financial time series.

3.4.2.2 Generalized Error Distribution (GED)

$$\varepsilon_t \sim GED(\lambda, 0, \sigma_t^2) \tag{13}$$

where λ controls the tail thickness. GED is flexible and can approximate both normal and heavy-tailed distributions.

3.4.3 Stationarity Assumption

For GARCH models to be valid, the time series must be stationary, meaning that its statistical properties (mean and variance) remain constant over time. This requires:

The mean of the stock returns to be constant.

The variance to be finite and positive.

The sum of the ARCH and GARCH coefficients to be less than 1:

$$\sum(\alpha_i + \beta_j) < 1 \tag{14}$$

If non-stationarity is detected, differencing or transformation is applied before modeling.

3.4.4 Independence and No Serial Correlation

For efficient parameter estimation, the error terms should be uncorrelated over time:

$$E(\varepsilon_t \varepsilon_{t-k}) = 0, \forall k \neq 0 \tag{15}$$

This is tested using the Ljung-Box test on residuals. If significant autocorrelation exists, the model may need further adjustments.

3.5 Model Selection Criteria

To determine the best-fitting model, the following model selection criteria will be used:

3.5.1 The Log-Likelihood function

It measures the probability of the observed data given a specific model. A higher LogL value indicates a better-fitting model. For a time series model with normally distributed errors, the log-likelihood function is given by:

$$L = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2}\sum_{t=1}^{n}\frac{\epsilon_t^2}{\sigma^2} \tag{16}$$

where:
L = log-likelihood,
n = number of observations,
σ^2 = variance of residuals,
ϵ_t = residual at time t.

3.5.2 Akaike Information Criterion (AIC)

$$AIC = -2lnL + 2k \tag{17}$$

Where:

L is the likelihood function and k is the number of parameters.
Lower AIC values indicate better model performance.

3.5.3 Schwarz Information Criterion (SIC):

$$SIC = -2lnL + kln(n) \tag{18}$$

Where:

n is the number of observations. Lower SIC values suggest a more parsimonious model.

3.5.4 Ljung-Box Test for Autocorrelation

The Ljung-Box test is used to check for serial correlation in residuals. It tests the null hypothesis that there is no autocorrelation up to a given lag m.

The Ljung-Box test statistic is given by:

$$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k} \tag{19}$$

where:
$Q(m)$ = Ljung-Box test statistic,
n = number of observations,
m = number of lags tested,
$\hat{r}_k$ = sample autocorrelation at lag k.

Under the null hypothesis H_0(no autocorrelation), the test statistic follows a chi-square distribution:

$$Q(m) \sim \chi^2(m) \tag{20}$$

where m is the number of lags. If the p-value is small (e.g., p < 0.05), we reject the null hypothesis, indicating significant autocorrelation.

3.5.5 ARCH-LM Test for Heteroskedasticity

The Autoregressive Conditional Heteroskedasticity- Lagrange Multiplier (ARCH-LM) test examines whether past squared residuals explain current residual variance. It tests for heteroskedasticity in time series data.

3.5.5.1 Step 1: Estimate the Mean Equation

Estimate the return equation:

$$r_t = \mu + \epsilon_t \tag{21}$$

Where:

$\epsilon_t$is the residual.

3.5.5.2 Step 2: Regress Squared Residuals on Lagged Squared Residuals

Estimate the auxiliary regression:

$$\epsilon_t^2 = \alpha_0 + \sum_{i=1}^{m}\alpha_i \epsilon_{t-i}^2 + \upsilon_t \tag{22}$$

where:
ϵ_t^2 is the squared residual,
α_0 is a constant,
α_i are coefficients of lagged squared residuals,
υ_t is the white noise error term,
m is the lag order.

3.5.5.3 Step 3: Compute the ARCH-LM Statistic

The test statistic is based on the R-squared from the auxiliary regression:

$$LM = nR^2$$

where:
n is the number of observations,
R^2 is the coefficient of determination from the regression.

Under the null hypothesis H_0 (no ARCH effects), the test statistic follows a chi-square distribution: $LM \sim \chi 2(m)$

Where: m is the number of lags. A small p-value (e.g., p<0.05) indicates the presence of ARCH effects, meaning volatility clustering exists.

3.6 Forecasting Evaluation

Forecasting evaluation is crucial in determining the accuracy and reliability of the selected Asymmetric GARCH models for predicting the volatility of Tin and Nickel stocks in Nigeria's stock market. This section assesses the model's forecasting performance using standard error measures and diagnostic tests.

3.6.1 Forecasting Accuracy Metrics

To evaluate the accuracy of the forecasts, the following statistical measures are used:

3.6.1.1 Mean Absolute Error (MAE)

MAE measures the average magnitude of the forecasting errors:

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |y_t - \hat{y}_t| \quad (23)$$

where:
y_t = actual value,
$\hat{y}_t$ = forecasted value,
n = number of observations.

