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RESEARCH ARTICLE

MODELING THE VOLATILITY FOR SOME SELECTED BEVERAGES STOCK RETURNS IN NIGERIA (2012-2021): A GARCH MODEL APPROACH

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ABSTRACT

The volatility of equity returns for two beverages traded on the Nigerian stock exchange is the subject of this study. The ARCH effect test demonstrated that the two beverages disprove the claim that there is no ARCH effect. According to the preliminary analysis, both beverages were volatile. CGARCH and EGARCH were chosen as the best volatility models for Guinness Nigeria Plc returns and Nigeria Breweries returns, respectively, based on model selection criteria. The EGARCH model, on the other hand, rejected the idea that Guinness Nigeria Plc's equity returns respond equally to negative and positive shocks of similar magnitude. This study's findings suggest that the government should be cautious about how it manages inflation and foreign direct investment because they affect the rising stock price. Financial stability will likely be a more direct and explicit part of the macroeconomic responsibilities of central banks in the coming years.

KEYWORDS

ARCH, Beverages, GARCH, Nigeria Stock, Nigeria Breweries, Volatility

1. INTRODUCTION

The dispersion of price changes or the variance in an asset's price are both associated with volatility. The variation in the cost of an investment in a period of time is measured by the stock market's volatility. If a stock is classified as volatile, it is possible that its mean will disperse consistently over time. On the other hand, a stock that trades less frequently will have a price that fluctuates relatively little over time. When a series' value changes rapidly and unpredictably from one period to the next, there is volatility (Greene, 2008; Adams et al., 2020; Adams and Bello, 2022; Engle, 2003). Economic managers place a significant amount of importance on the stipulation in a current variation used in capturing the right volatility equation. Additionally, investors use this information to make decisions about risk management and adjust their portfolios. According to Engle, a reliable volatility model is one that adequately accounts for clustering volatility, the (ARCH) asymmetry and impact in stock return series in addition to adequately modeling heteroscedasticity in the disturbance term (Engle, 1982).

According to some study, these models have shown that it is beneficial for discovering well-known characteristics of economic and financial time series, such as fat tails, large kurtosis, the leverage effect, and volatility clustering (Adams and Balogun, 2020). Several studies have used the following volatility models. Threshold GARCH, Exponential GARCH, Power GARCH, and generalized ARCH are all extensions of autoregressive conditional heteroscedasticity (ARCH). GARCH models allow the unconditional variance to remain constant while the conditional variance changes over time as a function of previous errors, in contrast to conventional econometric models, which estimate using the assumption of homogeneity of variance.

A group researchers utilized stock exchange in Nigerian returns to investigate the volatility of the emerging stock market (Ogum et al., 2005). They applied the EGARCH model to the series, and their analysis revealed that the Nigerian stock market experienced asymmetric volatility. Engle demonstrated how long-term volatility, option valuation, and risk can be predicted using dynamic volatility models (Engle, 2003). According to David there are two types of equation utilized in defining the attributes returns in market stocks: the quick learning equation and the lagging model utilized for learning (David, 1997). David discovered that when computing the discordance in volatility and returns using the exponential GARCH model, the quick knowledge model produces a non-positive association, whereas the lag equation produces stock with higher kurtosis (David, 1997). Terasvirta finds that GARCH models tend to overstate volatility persistence in a number of univariate models of conditional heteroscedasticity (Terasvirta, 2009).

In addition, Olowe investigated the relationship between stock market volatility and returns using the EGARCH-(M) equation, which relies on banking and indemnity reforms, the stock market crash, and the global financial crisis (Olowe, 2009). The results showed that insurance reforms and the financial crisis have no effect on stock returns, that there is some evidence of a connection between stock returns and volatility, and that the effects of banking reforms and the market crash are negative. When they account for these sudden changes in volatility in five Gulf area stock markets, a group researchers claim that the GARCH (1, 1) models significantly reduce the estimated persistence of the volatility of the Gulf stock markets (Hammoudeh and Li, 2008). Emenike fitted the GJR-GARCH (1,1) and GARCH (1,1) equation to the monthly NSE All-share index in order to investigate volatility persistence, leverage effects, and returns asymmetries (Emenike, 2010).

The results of the study showed that the returns process is characterized by fat-tail, leverage effects, and volatility persistence. In order to investigate how stock return volatility is affected by stock market liberalization, Jayasuriya estimates an asymmetric GARCH model using

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data from fourteen other emerging markets, including Nigeria (Jayasuriya, 2002). According to the study, positive (negative) price changes have been followed by negative (positive) price changes. Using the daily market capitalization index of the Nigerian stock exchange, Suleiman evaluated the robustness of the volatility of stock market returns as well as its effect on the performance of the capital market (Suleiman, 2011). ARCH and GARCH models were utilized in the study to estimate the variance of conditional returns. Due to the persistence of long-term volatility and the presence of volatility in the conditional variance, the study's findings indicated that the Nigerian stock market is inefficient.

Ade and Dallah utilize 26 insurance agency everyday gets back from 15th of December, 2000 to 9th June, 2008 as the assessment informational collection and June 10, 2008 to 9th September, 2008 as the out-of-test information to examine the unpredictability of Nigerian protection stocks' day to day stock returns (Ade and Dallah, 2010). EGARCH is better suited for modeling stock price returns because it outperforms the other models in model estimation evaluation and out-of-sample volatility forecasting. The outcomes of ARCH (1), GARCH (1), TARCH (1), and EGARCH (1) demonstrate this. To examine the volatility of exchange rates using GARCH models, Bala and Asemota use monthly exchange-rate return series for Naira/US dollar, Naira/British Pounds, and Naira/Euro returns from January 1985 to August 2011 (Bala and Asemota, 2013). The study contrasts GARCH variance models with and without volatility breaks for the US dollar. The outcome examined the three currencies' volatility. With regard to the US dollar, the study compares GARCH variance models with and without volatility breaks.

The equities of two (2) beverage returns that are listed on the NSE are the subjects of this research, which both models and empirically tests the presence of volatility clustering. The utilization of an inappropriate error distribution in a volatility model for financial time series could result in model misspecification due to the leptokurtic and autoregressive characteristics of such series, so the study will take into account the contribution of error assumptions in the arrangement to make sure the result is robustness. A robust volatility forecasting model with the most appropriate error distribution that could be used for policy decision-making was developed, the most volatile beverage in Nigeria was identified, and the goal was achieved.

2. Overview of The Nigerian Stock Market

The stock of equity market, is a trading centre where shares are traded over-the-counter or through exchanges. In their opinion, significant events ought to be included in GARCH models when estimating key asset price volatility. A place or organization where people and businesses can trade stocks. Additionally, it is the location where stock buyers and sellers meet. Securities can be traded on the equity market as either privately stocked trade (those marketed by dealers) or publicly traded stocks (those listed on the stock exchange). Following the enactment of the Government and other Securities (Local Trustees Powers) Act in 1957 and the formation of the Barback Committee to investigate the means of fostering a stock market in Nigeria, the Lagos Stock Exchange was established on September 15, 1960.

However, it began trading on June 5, 1961. Further developments in the Nigerian economy and financial system resulted in the renaming of the Lagos Stock Trade to the Nigerian Stock Trade (NSE) in order to establish exchanging floors in various parts of the country, the establishment of the second-level protections market, the establishment of the Protections and Trade Commission as the highest administrative body, the beginning of a web framework to provide the infrastructure necessary for internationalization, and the presentation of a mechanized clearing and repayment framework (It was established to provide electronic clearing, settlement, and delivery (CSD) services in addition to listing and trading services. Equity stocks, preference shares, Federal Government Development Loan Stocks, State Government Bonds, Commercial and Industrial stock loan, and other instruments are among the offerings on the exchange.