A lower **MAE** indicates better forecasting accuracy.

3.6.1.2 Root Mean Squared Error (RMSE)

RMSE is a commonly used metric that gives more weight to large errors:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \quad (24)$$

A lower RMSE suggests a better fit of the forecasted values to actual data.

3.6.1.3 Mean Absolute Percentage Error (MAPE)

MAPE expresses forecast errors as a percentage:

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{y_t} \quad (25)$$

A smaller MAPE value signifies a more accurate model.

3.6.2 Diebold-Mariano Test for Forecast Accuracy Comparison

The Diebold-Mariano (DM) test is used to compare the forecasting accuracy of different models. The test statistic is given by:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}(0)}{T}}} \quad (26)$$

where:
$\bar{d}$ = mean loss differential between two forecasting models,
$\hat{f}(0)$ = spectral density at frequency zero,
T = number of observations.

A significant DM statistic indicates a difference in forecast accuracy between the models.

4. Empirical Result

The descriptive statistics in Table 1 provided an overview of the properties of the stock return. These statistics help in understanding the distribution and volatility nature of the data.

Table 1: Descriptive Statistics for Tin and Nickel Stock Returns

Statistic	RNICKEL	RTIN
Mean	-0.003220	-0.003519
Median	0.000000	-0.001867
Maximum	0.382404	0.251711
Minimum	-0.581122	-0.182757
Std. Dev.	0.070007	0.053552
Skewness	-0.826375	0.468583
Kurtosis	11.48004	6.252485
Jarque-Bera	2401.006	368.5316
Probability	0.000000	0.000000
Sum	-2.485672	-2.716317
Sum Sq. Dev.	3.778648	2.211126
Observations	772	772

Table 1 reveal that both stocks experienced slight average declines, with negative mean returns (-0.003220 for RNICKEL and -0.003519 for RTIN). The median returns indicate a neutral trend for nickel (0.000000) and a slight negative trend for tin (-0.001867). Nickel stocks demonstrate higher volatility, as evidenced by a larger standard deviation (0.070007) compared to tin stocks (0.053552). The range of returns also highlights more extreme fluctuations in nickel stocks, with a maximum return of 0.382404 and a minimum of -0.581122, compared to tin stocks with a maximum return of 0.251711 and a minimum of -0.182757. Both return series show significant skewness and kurtosis, with nickel returns being negatively skewed (-0.826375) and tin returns positively skewed (0.468583), indicating asymmetric return distributions with frequent large negative and positive returns, respectively. The Jarque-Bera test results confirm the non-normality of the returns for both metals, with high test values (2401.006 for RNICKEL and 368.5316 for RTIN) and zero probabilities, indicating significant deviations from normal distribution. This non-normality is further supported by the high kurtosis values (11.48004 for RNICKEL and 6.252485 for RTIN), reflecting the presence of heavy tails and frequent extreme values. Figure 1 and 2 show the time plots and their return series for Nickel and Tin respectively

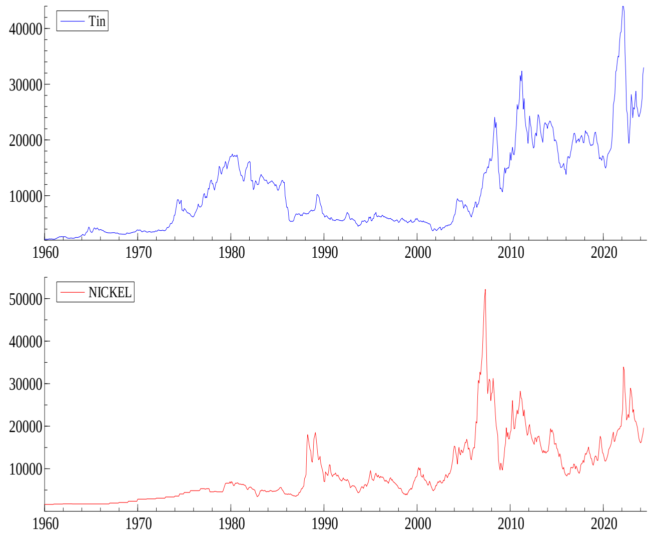

Figure 1: Time Plot of Nickel and Tin Monthly Stock Price from January, 1960 to May, 2024.

Figure 1 depicts the price trend of Tin and Nickel stock from January, 1960 to May, 2024, showing stable low price until significant increase in 2010 with Tin picking at around 40,000 units and Nickel at around 50,000 units, Nickel exhibiting greater volatility.

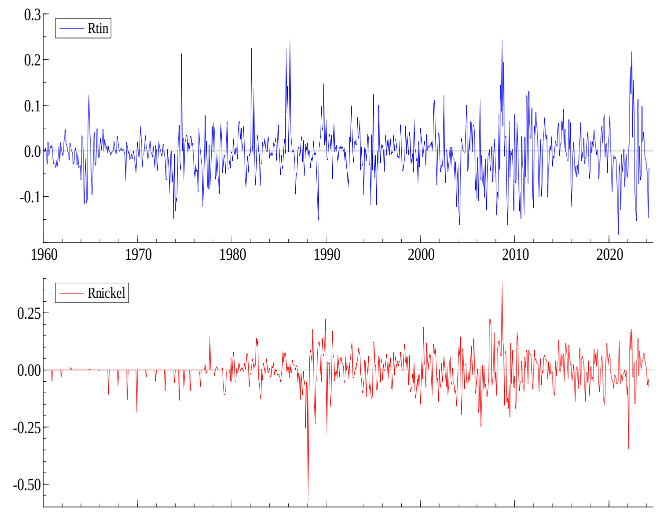

Figure 2: Time plot for the Return Series of Nickel and Tin Stock Prices from January, 1960 to May, 2024

Figure 2 shows the time plot of the return series for Nickel and Tin stock prices from January, 1960 to May, 2024. The plot shows consistent fluctuation for Nickel and Tin experiencing a notable drop in early 1980s followed by increased volatility after 2000s. The presence of ARCH effect is further confirm by the heteroskedastic test in Table 4.

4.1 Bivariate Relationship between the Study Stock

Table 2: Correlation of the study stock		
	Tin	***NICKEL***
Tin		0.6761
		(773)
		0.0000
NICKEL	0.6761	
	(773)	
	0.0000	

Correlation
(Sample Size)
P-Value

Table 2 shows Pearson product moment correlations between each pair of the stock. These correlations coefficients range between -1 and +1 and measure the strength of the linear relationship between the stocks. Also shown in parentheses is the number of pairs of data values used to compute each coefficient. The third number in each location of the table is a P-value which tests the statistical significance of the estimated correlations. In Table 2, a correlation value of 0.676 shows a strong positive correlation between Nickel and Tin stock prices.

4.2 Stationarity Testing: Augmented Dickey-Fuller (ADF) Test Results

Table 3 display the result of the ADF test

Table 3: Augmented Dickey-Fuller Test Results			
Null Hypothesis: D(NICKEL, TIN) has a unit root			
Exogenous: Constant			
Lag Length: 2 (Automatic - based on SIC, maxlag=20)			
		Nickel	Tin
		t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-16.53341	-13.51625
Test critical values:	1% level	-3.438627	-3.438616
	5% level	-2.865083	-2.865078
	10% level	-2.568712	-2.568709
	Prob.*	0.0000	0.0000
*MacKinnon (1996) one-sided p-values.			

Note: Stationarity was achieved at first difference

The ADF test results in Table 3 reveal that the monthly returns of both nickel (RNICKEL) and tin (RTIN) stocks are stationary at their first difference. The test statistics for nickel (-16.53341) and tin (-13.51625) are significantly lower than the critical values at the 1%, 5%, and 10% significance levels, leading to the rejection of the null hypothesis of a unit root. These data imply that the mean and variance of the returns for both nickel and tin stocks are stable over time when differenced once, which is a critical criterion for reliable volatility modeling. This stationarity facilitates the application of time series models like GARCH for evaluating the volatility dynamics of these base metal stocks on the Nigerian Stock Exchange.

4.3 ARCH Effect Test

The ARCH-LM (Lagrange Multiplier) test is used to detect the presence of ARCH effects in the residuals of a time series model. The test is performed on the residuals from an ordinary least squares (OLS) regression of the return series. The test involves the following steps:

Estimate the OLS regression for the return series r_t

$$r_t = \alpha + \varepsilon_t \tag{27}$$

where ε_t are the residuals.

Square the residuals and regress them on their own lagged values up to a certain lag order q:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2 + \mu_t \tag{28}$$

Compute the test statistic: LM = n x R^2

where n is the number of observations and R^2 is the coefficient of determination from the regression of squared residuals.

Compare the test statistic with the critical values from the chi-squared distribution with q degrees of freedom. If the test statistic is greater than the critical value, the null hypothesis of no ARCH effects is rejected.

Table 4: Heteroskedasticity Test: ARCH			
Nickel Stock			
F-statistic	7.402011	Prob. F (1,769)	0.0067
Obs*R-squared	7.350510	Prob. Chi-Square (1)	0.0067
Tin Stock			
F-statistic	13.36698	Prob. F (1,769)	0.0003
Obs*R-squared	13.17277	Prob. Chi-Square (1)	0.0003

The ARCH test results for nickel and tin stock returns in Table 4 suggest strong autoregressive conditional heteroskedasticity (ARCH) effects in both series. For nickel stocks, the F-statistic of 7.402011 and the Obs*R-squared value of 7.350510 both have p-values of 0.0067, which are statistically significant at the 1% level. This clearly implies the presence of time-varying volatility in the returns of nickel stocks, leading to the rejection of the null hypothesis of no ARCH effects.