In Nigeria, the stock trade contributes to the long-term financing of government development projects, provides funding for private sector long-term investments, and sparked the 2004 and 2005 banking system consolidation. The capitalization of market, indicates that the sum of trade value of every securities is increasing over time. As of March 31, 2015, the first quarter's market capitalization was N16.25 trillion, while the second quarter's was N17.02 trillion as of June 30, 2015.It was N17.01 trillion as of September 30, 2015, and it was N17.00 trillion as of December 31, 2015, for the fourth quarter of 2015.According to the NSE Fact Sheet 2016, it decreased from N15.88 trillion on March 31, 2016, to N17.28 trillion on June 30, 2016, in the second quarter of 2016.Despite this increase, Nigeria's listed domestic companies' market capitalization to GDP (percent of GDP), a means of the influence of trade stock actions on economic growth, has not remained stable, ranging from 13.70 in 2010 to 9.48 in 2011, 12.19 in 2012, 15.65 in 2013, 11.16 in 2014, and 10.4 in 2015.In 2007, it reached its 21st-highest value of 51.00, while in 2002, it reached its 21st-lowest value of 4.02. As of March 31, 2015, the first quarter's equity market capitalization was N10.73 trillion, while the second quarter's was N11.43 trillion as of June 30, 2015.

As of September 30, 2015, it was N10.74 trillion, and as of December 31, 2015, it was N9.86 trillion in the fourth quarter of 2015.According to the NSE Fact Sheet 2016, it increased in the second quarter of 2016 as of June 30, 2016 after continuing to decrease in the first quarter of 2016 to N8.71 trillion (as of March 31, 2016). In 2010, the stock traded turnover ratio of domestic shares (percentage of GDP), which divides the average market capitalization by the total value of shares traded over a given time, was 10.1. However, it fell to 9.9 in 2011 and 8.2 in 2014 and 2015, respectively. The year 2008 saw its highest value of 384.8, while 2014 and 2015 saw its lowest values of 8.2 each (World Bank, 2016). The number of equity listings on the Nigerian stock market has not grown significantly. From an unassuming number of 252 protections in the principal quarter of 2015 and 257 protections in the second quarter of 2015, it decreased to 255 protections in the second from last quarter of 2015 and afterward increment back to 257 protections in the final quarter of 2015.In the first quarter of 2016, this number decreased to 251 securities, and in the second quarter of 2016, it increased to 261 securities.in the year 2005 (NSE Fact Sheet 2016,Tragically, be that as it may, the majority of these protections are not effectively exchanged. On a daily basis, less than fifty percent are traded on average.

According to studies, the Nigerian stock market has not grown rapidly due to an unstable macroeconomic environment, inadequate regulation and supervision, a limited selection of securities, an inactive bond market, and dwindling investor confidence (Osaze, 2000). This is the case despite the increase in market capitalization and listed securities. Since the drop in oil prices that began in the middle of 2014 and continued into 2016, it cannot be overstated how this has affected the Nigerian stock market. The price of oil has a positive effect on the performance of the Nigerian stock market, so it would hurt the market when things are going badly. However, it has been discovered that devaluing the naira is a good way to cushion the stock market's impact of falling crude oil prices (Abraham, 2016). According to Peterside, the stock market is used as a barometer to gauge the impact of the declining oil price on the economy (Peterside, 2012).

Oil prices have an impact on Nigeria's stock markets. A rise in world oil prices improves the trade balance in a country like Nigeria that exports oil, resulting in a larger current account surplus and improved net foreign asset position. Additionally, it tends to raise private disposable income throughout the nation. According to Basher and Sadorsky, domestic demand and stock prices rise as a result of this rise in corporate profitability (Basher and Sadorsky, 2006). According to some study, the establishment of links between the oil price, exchange rate, and stock markets is crucial for a number of reasons because economies are intertwined by increasing globalization of markets (Adebiyi et al., 2009; Zubair et al., 2022). One of the main reasons is that this information could help the government avoid an economic crisis brought on by changes in the exchange rate and crude oil price.

The particular of suitable unpredictability model for catching varieties in Stock returns is of huge strategy significance to monetary directors, and furthermore helps financial backers in their gamble the executive's choice and portfolio change. Engle, opined that a moderate model of volatility is one that adequately accounts for clustering in volatility, (ARCH) asymmetry and influence in stock return series in addition to adequately modeling heteroscedasticity in the disturbance term (Engle, 1982). Larger-tails, large kurtosis, the leverage effect, and volatility clustering are all well-known characteristics of financial or economic time series that have been captured by these models. The majority of studies used the following volatility models: Threshold GARCH, Exponential GARCH, Power GARCH, and generalized ARCH are all extensions of (ARCH). GARCH equation allow the unconditional variance to remain constant while the conditional variance changes over a period of time a function of previous errors, in contrast to conventional econometric models, which estimate using the assumption of homogeneity of variance.

3. Methodology

From November 4, 2012 to November 1, 2021, daily secondary data were used in this study. Companies that make beverages include: Nigeria Breweries and Guinness Nigeria Plc. OxMetrics Software was used for data analysis.

3.1 Unit Root Tests

The order of the variables' integration is determined prior to modeling the equity return series. The stock returns must pass the unit root test because stationarity of the series is required for any meaningful econometrics time series modeling. The crucial test statistics that are used to evaluate the econometric results become unreliable if the series are not stationary. The order of integration of the six banks equity return series is examined using the following unit root tests.

Augmented Dickey-Fuller (ADF) Test: The ADF unit root test is applied to determine if the daily stock index returns y_t is stationary based on the following regression:

$$\Delta y_t = \varphi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \mu_t \quad (1)$$

Where; $\mu_t$is a white noise error term and Δy_{t-1}=$y_{t-1} - y_{t-2}$, Δy_{t-2}= $y_{t-2} - y_{t-3}$ etc. equation 1 test the hypothesis of a unit root against a trend stationary alternative.

The Philips-Perron (PP) Test: It uses model similar to the Dickey-Fuller test but with Newey-West non-parametric correction for possible autocorrelation rather than the lagged variable method employed in the ADF test. The Philips-Perron equation modifies the Dickey-fuller test (Philips and Perron, 1988). The Philips-Perron test is computed from the equation below:

$$y_t = \delta_t + \gamma y_{t-1} + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + \mu_t \quad (2)$$

Where; δ_t may be 0, φ or φ + β_t

Having determined the asymptotic distributions of the test statistic, the null hypothesis is rejected if the estimated value of the ADF and the PP test statistic are less than the critical values.

3.2 Models for Volatility

Over the past decade or so, academics and practitioners alike have conducted extensive empirical and theoretical research into modeling and forecasting stock market volatility. One could argue that volatility is one of the most significant ideas in all of finance. The standard deviation of returns, or volatility, is frequently used as a crude measure of financial assets' total risk. The estimation or forecast of a volatility parameter is required by many market risk measurement value-at-risk models. ARCH/GARCH models are suitable for capturing the six banks equity return series' stylized volatility features. Two types of conditional heteroscedastic models exist. The first group uses exact functions to control the evolution of σ_t^2, while the second group describes $\sigma_t^2$with stochastic equations. The first category includes GARCH models, while the second category includes stochastic volatility models.

3.2.1 Specifications for the Model

3.2.1.1 The Autoregressive Conditional Heteroskedasticity (ARCH) Family of Models

Every model in the ARCH or GARCH family needs two distinct specifications: the equations for mean and variance. The ARCH model can be used to model the conditional mean equation, which describes how the dependent variable, y_t changes over time. The model expresses the mean equation in the following manner:

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} \beta_4 x_{4t} + \mu_t \quad \mu_t \sim N(0, \sigma_t^2) \quad (3a)$$
$$\sigma_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 \quad (3b)$$

Where; μ_t is the error from the mean equation at time t. This equation also applies to other GARCH family models. According to equation (3b), the ARCH model models the "autocorrelation in volatility" by allowing the conditional variance of the error term, σ_t^2, to depend on the value of the squared error that came before it. Because the conditional variance is only dependent on a single lagged squared error, the model above is called an ARCH (1).

The ARCH (q) model was first proposed (Engle, 1982). In this model, the conditional variance _t2 is a linear function of the lagged squared residuals μ_t.The following is the formula for an ARCH model of order q's variance equation:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \mu_{t-i}^2 \quad (4)$$

Where β_0> 0; $\beta_i \geq$ 0; $\forall i$ = 1,…,q

The ARCH (q) model in equ. (4) allows for a time-varying variation in conditional variance in relation to previous errors. The unconditional distribution of _t in ARCH models is always leptokurtic. The required lag q often turned out to be quite large in applications of the ARCH (q) model. The generalized ARCH (p, q) model (GARCH (p, q)) was developed by Bollerslev (1986) with the intention of achieving a parameterization that is more constrained.

3.2.1.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Models

According to empirical evidence, a high ARCH order is required to capture the conditional variance dynamics. The Generalized ARCH (GARCH) model was proposed by Bollerslev as a solution to the issue of high ARCH orders (Bollerslev, 1986). The number of estimated parameters is reduced from an infinite number to a small number by the GARCH. According to Bollerslev, a straightforward GARCH model performs marginally better than an ARCH model with a long lag (Bollerslev, 1986). The conditional variance, or volatility, of a variable can be modeled using a variety of GARCH specifications.

For the GARCH (p, q) model, the conditional variance is expressed as:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \mu_{t-i}^2 + \sum_{j=1}^{p} \alpha_j \sigma_{t-i}^2 \quad (5)$$

Where; The conditional variance is denoted byσ_t^2, the disturbance term byμ_t^2, the constant term by β_0, and the order of the ARCH and GARCH terms by q and p, respectively. β_0> 0; $\beta_i \geq$ 0; i = 1,…,q; j = 1,...,p

The lag of the squared residual from the mean equation is the ARCH term.

It will reveal whether volatility responds to changes in the market, or whether volatility from a previous period influences volatility in the current period. The forecasted variance from the previous period is the GARCH parameter. If volatility shocks persist, we will be able to determine this by adding the ARCH and GARCH terms. The shocks would gradually fade away if the sum was less than unity; otherwise, they would disappear quickly. GARCH is the first-order representation of GARCH (p, q).By regressing squared residual series on its lag(s), the GARCH (1, 1) is a generalization of the ARCH (q) model proposed by Engle (1982) to explain why large residuals tend to cluster together. To capture all of the data's volatility clustering, the lag order (1, 1) suffices. Bollerslev first derived the standard GARCH (1, 1) model by substituting an ARMA (p, q) representation for the AR (P) representation (Bollerslev, 1986):

$$yy_t = \mu + y_{t-1}' \gamma + \mu_t \qquad \mu_t \sim N(0, \sigma_t^2) \quad (6a)$$
$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \alpha \sigma_{t-1}^2 \quad (6b)$$

The average model in (6a) has an error term that is a function of explanatory variables. The conditional variance equation is σ_t^2because it is a one-period ahead forecast variance based on information from the past. The GARCH term (σ_{t-1}^2), which is the forecasted variance from the previous period, the ARCH term (σ_{t-2}^2), which is information about the volatility that was observed in the previous period, and the mean (μ_t), which is a log-term weighted mean, are the three terms that are used to describe this in (6b).The three parameters (β_0, β_1 and α) are not negative, the persistence σ_t^2denoted by β_1+ α, and covariance stationarity requires that $\beta_1 + \alpha < 1$. When estimating GARCH models, maximum likelihood estimation (MLE) is typically used. The maximum likelihood (MLE) method, according to Engle, assists in selecting parameters that maximize the likelihood of a particular outcome occurring (Engle, 1982). The standard notation for a GARCH (1, 1) model is "1,1," where the first number denotes the equation's number of autoregressive lags, or ARCH terms, and the second number denotes the specified number of moving average lags, or GARCH terms.

Time-varying asymmetry is a major component of volatility dynamics, according to some study, despite the fact that the straightforward GARCH (1, 1) model captures volatility's symmetric behavior (Ajayi et al., 2019; Hsieh, 1991). The ARCH parameter can also be thought of as a "news/announcement" coefficient, and the GARCH parameter can be thought of as the persistence coefficient, assuming that markets are efficient. In addition, a rise or fall in the ARCH parameter suggests that news is incorporated into prices more rapidly (slowly). A decrease suggests that old news has less of an impact on price changes over time. Additionally, a rise indicates greater perseverance. Additionally, the volatility shocks are persistent when the sum of the ARCH and GARCH terms approaches unity.

3.2.1.3 The Unconditional Variance Under A GARCH Specification

The conditional variance fluctuates, but the unconditional variance of _t remains constant and can be expressed as:

$$\text{Var}(\mu_t) = \frac{\beta_0}{1-\beta_1+\alpha} \quad (7)$$

as long as $\beta_1 + \alpha$<1. For $\beta_1 + \alpha$≥1.This would be referred to as "non-stationarity in variance" if the unconditional variance of $\beta_1 + \alpha$ = 1 is not defined for $\beta_1 + \alpha$ = 1. A "unit root in variance" would be defined as$\beta_1 + \alpha$ = 1.As long as $\beta_1 + \alpha$ =1, $\mu_t$is the unconditional variance, which measures the volatility over time, according to equation (7).We can get the unconditional variance if $\mu_t$is squared.The bank with the highest level of equity volatility would be determined as a result.

3.2.1.4 Extensions to the Basic GARCH Model

Since the GARCH model was proposed due to perceived issues with conventional GARCH (p, q) models, numerous GARCH model extensions have been proposed. The estimated model may first violate the non-negativity conditions. This could only be avoided by forcing the model coefficients to be non-negative by imposing artificial constraints on them. Positive conditional variances are guaranteed by this. Second, GARCH models can account for volatility clustering and leptokurtosis in a series, but they cannot account for leverage effects. Specifically, GARCH models assume that the magnitude of the innovation alone, rather than its sign, determines how news affects conditional variance. Some modifications to the initial GARCH model were suggested as a means of getting around these limitations .Models from the asymmetric GARCH family, such as: Zakoian proposed Threshold GARCH (TGARCH), Nelson proposed Exponential GARCH (EGARCH), and Ding et al. proposed Power GARCH (PGARCH) in 1994; 1993; Zakoian, 1994).These models are based on the idea that the conditional variance is affected differently by good news (positive shocks) and bad news (negative shocks) of the same magnitude.

3.2.1.5 The Threshold GARCH (TGARCH) Model

Asymmetry and leverage (the fact that volatility is negatively correlated with changes in stock returns) are not taken into account by either the ARCH or GARCH models. Despite the fact that GARCH (p, q) models provide adequate fits for the majority of equity-return dynamics, these models frequently fail to accurately model the volatility of stock returns due to their assumption of a symmetric response between returns and volatility. As a result, the leverage effect of stock returns cannot be taken into account by GARCH models. When it comes to stocks, it is frequently observed that when the market experiences a decline of the same magnitude, volatility is higher than when it experiences a rise of the same magnitude. The threshold GARCH (TGARCH) model was developed by Zakoian to take into account the existing leverage effect (Zakoian, 1994).

The TGARCH model was defined by Zakoian by permitting the conditional standard deviation to depend on a single lag in innovation (Zakoian, 1994). Parameter restrictions that guarantee the conditional variance to be positive are not shown in the specification. However, the TGARCH model's parameters must be restricted, and the error distribution chosen to account for stationarity in order to guarantee stationarity. The GJR-GARCH model is another name for the threshold GARCH model. A straightforward addition to the GARCH model, the GJR model adds a term to account for potential asymmetries.

Using TGARCH (p, q), the following is the generalized specification for the conditional variance:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \mu_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \mu_{t-i}^2 d_{t-i} + \sum_{j=1}^{p} \alpha_j \sigma_{t-j}^2 \quad (8)$$

Where d_{t-i}= 1 ifμ_t< 0 and 0 if $\mu_t \geq 0$.

The condition for non-negativity will be β_0> 0, β_i> 0, α_j≥ 0, and β_i +γ≥ 0

In this model, good news implies that μ_{t-i}^2> 0 and has an impact of β_i and bad news implies that μ_{t-i}^2< 0 with an impact ofβ_i+γ_i . Bad news increases volatility whenγ_i > 0, which implies the existence of leverage effect in the *i*-th order, and when $\gamma_i \neq 0$ the news impact is asymmetric. These two shocks of equal size have different effects on the conditional variance.

The first order representation of TGARCH (p, q) is TARCHG (1, 1) given as:

$$\sigma_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \gamma_1 \mu_{t-1}^2 d_{t-1} + \alpha_1 \sigma_{t-1}^2 \quad (9)$$

In this model, good news has a positive impact of β_1 and negative news has a negative impact of β_1+γ_1 .