Similarly, for tin stocks, the F-statistic of 13.36698 and the Obs*R-squared value of 13.17277 both have p-values of 0.0003, similarly significant at the 1% level. This confirms the presence of ARCH effects in the tin stock returns. The finding of these ARCH effects validates the use of GARCH models to capture the time-varying volatility in the return series of both nickel and tin equities on the Nigerian Stock Exchange.

Table 5: Variance Inflation Factor			
	Coefficient	**Uncentered**	**Centered**
Variable	**Variance**	**VIF**	**VIF**
RTIN	0.001997	1.004322	1.000000
RNICKEL	0.000684	1.002118	1.000000

The Variance Inflation Factor (VIF) test results in Table 5 indicate no significant multicollinearity between the variables, RTIN and RNICKEL. The Uncentered VIF values (1.004322 for RTIN and 1.002118 for RNICKEL) are very close to 1, while the Centered VIF values are exactly 1.000000, confirming that these variables are not correlated with each other in the presence of other predictors.

Since VIF values below 5 suggest no multicollinearity concerns, these results imply that RTIN and RNICKEL can be used together in the model without affecting the reliability of the coefficient estimates. This is an important pre-diagnostic check, ensuring that the GARCH model's volatility estimates remain unbiased and stable. Figure 3 provide the test for normality.

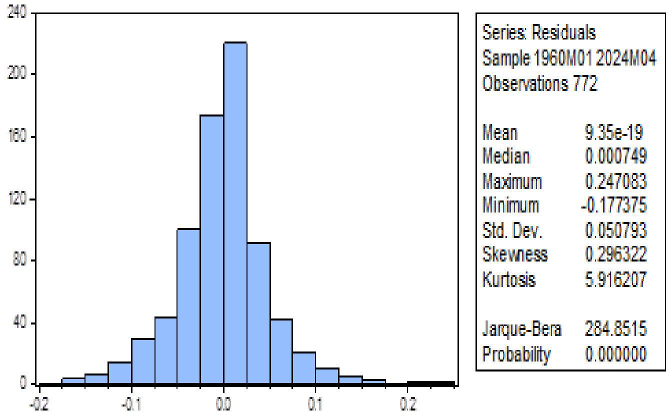

Figure 3: Test for Normality

Figure 3 is a Normality test for residual of the time series. The Jarque-Bera test statistic (284.8515) with a probability of 0.000000 strongly rejects the null hypothesis of normality, confirming that the residuals deviate from a normal distribution. This non-normality suggests that asymmetric GARCH models, which account for heavy tails and skewness, may be more appropriate for modeling this volatility.

4.4 Parameter Estimates

The estimated parameters for the ARCH/GARCH models are reported in the Tables 6 and 7.

Table 6: Parameter Estimates for Nickel Stocks

Parameter	ARCH	GARCH	EGARCH	TGARCH	PARCH	CGARCG	IGARCH
Constant (C)	-0.003128 (0.001564)	-0.002432 (0.001686)	-0.003975 (0.000476)	-0.002713 (0.001811)	-0.002241 (0.000556)	-0.002456 (0.001538)	-0.011934 (0.000171)
Intercept (β_0)	0.002216 (0.000105)	1.99E-05 (2.50E-06)	-0.188867 (0.020594)	1.67E-05 (2.19E-06)	0.018639 (0.006100)	0.014048 (0.002558)	
ARCH term (β_1)	0.988260 (0.067803)	0.068232 (0.004198)	0.092710 (0.009587)	0.034567 (0.007572)	0.008495 (0.005793)	0.999185 (2.47E-05)	0.047909 (0.002301)
GARCH term (α_1)		0.936951 (0.004406)	-0.050946 (0.006078)	0.940397 (0.004528)	1.000000 (2.1E-104)	-0.026993 (0.007218)	0.952091 (0.002301)
Γ			0.976998 (0.002511)	0.053071 (0.008594)	0.970507 (0.002394)	0.164389 (0.018258)	
D					1.0000		
Ø					0.113488 (0.103705)	0.765272 (0.031143)	
P							
$\beta_1 + \alpha_1$		1.005183	0.041764	0.974964	1.008495	0.972192	1.000
μ	-0.003220	-0.003220	-0.003220	-0.003220	-0.003220	-0.003220	-0.003220
Log L	1007.904	1130.282	1153.484	1135.724	1161.455	1164.653	1074.528
AIC	-2.603378	-2.917829	-2.975348	-2.929337	-2.993407	-3.001692	-2.778570
SIC	-2.585312	-2.893741	-2.945238	-2.899227	-2.957275	-2.965560	-2.766526
Observed	772	772	772	772	772	772	772