3.2.1.6 The Exponential GARCH (EGARCH) Model

Nelson's exponential GARCH (EGARCH) model allows for asymmetric effects between assets returns that are positive and negative (Nelson's, 1991). Three major shortcomings of the GARCH model were proposed to be addressed by the EGARCH, which takes into account the asymmetric properties of volatility and returns. They are:

Restrictions on parameters that guarantee positive conditional variance, insensitivity to volatility's asymmetric response to shock, and difficulty measuring persistence in a strong stationary series

The EGARCH model's log of the conditional variance indicates that the leverage effect is exponential rather than quadratic. A major advantage of the EGARCH model over the symmetric GARCH model is that it does not restrict the sign of the model parameters because volatility is specified in terms of its logarithmic transformation. As a result, there are no restrictions on the parameters to ensure that the variance is positive (Ma Jose, 2010).

The following is a general description of the EGARCH (p, q) model's conditional variance.

$$\log(\sigma_t^2) = \beta_0 + \sum_{i=1}^{q} \beta_i \left|\frac{\mu_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{q} \gamma_i \frac{\mu_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \alpha_j \log(\sigma_{t-j}^2) \quad (10)$$

In this model, good news implies that μ_{t-i} is positive with total effects $(1+\gamma_i)|\mu_{t-i}|$ and bad news implies μ_{t-i} is negative with total effect$(1-\gamma_i)|\mu_{t-i}|$. Whenγ_i< 0, the expectation is that bad news would have higher impact on volatility (leverage effect is present) and the news impact is asymmetric if $\gamma_i \neq 0$. The EGARCH model achieves covariance stationarity when $\sum_{j=1}^{p} \alpha_j$< 1. The EGARCH (1, 1) is specified as:

$$\log(\sigma_t^2) = \beta_0 + \beta_1 \left|\frac{\mu_{t-1}}{\sigma_{t-1}}\right| + \gamma_1 \frac{\mu_{t-1}}{\sigma_{t-1}} + \alpha_1 \log(\sigma_{t-1}^2) \quad (11)$$

The total effect of good news for EGARCH (1, 1) is $(1+\gamma_1)|\mu_{t-1}|$ and the total effect of bad news for EGARCH is $(1-\gamma_1)|\mu_{t-1}|$. If the null hypothesis that γ_1= 0 is rejected then, leverage effect is present, that is, bad news have stronger effect than good news on the volatility of the stock index return and that the forecasts can be tested by the hypothesis γ_1< 0.

3.2.1.7 The Power GARCH (PGARCH) Model

The (PARCH) model proposed by Taylor and Schwert, which the assistance of others, introduced the standard deviation GARCH model (Taylor, 1986; Schwert, 1989). Time-varying asymmetry is a major component of volatility dynamics. Ding and co. Power GARCH (PGARCH) was a more generalized version of the standard deviation GARCH model first proposed (Taylor, 1986; Schwert, 1989). The lagged conditional standard deviations and the lagged absolute innovations raised to the same power are linked in this model to the conditional standard deviation raised to a power d (positive exponent). When the positive exponent is set to two, this expression becomes a standard GARCH model. The model's adaptability is enhanced by the power switching feature.

The conditional variance of PGARCH (p, d, q) as;

$$\sigma_t^d = \beta_0 + \sum_{i=1}^{p} \beta_i \left(|\mu_{t-i}| + \gamma_i \mu_{t-i}\right)^d + \sum_{j=1}^{q} \alpha_j \left(\sigma_{t-j}^d\right) \quad (12)$$

Here, d > 0,$|\gamma_i| \leq 1$ for *i* = 1,…,r, γ_i = 0 for all *i*> r, and r ≤ p establishes the existence of leverage effects. The symmetric model sets γ_i = 0 for all *i*.

If d is set at 2, the PGARCH (p, q) replicates a GARCH (p, q) with a leverage effect. If d is set at 1, the standard deviation is modeled.

The first order of PGARCH (1, d, 1) is expressed as:

$$\sigma_t^d = \beta_0 + \alpha_1 \left(|\mu_{t-1}| + \gamma_1 \mu_{t-1}\right)^d + \beta_1 \left(\sigma_{t-1}^d\right) \quad (13)$$

If the null hypothesis that $\gamma_1 = 0$is rejected then, leverage effect is present. The impact of news on volatility in PGARCH is similar to that of TGARCH when d is 1.

3.2.1.8 The Integrated GARCH (IGARCH) Model

If the parameters of GARCH models are restricted to sum to one, and the constant term is dropped, it gives the integrated GARCH (IGARCH) model which is given by:

$$\sigma_t^2 = \sum_{i=1}^{p} \beta_i \mu_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \sigma_{t-j}^2 \quad (14)$$

The conditional variance of a typical IGARCH (1, 1) model is given by

$$\sigma_t^2 = \beta_0 + \beta_1(\mu_{t-1}^2 - \beta_0) + \alpha_1(\sigma_{t-1}^2 - \beta_0)$$

It shows means reversion to β_0, and is a constant for all time.

3.2.1.9 The Component GARCH (CGARCH) Model

Unlike the integrated GARCH model, the component model allows mean reversion to a varying levelq_t, such that:

$$\sigma_t^2 - q_t = \beta_1 (\mu_{t-1}^2 - q_{t-1}) + \alpha_1(\sigma_{t-1}^2 - q_{t-1}) \quad (15a)$$
$$q_t = \beta_0 + \rho(q_{t-1} - \beta_0) + \emptyset(\mu_{t-1}^2 - \sigma_{t-1}^2) \quad (15b)$$

Combining the transitory and permanent equation above, we have

$$\sigma_t^2 = (1 - \beta_i - \alpha_j)(1 - \rho)\beta_0 + (\beta_i + \emptyset)\mu_{t-1}^2 - (\beta_i \rho + (\beta_i + \alpha_j)\emptyset)(\alpha_j \emptyset)\mu_{t-2}^2 + \quad (16)$$

$$(\alpha_j + \emptyset)\mu_{t-1}^2 - (\alpha_j \rho - (\beta_i + \alpha_j)\emptyset)\sigma_{t-2}^2$$

The above equation shows that the component model is a restricted GARCH (2, 2) model. The asymmetric component model combines the component with asymmetric TARCH model. This equation introduces asymmetric effects in the transitory equation and estimates model of the form:

$$q_t = \beta_0 + \rho \ (q_{t-1} - \beta_0) + \emptyset(\mu_{t-1}^2 - \sigma_{t-1}^2) + \psi_2 z_{1t} \quad (17a)$$
$$\sigma_t^2 - q_t = \beta_i \ (\mu_{t-1}^2 - q_{t-1}) + \gamma(\mu_{t-1}^2 - q_{t-1})d_{t-1} + \alpha_j(\sigma_{t-j}^2 - q_{t-1}) + \psi_2 z_{2t} \quad (17b)$$

Where z is the exogenous variable and d is the dummy variable indicating negative shocks.

$\gamma > 0$ indicates presence of transitory leverage effects in the conditional variance.

3.3 Distributional Assumptions

Some stylized facts about high frequency series like stock returns include volatility clustering, fat-tail, and asymmetry. As a result, the traditional normality assumption in financial time series volatility modeling could compromise the robustness of parameter estimates. The traditional normality assumption was used by Bollerslev to account for time-varying volatility in high frequency data by assuming that such data follow the student t-distribution (Bollerslev, 1986). Additionally, a group researchers demonstrate that kurtosis and slowly decaying autocorrelations in return series cannot be adequately explained by a GARCH model with normally distributed errors (Bollerslev et al., 1994). In a similar vein, Malmsten and Terasvirta contend that the first-order EGARCH model for normal error is insufficiently adaptable to account for stock returns' kurtosis and autocorrelation (Malmsten and Terasvirta, 2004).

However, they suggested replacing the normal error distribution in the standard GARCH model with a more fat-tailed error distribution. The standard GARCH model can better capture the kurtosis and low autocorrelations in stock return series if the kurtosis of the error distribution is increased. A student-t could imply infinite unconditional variance for the errors (Nelson, 1991). As a result, the autocorrelation of the squared observations will be lessened and the kurtosis will be improved by an error distribution that is more fat-tailed than normal. Nelson recommended including a generalized error distribution (GED) in the EGARCH model because he makes the assumption that the innovation is stationary if it has a GED (Nelson, 1991).

According to Ma Jose the stationarity TGARCH model is dependent on the disturbance term distribution, which is typically assumed to be Gaussian or student-t (Ma Jose, 2010). The leverage effect that is captured by the TGARCH model shrinks and loses more flexibility as the fat-tailed error distribution grows. The kurtosis in returns, which is not adequately captured by the normality assumption, is typically taken into account by the TGARCH and EGARCH models under the assumption that they follow GED (Akano and Adams, 2019). To further prove that modeling of the return series is inefficient with a Gaussian process for high frequency financial time series, the Parameter vectors θ=[$\beta_0, \beta_i, \alpha_j, \gamma_i, \gamma, \phi$ and ρ] of the conditional variance equations are estimated with a normal distribution by maximizing the log likelihood function:

3.3.1 The Normal (Gaussian) Distribution

The Normal distribution log-likelihood contributions are assumed to be of the form:

$$LogL(\theta)_t = \sum_{t=1}^{T} L(\theta)_t = -\frac{T}{2} Log[2\pi] - \frac{1}{2}\sum_{t=1}^{T} Log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T} \frac{\mu_t^2}{\sigma_t^2} \quad (18)$$

Where ε_t^2= $[y_t - \gamma y_{t-1}]^2$, T is the sample size, and

$$L(\theta)_t = -\frac{1}{2}\log[2\pi] - \frac{1}{2}\log[\sigma_t^2] - \frac{1}{2}[y_t - \gamma y_{t-1}']^2/\sigma_t^2$$

σ_t^2 is specified in each of the GARCH models.

3.3.2 The Student's t-Distribution

The student's t-distribution, log-likelihood contributions are assumed to be of the form:

$$L(\theta)_t = -\frac{1}{2}\log\left[\frac{\pi[v-2]\Gamma\left[\frac{v}{2}\right]^2}{\Gamma\left[\frac{v+1}{2}\right]^2}\right] - \frac{1}{2}log\sigma_t^2 - \frac{[v+1]}{2}\log\left[1 + \frac{[y_t - x_t'\gamma]^2}{\sigma_t^2[v-2]}\right] \quad (19)$$

Where σ_t^2 is the variance at time t, and the degree of freedom $v > 2$ controls the tail behavior.

3.3.3 Generalized Error Distribution (GED)

The assumption that GARCH models follow GED tends to account for the kurtosis in returns, which are not adequately captured with normality assumption. The volatility models are estimated with GED by maximizing the likelihood function below:

$$L(\theta)_t = -\frac{1}{2}\log\left[\frac{\Gamma 1/r)^3}{\Gamma\left[\frac{3}{r}\right]\left[\frac{r}{2}\right]^2}\right] - \frac{1}{2}\log\sigma_t^2 - \left[\frac{\Gamma\left[\frac{3}{r}\right][y_t - x_t'\gamma]^2}{\sigma_t^2\Gamma\left[\frac{1}{r}\right]}\right]^{r/2} \quad (20)$$

r is the shape parameter which account for the skewness of the returns and Where the tail parameter r > 0. The higher the value of r, the greater the weight of tail. The GED is a normal distribution if r = 0 and fat-tailed if r < 2.

3.4 The Daily Stock Returns

Conditional variance models are fitted to continuously compound daily stock returns y_t

$$y_t = 100(lnk_t - lnk_{t-1}) \quad (21)$$

Where y_t=denotes the continuously compounded return at time t, k_t denotes the asset price at time t,k_{t-1}= previous asset price, and ln denotes the natural logarithm.

The existence of volatility clustering in the daily stock index returns y_t, is established by plotting the residual of the equation:

$$y_t = k + \xi_t \quad (22)$$

Equation (22) tends to show that prolong period of low volatility are followed by prolong period of high volatility. k is a constant, ξ_t is the residual series and y_t is return series.

3.5 The Lagrange Multiplier (Lm) Test

The Lagrange Multiplier test for ARCH in the residuals ξ_t is used to test the null hypothesis that there is no ARCH ($H_0: \pi_l = 0$) up to order q at 5% significant level using the equation below:

$$\xi_0^2 = \psi_0 + \sum_{l=1}^{q} \pi_l \xi_{t-l}^2 + \mu_t \quad (23)$$

Where ψ_0 is constant and μ_t is error term. The expectation is that there should be no evidence to accept the null hypothesis for GARCH model to be applicable. The presence of ARCH effect is a precondition for GARCH modeling and GARCH models account for ARCH effect in financial series.

The mean equation of the stationary return series with ARCH effect is specified in a univariate form as:

$$y_t = \rho + \varpi y_{t-1} + \varepsilon_t \quad (24)$$

where y_t is the daily returns, ρ is constant, ϖ is the estimated autoregressive coefficient, y_{t-1} is one period lag of the returns and ε_t is the standardized residuals of the returns at time t.

3.6 Model Selection Priorities

The aforementioned first-order volatility models are estimated by allowing for the normal, student's t, and generalized error distributions of ε_t in (y) for each variance equation. The following criteria are used to select the best model for each stock return: The Schwarz information criterion, the Bayesian information criterion, and the Akaike information criterion. Estimated coefficients of the best conditional variance models serve as the basis for a comparison of the stock returns volatility of the selected equities; the model with the least value for these criteria across the error distributions is deemed to be the most well-suited. The best-fitting conditional variance models for stock returns are generated by this selection.

The Akaike information criterion (AIC) is: $2k + n\ln\left(\frac{RSS}{n}\right)$

Bayesian information criterion (BIC) is: $n\ln\left(\frac{RSS}{n}\right) + \frac{2(k+2)n\sigma^2}{RSS} + \frac{2n^2\sigma^4}{RSS^2}$

Schwarz information criterion (SIC)is: $n\ln\left(\frac{RSS}{n}\right)$+klogn

The constant k denotes the number of estimated parameters in the fitted model, n denotes the sample size, RSS denotes the pure error variance fitting the entire model, and 2 denotes the residual sum of squares. The fact that a single, all-encompassing decision can be made about the model that is best supported by the data rather than a series of potentially conflicting significance tests is the primary reason why using a model selection procedure like AIC, BIC, or SIC is preferred to traditional significance tests. Furthermore, the range of possible interpretations is expanded by the fact that models can be ranked from best to worst based on how well they are supported by the data at hand.

The ability to demonstrate the leverage effect, which states that equal magnitudes of bad news (negative shocks) have a stronger impact on the volatility of stock index return than positive shocks, is another method for determining whether or not asymmetric volatility models are adequate. The null hypothesis is tested at the 5% level of significance to determine whether or not there is a leverage effect among the asymmetric models. The existence of a leverage effect is implied by the rejection of the null hypothesis. The news impact curve (NIC) graph further supports this. The NIC investigates the connection between the news and the volatility of stock returns in the future. The best-fitted volatility models' NICs are plotted to show how well they capture the debt-to-equity ratio.The higher the debt-to-equity ratio, the more risky stock investments are.

In each of the best-fitted models, the diagnostic test for standardized residuals (Ljung-Box) of stock returns is carried out. To determine the robustness of the estimated models, the ARCH-LM test for the residual ARCH effect and Q-Statistics for post-estimation evaluation analysis of the fitted models (correlogram of Residuals) are carried out. The conditional variance model is less effective when serial correlation and the ARCH effect are present in the standardized residual of the mean equation. Consequently, the assumption is that the two speculations that there is no Curve impact and there is no sequential connection should not be dismissed at 5% importance level. Standardized residuals' normality can be verified with the QQ-plot. The point in the QQ-plots will be on a straight line for a Gaussian process.