Note: Numbers in parenthesis indicates standard error

In table 6, the analysis of volatility models for nickel stock returns demonstrates clear differences in their ability to capture persistence, asymmetry, and structural dynamics. The ARCH model shows strong short-term volatility persistence ($\beta_1 = 0.9883$), but its relatively lower log-likelihood (1007.904) and higher AIC (−2.6034) and SIC (−2.5853) indicate a weaker fit. The GARCH model enhances performance by incorporating long-term persistence, with $\beta_1 = 0.0682$ and $\alpha_1 = 0.9369$, resulting in a higher log-likelihood (1130.282) and lower information criteria values (AIC = −2.9178, SIC = −2.8937). Models that capture asymmetry, such as EGARCH and TGARCH, show further improvements. The EGARCH model, with a leverage effect (Γ = 0.9770) and a negative intercept ($\beta_0 = -0.1889$), achieves a strong fit (log-likelihood = 1153.484; AIC = −2.9753), while the TGARCH model captures moderate short-term ($\beta_1 = 0.0346$) and high long-term ($\alpha_1 = 0.9404$) persistence, producing a robust though slightly less efficient fit (log-likelihood = 1135.724; AIC = −2.9293). Advanced models such as PARCH and CGARCH demonstrate superior performance by incorporating more flexible volatility structures. The PARCH model introduces a power parameter (d = 1.0000) that enhances the responsiveness of volatility to return shocks, resulting in a very strong fit (log-likelihood = 1161.455; AIC = −2.9934; SIC = −2.9573). The CGARCH model, which separates short-term and long-term volatility components, provides the best overall performance, with extremely high short-term persistence ($\beta_1 = 0.9992$), moderate long-term mean reversion ($\alpha_1 = -0.0270$), and a long-run equilibrium effect (Ø = 0.1135). Its log-likelihood (1164.653) and the lowest AIC (−3.0017) and SIC (−2.9656) values confirm it as the most efficient model. In contrast, the IGARCH model, despite its sustained volatility ($\beta_1 + \alpha_1 = 1.000$), performs less efficiently (log-likelihood = 1074.528; AIC = −2.7786). the results show that while basic models capture short-term dynamics, the CGARCH model most effectively represents the complex, persistent, and mean-reverting volatility behavior of nickel stock returns. Figure 4 is the conditional volatilities from fitted CGARCH model for Nickel Stock Returns.

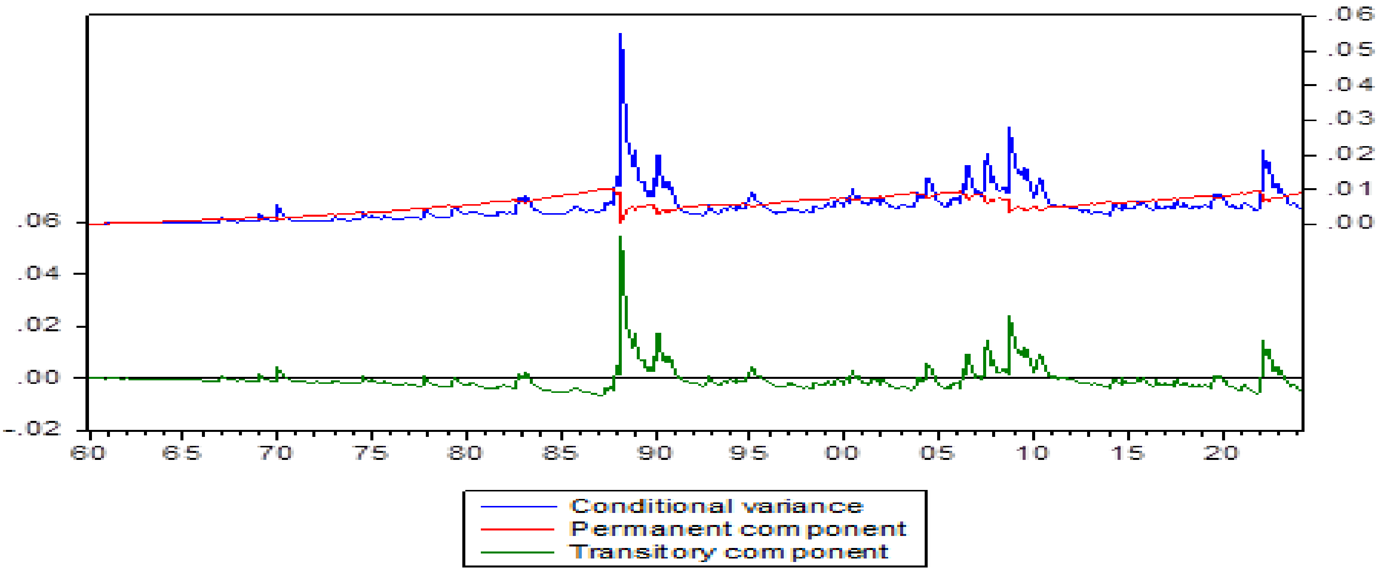

Figure 4: Conditional volatilities from fitted CGARCH model for Nickel Stock Returns