3.7 Forecasting Evaluation

When evaluating the predictive power of volatility models, the best predictive model's out-of-sample forecasting power remains the deciding factor. Consequently, the out-of-test model determination measures that will be utilized to assess the prescient capacity of the contending models are:

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{\sum_{t=T+1}^{T+k}\left(\hat{\sigma}_t^2-\sigma_t^2\right)^2}{K}} \quad (25)$$

$$\text{Theil Inequality Coefficient (TIC)} = \sqrt{\frac{\sum_{t=T+1}^{T+k}\left(\hat{\sigma}_t^2-\sigma_t^2\right)^2/k}{\sqrt{\sum_{t=T+1}^{T+k}\left(\hat{\sigma}_t^2\right)^2/k}\sqrt{\sum_{t=T+1}^{T+1}\left(\sigma_t^2\right)^2/k}}} \quad (26)$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{k}\sum_{t=T+1}^{T+k}\left|\sigma_t^2-\hat{\sigma}_t^2\right| \quad (27)$$

The model's forecasting ability increases with decreasing RMSE and TIC.A set of forecasts' errors variation can be diagnosed using both the RMSE and the MAE. The MAE will never be smaller than the RMSE. The sample's individual error variance increases proportionally to the difference between them. The basis for comparison is the examination of these estimated volatility models in terms of conditional volatility's speed of reaction to market events (measured by the ARCH coefficient) and volatility persistence (measured by the GARCH coefficient).

4. Empirical Results

4.1 Data Presentation

Data Presentation The secondary data used in this study were obtained from the website of the Nigerian Securities and Exchange Commission. Daily stock prices for two Nigerian beverage industries make up the data, the Nigeria Breweries and Guinness Nigerian Plc. Between October 10, 2012 and November 1, 2021, the data are available. Figures 1 and 2, respectively, display the graphical representations below.

Figure 1: Time Plots for Nigeria Breweries and Guinness Nigeria Plc Stock returns from 10th October, 2012 and 1st November, 2021.

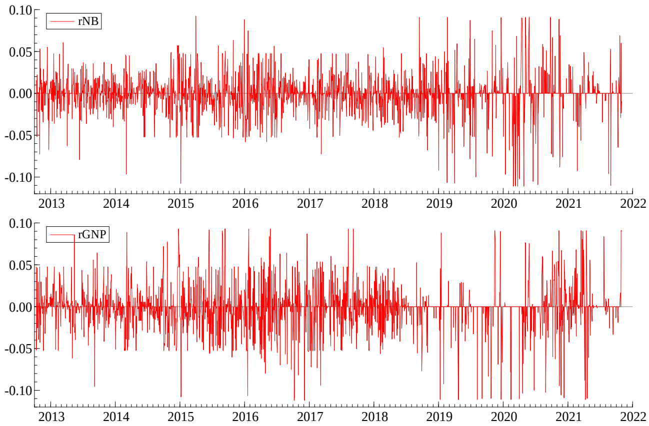

Figure 2: Time-Plots for Stock Returns.

Returns over the time periods are depicted in Figure 2. Volatility clustering occurred in all stock prices, with positive and negative values of varying magnitude. Throughout the study, these fluctuating returns are a sign of the stock series' volatility. However, a comprehensive statistical analysis of the data is required before a solid conclusion can be drawn from the trends alone.

Table 1: Summary Statistics of Stock Return

	Guinness Nigeria Plc Stock Returns	Nigeria Breweries Stock Returns
Mean	-0.001144	-0.000714
Median	0.000000	0.000000
Maximum	0.092917	0.092459
Minimum	-0.112173	-0.111111
Std. Dev.	0.026936	0.023722
Skewness	-0.288090	-0.433394
Kurtosis	6.988794	7.672164
Jarque-Bera	1515.286	2106.567
Probability	0.000000	0.000000
Sum	-2.561038	-1.598630
Sum Sq. Dev.	1.623786	1.259429
Observations	2239	2239

The descriptive statistic of the stock returns can be found in Table 1. The result indicates that prices have decreased throughout the study period because the mean of all returns is negative (-0.001144, -0.000714 for Guinness Nigeria Plc Returns, and -0.000714 for Nigeria Breweries Returns, respectively). Additionally, the two returns series in Table 1 are negatively skewed, indicating a low likelihood of earning returns below the mean. The fact that all of the return series have kurtosis values greater than 3, which indicates that all of the return series do not follow a normal distribution and have a fat tail, further supports the findings of the Jarque-Bera test, which is significant at the 5% level, rejecting the null hypothesis of normality.

Table 2: Test for Stationarity

		Guinness Nigeria Plc	Nigeria Breweries
		t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-43.32762	-29.21302
Test critical values:	**1% level**	-3.433076	-3.433078
	5% level	-2.862630	-2.862631
	10% level	-2.567396	-2.567397
	Prob.*	0.0000	0.0000

The outcomes of the stock price unit root test are presented in Table 2. At the first difference, the stock prices stay the same. All p-values less than 0.05 in the ADF statistics for stock prices indicate that the data are stationary and fall below the critical values. Since the study will utilize stationary data, reliable policy results will be derived.

4.2 ARCH Effect Test

The ARCH – LM test can be used to determine whether the return series residual contains an ARCH effect. With the assistance of the ACF and PACF functions, the model is first stabilized as an ARIMA (1,1) model. The ARIMA (1,1) model's residuals are saved and squared ε_t^2 to create the variable. The residual's variance (ε_t^2) is then used to create additional variables. The following model was used:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_t \varepsilon_{t-1}^2$$

Where ω and α_i, i = 1,p are non-negative constants. Table 3 is the result of the test

Table 3: Heteroskedasticity Test: ARCH

Guinness Nigeria Plc Returns			
F-statistic	159.8508	Prob. F(1,2236)	0.0000
Obs*R-squared	149.3190	Prob. Chi-Square(1)	0.0000
Nigeria Breweries Returns			
F-statistic	109.4103	Prob. F(1,2236)	0.0000
Obs*R-squared	104.3998	Prob. Chi-Square(1)	0.0000

According to ARCH result presented in Table 3, the test statistics for each and every stock return are highly significant. Since p< 0.05, we reject the null hypothesis of "no arch effect" at the 5% level, agreeing that the ARCH effect is present in the time series' residuals, and can now proceed with the GARCH family Model estimation.

4.3 ARCH/GARCH Estimation Results

The estimation of ARCH/GARCH family models for Guinness Nigeria Plc returns and Nigeria Breweries Returns using a student's t distribution was supported by the ARCH effect and other estimated stylized facts of these series. All of the ARCH models' coefficients for the two-return series are positive, meeting the requirements for the ARCH family model.

Table 4: Parameter Estimates for ARCH/GARCH Models for Guinness Nigeria Plc Returns

Parameter	ARCH	GARCH(1 1)	EGARCH	TGRACH	PARCH	CGARCG	IGARCH
Constant (C)	-0.00114 (0.000573)	-0.00160 (0.000518)	-0.00172 (0.000449)	-0.00126 (0.000529)	-0.00126 (0.000534)	-0.00165 (0.000516)	-0.00133 (0.000539)
Intercept (β_o)	0.000199 (0.000445)	0.000185 (1.31E-05)	-2.46425 (0.158601)	0.000185 (1.30E-05)	8.59E-05 (7.98E-05)	0.000735 (4.53E-05)	
ARCH term (β_1)	0.724640 (0.614578)	0.213315 (0.021168)	0.354574 (0.023918)	0.283075 (0.035621)	0.198980 (0.022608)	0.901349 (0.016164)	0.015818 (0.000498)
GARCH term (α_1)		0.535423 (0.028855)	0.062933 (0.018137)	0.540752 (0.028412)	-0.182253 (0.038065)	0.078669 (0.018032)	0.984182 (0.000498)
Γ			0.694073 (0.020570)	-0.14729 (0.036498)	0.520135 (0.032577)	0.159057 (0.027037)	
D					1.0000		
Ø						0.264548 (0.0879)	
ρ							
$\beta_1 + \alpha_1$		0.748738	0.417507	0.823827	0.016727	0.980018	0.999938
μ		-0.00114	-0.00114	-0.00114	-0.00114	-0.00114	-0.00114
Log L	4916.660	5073.828	5067.789	5080.607	5080.804	5081.127	4939.024
AIC	-4.38915	-4.52865	-4.52236	-4.53381	-4.53309	-4.53338	-4.41002
SC	-4.38150	-4.51844	-4.50960	-4.52105	-4.51778	-4.41807	-4.40492
Observed	**2239**	**2239**	**2239**	**2239**	**2239**	**2239**	**2239**

Note: Numbers in parenthesis indicates standard error

Table 4 shows the parameter estimations for the ARCH/GARCH Models for the returns of Guinness Nigeria Plc. The standard error is indicated by the numbers enclosed in parenthesis in the power model. At times, the power parameter d of standard deviation is imposed, and other times, it is estimated. The ARCH term and the ARCH model's intercept are both positive and statistically significant at the 5% level, with the exception of EGARCH. The value of the ARCH coefficient indicates that the square-lagged error terms have a positive and significant effect on the current period volatility of Guinness Nigeria Plc. Stock volatility also reacts quickly to market events. The fact that the estimated GARCH (1, 1) model's coefficient is positive and significant suggests that conditional volatility at the current period is significantly influenced by volatility in the previous period. All variance equation parameter estimates are shown to be positively significant at the 5% level by the estimated GARCH (1, 1) model.