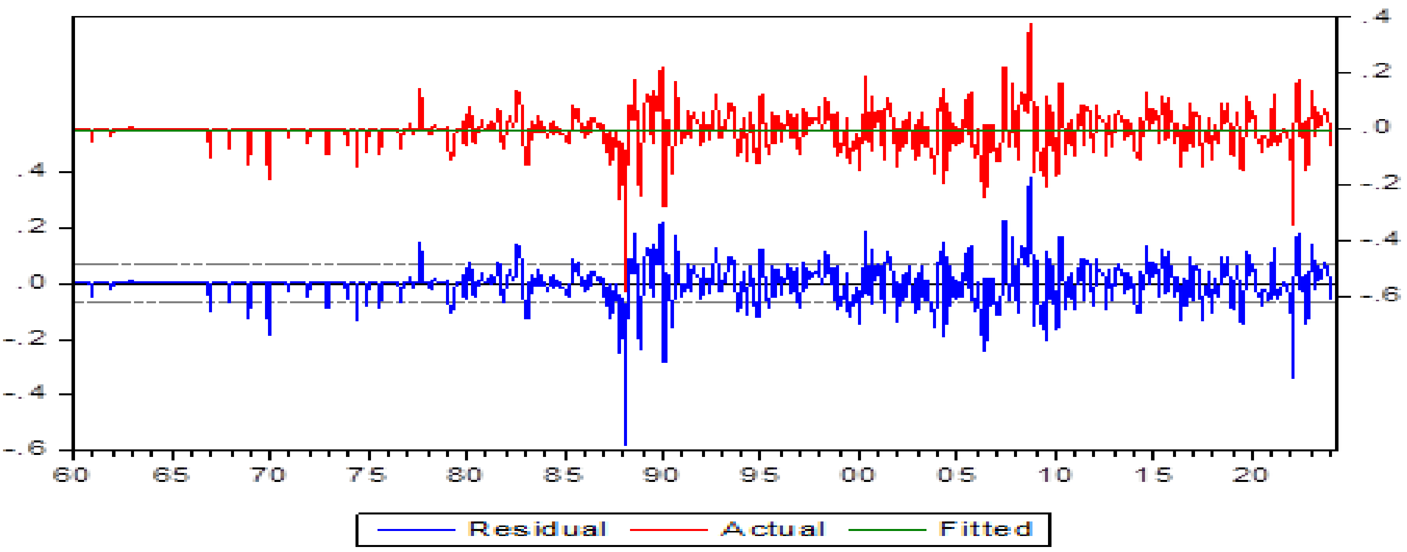

Figure 5: Residual, Actual and Fitted CGARCH Plot for Nickel Stock Return

Table 7: Parameter Estimates for Tin Stocks

Parameter	ARCH	GARCH	EGARCH	TGARCH	PARCH	CGARCH	IGARCH
Constant (C)	-0.001605 (0.001783)	0.000456 (0.001500)	-0.000578 (0.001352)	-0.000479 (0.001494)	-2.72E-10 (0.000941)	0.000306 (0.001462)	-0.002407 (0.000802)
Intercept (β_0)	0.001753 (7.14E-05)	0.000110 (2.06E-05)	-0.740597 (0.095629)	9.94E-05 (1.98E-05)	0.004998 (0.002828)	0.385101 (0.416397)	
ARCH term (β_1)	0.512637 (0.062187)	0.221921 (0.032192)	0.393091 (0.042213)	0.135077 (0.023395)	0.205322 (0.022923)	0.999724 (0.000308)	0.086257 (0.003538)
GARCH term (α_1)		0.772102 (0.024096)	-0.077413 (0.022910)	0.776349 (0.026499)	0.221458 (0.048822)	0.238172 (0.025646)	0.913743 (0.003538)
Γ			0.925353 (0.012334)	0.165241 (0.047961)	0.791508 (0.022860)	0.002653 (0.001782)	
D					1.0000		
Ø					0.829816 (0.176268)	-0.994265 (0.005357)	
P							
$\beta_1 + \alpha_1$		0.994023	0.315678	0.911426	0.42678	1.237896	1.000
μ	-0.003519	-0.003519	-0.003519	-0.003519	-0.003519	-0.003519	-0.003519
Log L	1201.636	1259.840	1274.756	1267.157	1272.226	1263.908	1217.450
AIC	-3.105275	-3.253472	-3.289523	-3.269837	-3.280379	-3.258829	-3.148834
SIC	-3.087209	-3.229384	-3.259413	-3.239727	-3.244247	-3.222697	-3.136790
Observed	772	772	772	772	772	772	772