Additionally, the ARCH coefficient demonstrated that volatility is highly responsive to market events and that previous error terms have a positive and significant effect on current period volatility. With the exception of the EGARCH and PARCH models, shocks to returns of this beverage die out very slowly because the sum for all estimated models is high. The IGARCH (1, 1) model, on the other hand, has the highest volatility persistence because the value is approximately 1, indicating that it more accurately accounts for volatility persistence and that it will diminish very slowly. The long-term average variance, or unconditional variance of returns (), is -0.00114.

The intercept parameter is negative and significant in the EGARCH model, whereas the ARCH and GARCH terms are both positive and highly significant. According to the ARCH term, Guinness Nigeria Plc's returns have a significant and significant degree of volatility when subjected to market shocks. Additionally, since 1 is less than 1, previous period volatility has no effect on current period volatility and is covariance stationarity. The leverage effect term is significant at the 5% level, indicating its existence. The ARCH term and intercept are significant in the TGARCH model. That is, volatility in the current period is influenced significantly by the squared lagged error, and volatility reacts quickly to market shocks. Additionally, the GARCH coefficient indicates that volatility persistence is high and that previous period variance influences conditional volatility.

The leverage effect is positive and significant at the 5% level, indicating that positive shock drives volatility of equal magnitude, and the long-run average is (11 1− /2 = 0.16173).The Power ARCH (PARCH) model revealed that when d = 1, all coefficients are positive and statistically significant at the 5% level. Volatility has a moderately quick response to market shocks and a low persistence. The CGARCH model's parameter estimates show that, with the exception of the intercept, all other coefficients are positive and significant. Volatility is extremely quick to react to market events. EGARCH is the best-fitting model for Guinness Nigeria Plc returns when all estimated models are compared using log likelihood statistics and information criteria.

Parameter Estimates for Nigeria Breweries Returns in ARCH/GARCH Models. The returns from the GARCH Models of Nigeria Breweries are shown in Table 5, and the numbers in parenthesis indicate the standard error. At conventional levels, the ARCH term is positive and significant, and the ARCH model's intercept is positive and significant. The reaction of conditional volatility to market shock is strong. The coefficient of the GARCH term is positive and significant at the 5% level, as are the intercept and the ARCH term of the GARCH (1, 1) model. The fact that the GARCH term has a significant value indicates that the conditional volatility for the current period is low and that the volatility persistence is low. The covariance stationarity requirement has been satisfied by the GARCH (1, 1) model. With the exception of the PARCH and EGARCH models, volatility persistence is greater than 0.5 and nearly equal.

As a result, the beverage's shocks fade very slowly. However, the CGARCH (1,1) and IGARCH (1, 1) models have the highest persistence of volatility because their values are 1.In the EGARCH model, both the ARCH term and the GARCH term are significant and positive. The unconditional standard deviation of returns () is 0.000714.Since 1 is less than 1, EGARCH is covariance stationarity. Nigeria Breweries' returns have a significant tendency to be volatile in response to market shocks, with a high degree of response and moderate volatility persistence. At the 5% level, the term "leverage effect" is significant. The intercept, the GARCH term, and the ARCH term are all significant in the TGARCH model. The leverage effect is significant at the 5% level, and the long-run average is (1–1–/2 = 0.0568085).With the exception of the GARCH term when d = 1, the power ARCH (PARCH) model's results showed that all coefficients were positive and statistically significant at the 5% level. The CGARCH model's parameter estimates show that all coefficients are positive and significant. CGARCH is the most suitable model for Nigeria Breweries returns when all estimated models are compared using log likelihood statistics and information criteria.

Table 5: Parameter Estimates for ARCH/GARCH Models for Nigeria Breweries Returns

Parameter	ARCH	GARCH(1 1)	EGARCH	TGRACH	PARCH	CGARCG	IGARCH
Constant (C)	-0.0007 (0.0005)	-0.00069 (0.0004)	-0.00152 (0.0004)	-0.00040 (0.0004)	-0.00040 (0.0004)	-0.00071 (0.0004)	-0.00078 (0.0004)
Intercept (β_o)	0.00064 (0.0432)	4.47E-05 (3.7E-06)	-1.32572 (0.0852)	5.02E-05 (3.98E-06)	7.20E-07 (9.51E-07)	0.000579 (5.62E-05)	
ARCH term (β_1)	-0.1530 (76.895)	0.101530 (0.0077)	0.233213 (0.01344)	0.134509 (0.0122)	0.074588 (0.0117)	0.988697 (0.0018)	0.020728 (0.0004)
GARCH term (α_1)		0.818648 (0.01105)	0.029278 (0.00945)	0.803044 (0.0116)	-0.14144 (0.0235)	0.028654 (0.0033)	0.97927 (0.0004)
Γ			0.844392 (0.0107)	-0.05117 (0.0129)	0.773375 (0.0194)		
D					3.09475 (0.3459)		
Ø						0.20519 (0.02087)	
ρ						0.27761 (0.04974)	
$\beta_1 + \alpha_1$		0.920178	0.262491	0.937544	-0.0668	1.0000	1.0000
μ							
Log L	5200.35	5350.936	5316.227	5354.320	5360.77	5383.003	5282.54
AIC	-4.6425	-4.77618	-4.74428	-4.77831	-4.7831	-4.80304	-4.71688
SC	-4.6349	-4.76597	-4.73152	-4.76555	-4.7678	-4.78772	-4.7117
Observed	**2239**	**2239**	**2239**	**2239**	**2239**	**2239**	**2239**

Note: Numbers in parenthesis indicate standard error

Table 5 displays the GARCH Models of Nigeria Breweries returns. At conventional levels, the ARCH term is positive and significant, and the ARCH model's intercept is positive and significant. The reaction of conditional volatility to market shock is strong. The coefficient of the GARCH term is positive and significant at the 5% level, as are the intercept and the ARCH term of the GARCH (1, 1) model. The fact that the GARCH term has a significant value indicates that the conditional volatility for the current period is low and that the volatility persistence is low. The covariance stationarity requirement has been satisfied by the GARCH (1, 1) model. Instability diligence are more prominent than 0.5 and they are near solidarity, except for Dry and EGARCH model.

As a result, the beverage's shocks fade very slowly. However, the CGARCH (1,1) and IGARCH (1, 1) models have the highest persistence of volatility because their values are 1.In the EGARCH model, both the ARCH term and the GARCH term are significant and positive. The unconditional standard deviation of returns () is 0.000714.Since 1 is less than 1, EGARCH is covariance stationarity. Nigeria Breweries' returns have a significant tendency to be volatile in response to market shocks, with a high degree of response and moderate volatility persistence. At the 5% level, the term "leverage effect" is significant. The intercept, the GARCH term, and the ARCH term are all significant in the TGARCH model. The leverage effect is significant at the 5% level, and the long-run average is (1–1–/2 = 0.0568085).With the exception of the GARCH term when d = 1, the power ARCH (PARCH) model's results showed that all coefficients were positive and statistically significant at the 5% level. The CGARCH model's parameter estimates show that all coefficients are positive and significant. CGARCH is the most suitable model for Nigeria Breweries returns when all estimated models are compared using log likelihood statistics and information criteria.