Note: Numbers in parenthesis indicates standard error

In Table 7, the ARCH model captures only modest short-term volatility persistence (β_1 = 0.5126), indicating limited volatility clustering in tin stock returns. While both the constant (C = −0.0016) and intercept (β_0 = 0.0018) are statistically significant, the model's log-likelihood (1201.636) and higher AIC (−3.1053) and SIC (−3.0872) values suggest a weaker fit. The GARCH model enhances this performance by incorporating both short- and long-term volatility components, with β_1 = 0.2219 and α_1 = 0.7721, demonstrating substantial persistence. Its log-likelihood (1259.840) is notably higher, while AIC (−3.2535) and SIC (−3.2294) values are lower, indicating improved efficiency. Models capturing asymmetry, such as EGARCH and TGARCH, perform even better. The EGARCH model shows strong evidence of asymmetric volatility responses, with a significant leverage effect (Γ = 0.9254), a negative intercept (β_0 = −0.7406), and superior model fit (log-likelihood = 1274.756; AIC = −3.2895; SIC = −3.2594).

The TGARCH model, with Γ = 0.1652, β_1 = 0.1351, and α_1 = 0.7763, also captures long-term persistence but performs slightly below EGARCH (log-likelihood = 1267.157). PARCH, CGARCH, and IGARCH provide additional insights into volatility structure. The PARCH model, incorporating a power term (d = 1.0000), achieves a strong fit with log-likelihood = 1272.226, AIC = −3.2804, and SIC = −3.2442, suggesting a robust specification with moderate persistence (β_1 = 0.2053; α_1 = 0.2215). The CGARCH model captures both short- and long-term components, showing near-perfect short-term persistence (β_1 = 0.9997) and long-run effects (α_1 = 0.2382; Ø = 0.8298), but delivers a slightly lower fit (log-likelihood = 1263.908; AIC = −3.2588). The IGARCH model, constrained by $\beta_1 + \alpha_1$ = 1.000, indicates sustained volatility (β_1 = 0.0863; α_1 = 0.9137) but exhibits lower performance (log-likelihood = 1217.450; AIC = −3.1488). The EGARCH model provides the best fit for tin stock volatility, as it effectively captures the asymmetric and leverage effects present in financial market dynamics. Figure 6 shows the conditional volatilities from fitted EGARCH model for Tin Stock Returns

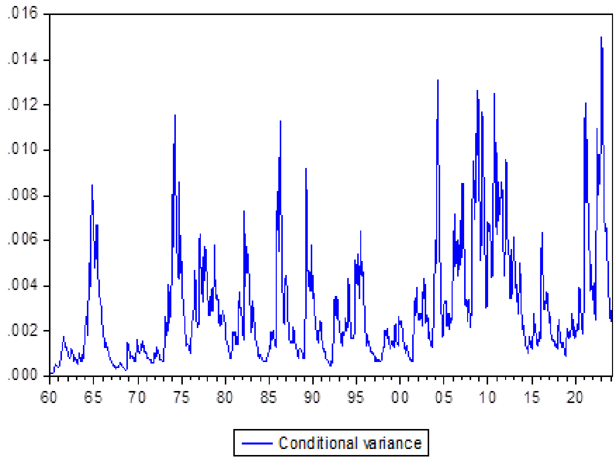

Figure 6: Conditional volatilities from fitted EGARCH model for Tin Stock Returns

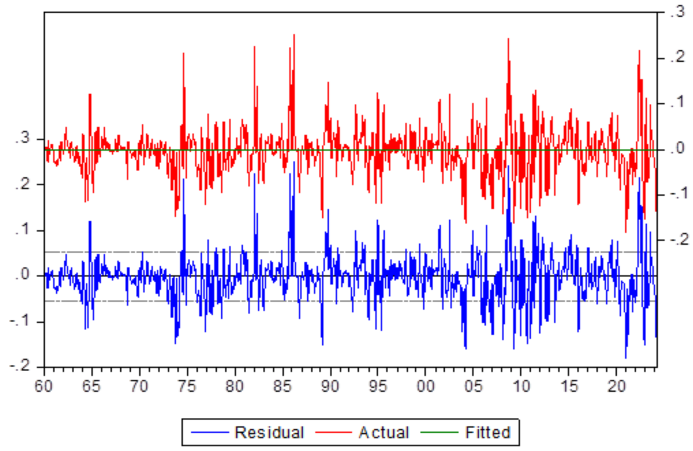

Figure 7: Residual, Actual and Fitted EGARCH Plot for Tin Stock Returns

4.5 Diagnostic Testing

Diagnostic tests are undertaken to evaluate the appropriateness of the fitted models.