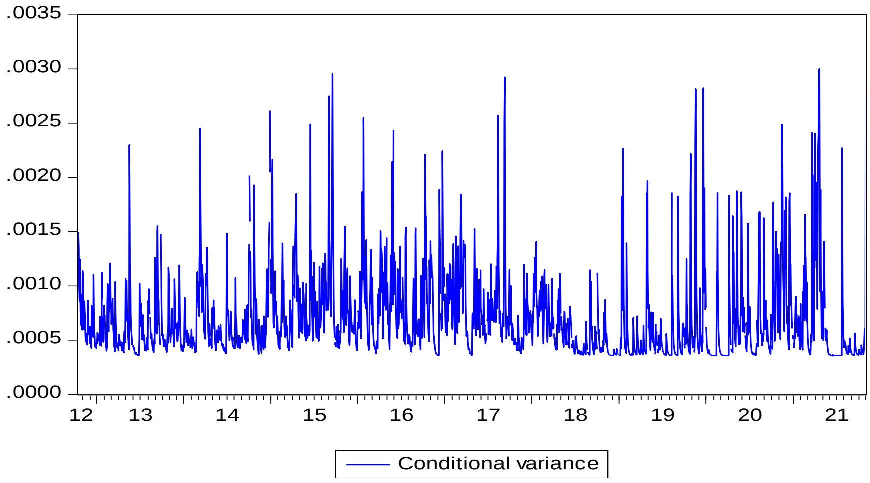

Figure 3: Conditional volatilities from fitted EGARCH model for Guinness Nigeria Plc returns.

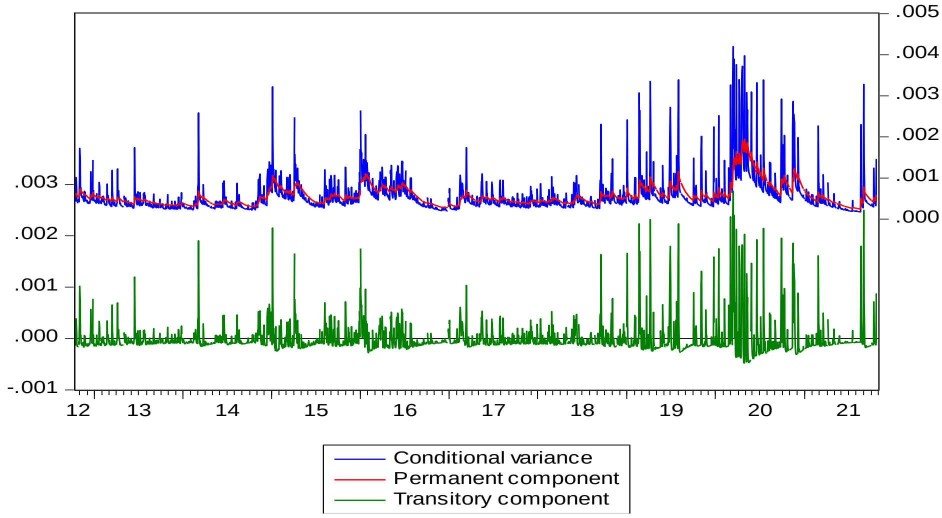

Figure 4: Conditional volatilities from fitted CGARCH model for Nigerian Breweries returns

Plots of the conditional volatilities of the fitted GARCH models show that the chosen volatility models capture the major trends as well as periods of high and low equity returns for Nigerian Breweries returns, as depicted in Figures 3 and 4.

4.4 Diagnostics

Diagnostics tests results are presented in Table 6 and 7.

Diagnostic Test for the Two Best-Fitted GARCH Family Models Based on the Chi-squared statistic, the null hypothesis that there is no remaining ARCH effect in the models cannot be rejected at the 5% significance level. Goodness of fit is shown by the estimated model's residuals adhering to homoscedasticity. All lags have probability values in Table 7 that are greater than 0.05, indicating that there is no serial correlation in the estimated models' standardized residuals at the 5% significance level.

Table 6: Diagnostic Test for the Two Best Fitted GARCH Family Models

Heteroskedasticity Test: ARCH			
	EGARCH(1,1)		
F-statistic	0.460903	Prob. F(1,2236)	0.4973
Obs*R-squared	0.461221	Prob. Chi-Square(1)	0.4971
	CGARCH (1,1)		
F-statistic	0.004864	Prob. F(1,2236)	0.9444
Obs*R-squared	0.004868	Prob. Chi-Square(1)	0.9444

Table 7: Serial Correlation Test Results of The Two Best Fitted Volatility Models

	EGARCH (1,1)				**CGARCH (1,1)**			
Lag	**AC**	**PAC**	**Q-Stat**	**Prob***	**AC**	**PAC**	**Q-Stat**	**Prob***
1	0.014	0.014	0.4619	0.497	0.001	0.001	0.0049	0.944
2	0.017	0.017	1.1082	0.575	-0.019	-0.019	0.8425	0.656
3	-0.021	-0.021	2.0952	0.553	0.009	0.009	1.0387	0.792
4	0.009	0.009	2.2788	0.685	-0.014	-0.014	1.4598	0.834
5	-0.013	-0.013	2.6839	0.749	0.004	0.004	1.4966	0.913
6	-0.006	-0.007	2.7753	0.836	0.009	0.008	1.6621	0.948
7	-0.009	-0.008	2.9429	0.890	0.062	0.063	10.400	0.167
8	-0.005	-0.005	2.9911	0.935	0.033	0.033	12.919	0.115
9	0.020	0.021	3.9138	0.917	0.000	0.003	12.919	0.166
10	0.009	0.008	4.0895	0.943	-0.004	-0.004	12.952	0.226

5. CONCLUSION

The ARCH model's intercept and ARCH term for Guinness Nigeria Plc are both significant and non-negative at the 0.05 level of significant, with the exception of EGARCH. The value of the ARCH coefficient indicates that the error of square and lagged terms have a significant and non-negative influence on the present period volatility of Guinness Nigeria Plc. Stock volatility also reacts quickly to market events. The fact that the estimated GARCH (1, 1) equation coefficient is non-negative and significant suggests that conditional volatility at the present time is significantly influenced by volatility in the previous period. All variance equation parameter estimates are shown to be positively significant at the 5% level by the estimated GARCH (1, 1) model. Additionally, the ARCH coefficient demonstrated that volatility is highly responsive to market events and that previous error terms have a positive and significant effect on current period volatility.

Because the sum for all estimated models is high, shocks to this beverage's returns die out very slowly, with the exception of the EGARCH and PARCH models. On the other hand, the IGARCH (1, 1) model has the highest volatility persistence because the value is roughly 1, indicating that it better accounts for volatility persistence and that it will decrease slowly. The unconditional variance of returns or long-term average variance is 0.00114.The intercept of the ARCH model is also significant and non-negative, as is the ARCH term. Conditional volatility exhibits a robust response to market shock. At the 5% level, both the GARCH (1, 1) model's intercept and ARCH term have positive coefficients that are statistically significant. The fact that the GARCH term has a significant value indicates low conditional volatility and low volatility persistence for the current period. The GARCH (1, 1) model has met the requirement for covariance stationarity.

The volatility persistence is greater than 0.5 and nearly identical, with the exception of the PARCH and EGARCH models. The beverage's shocks therefore fade very slowly. However, the unconditional standard deviation of returns of 1.0.000714 indicates that the CGARCH (1,1) and IGARCH (1,1) models have the highest persistence of volatility. Based on model selection criteria, EGARCH and CGARCH were chosen as the best volatility models for the returns of Nigeria Breweries and Guinness Nigeria Plc, respectively. On the other hand, the EGARCH model did not support the hypothesis that Guinness Nigeria Plc's equity returns respond in the same way to positive and negative shocks of the same magnitude. Given the level of risk associated with portfolio investment, the study suggests that financial analysts, investors, and empirical work should take into account variants of GARCH models with alternative error distributions in order to ensure the robustness of the results. In addition, we recommend that the Nigerian government implement sufficient regulatory measures against the beverage industry to increase investors' confidence in the sector, enhance the performance of their stocks, and reduce volatility.

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