Table 8: Ljung-Box Test for Autocorrelation for Nickel

Lag	AC	PAC	Q-Stat	Prob*
1	-0.026	-0.026	0.5373	0.464
2	-0.019	-0.020	0.8178	0.664
3	0.022	0.021	1.1796	0.758
4	-0.026	-0.025	1.7008	0.791
5	-0.042	-0.043	3.0796	0.688
6	-0.014	-0.017	3.2229	0.780
7	-0.018	-0.020	3.4837	0.837
8	-0.025	-0.026	3.9922	0.858
9	-0.016	-0.020	4.1874	0.899
10	-0.003	-0.007	4.1941	0.938
11	-0.036	-0.038	5.2025	0.921

The results from Table 8, which tests for autocorrelation in the Nickel stock return residuals, show that both the autocorrelation (AC) and partial autocorrelation (PAC) coefficients are small and close to zero across all lags from 1 to 11. These values range from -0.042 to 0.022, indicating weak to negligible autocorrelation. For instance, the AC and PAC at lag 1 are both -0.026, and at lag 5, they are -0.042 and -0.043, respectively. This pattern suggests that the residuals do not display significant serial correlation, meaning the residuals are fairly independent over time. The Ljung-Box Q-statistics and their associated p-values support this conclusion. The Q-statistics incrementally increase from 0.5373 at lag 1 to 5.2025 at lag 11, but the corresponding p-values remain high, all exceeding common significance thresholds (0.05, 0.10). The evidence suggests that the model used to estimate the Nickel stock returns has effectively captured the time-series dynamics, resulting in residuals that do not exhibit significant autocorrelation.

Table 9: Ljung-Box Test for Autocorrelation for Tin

Lag	AC	PAC	Q-Stat	Prob*
1	0.007	0.007	0.0419	0.838
2	0.007	0.007	0.0839	0.959
3	-0.000	-0.000	0.0840	0.994
4	-0.021	-0.021	0.4316	0.980
5	0.065	0.066	3.7516	0.586
6	-0.037	-0.038	4.8177	0.567
7	0.031	0.030	5.5451	0.594
8	-0.003	-0.003	5.5515	0.697
9	-0.032	-0.030	6.3653	0.703
10	0.025	0.020	6.8400	0.740
11	-0.016	-0.010	7.0307	0.797
12	0.009	0.004	7.0953	0.851

The Ljung-Box test results for the Tin stock return residuals, presented in Table 9, show that both the autocorrelation (AC) and partial autocorrelation (PAC) coefficients are generally very small, ranging from -0.037 to 0.065. Most values hover around zero, indicating minimal to no significant autocorrelation across the 12 lags tested. For instance, at lag 1, the AC and PAC are both 0.007, suggesting negligible autocorrelation, and even the highest AC value at lag 5 (0.065) indicates only minor potential autocorrelation. This pattern suggests that the residuals do not exhibit significant serial correlation. The Ljung-Box Q-statistics and associated p-values support the conclusion of no significant autocorrelation. This indicates that the model is appropriate for explaining the behavior of Tin stock returns without autocorrelation issues.

Table 10: ARCH-LM Test for Heteroskedasticity

Heteroskedasticity Test: ARCH			
(Nickel)			
F-statistic	0.533546	Prob. F(1,769)	0.4653
Obs*R-squared	0.534562	Prob. Chi-Square(1)	0.4647
Tin			
F-statistic	0.041576	Prob. F(1,769)	0.8385
Obs*R-squared	0.041681	Prob. Chi-Square(1)	0.8382

The ARCH-LM test results for both Nickel and Tin stock returns, as shown in Table 4.10, indicate no significant evidence of heteroskedasticity in the residuals. For Nickel, the F-statistic is 0.533546 with a corresponding p-value of 0.4653, and the Obs*R-squared value is 0.534562 with a p-value of 0.4647. These p-values are well above the common significance levels, suggesting that we fail to reject the null hypothesis of no heteroskedasticity. This implies that the residuals from the Nickel stock return model have constant variance over time, indicating that the model does not suffer from issues related to changing variability.

The results for Tin stock returns show an F-statistic of 0.041576 with a p-value of 0.8385, and an Obs*R-squared value of 0.041681 with a p-value of 0.8382. These high p-values also indicate that we fail to reject the null hypothesis of no heteroskedasticity for the Tin stock returns. Consequently, the residuals for the Tin stock return model are likely to have constant variance over time, suggesting that the model is well-specified and does not experience issues related to changing variability. Both models appear robust in capturing the variance dynamics of their respective stock returns.

5. Conclusion

The application of Asymmetric GARCH models provided valuable insights into the volatility behavior of Tin and Nickel stocks in Nigeria's stock market. The results demonstrated that asymmetric models, such as EGARCH, CGARCH and TARCH, are effective in capturing the differential impact of market shocks on volatility. The higher sensitivity of volatility to negative shocks suggests that market participants react more strongly to bad news than to good news, which is consistent with behavioral finance theories. This study contributes to the literature by providing empirical evidence on the volatility patterns of base metal stocks in an emerging market context. The findings have significant implications for investors and policymakers. Investors can use these insights to develop more effective risk management strategies, while policymakers can implement measures to enhance market stability and protect against extreme volatility.

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