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VOLATILITY MODELLING OF NIGERIA CONSUMER STAPLES STOCKS IN THE PERIOD OF GLOBAL ECONOMIC CRISIS (2012–2024)

Iro Godwin Arunsi and *Yahaya Haruna Umar

Department of Statistics, University of Abuja, Abuja, Nigeria.

Corresponding author email: yahaya.umar@uniabuja.edu.ng

ABSTRACT
The period from 2012 to 2024 was faced with significant economic events and policy shifts in Nigeria, including fluctuations in oil prices, movements in consumer staple stocks, changes in government policies, currency devaluations, and the global impact of the COVID-19 pandemic. This study focuses on consumer staple stocks, specifically Nestle Nigeria Plc and Presco Plc which are the two leading consumer staple stocks listed on the Nigerian stock market. An empirical, quantitative time-series design using daily closing prices of these stocks of 2,809 observations per stock from 5th March 2012 to 11th June, 2024 were sourced and analysed. The analysis employs descriptive statistics, stationarity tests, and ARCH/GARCH family models to examine the return dynamics of Nestle Nigeria Plc and Presco Plc. The results reveal that Nestle Nigeria Plc had an average return of 0.000271 with a standard deviation of 0.020553, while Presco Plc recorded a higher average return of 0.001213 and exhibited greater volatility with a standard deviation of 0.027072. The Augmented Dickey-Fuller test confirmed that both stock return series were stationary at first differencing. The presence of significant ARCH effects in both series justified the application of GARCH-type models. Among the models evaluated, the Component GARCH (CGARCH) model provided the best fit for Nestle Nigeria Plc, while the Power ARCH (PARCH) model was most suitable for capturing the volatility of Presco Plc, based on the lowest AIC and SIC values. The study recommends further refinement of volatility models and the implementation of policy measures aimed at stabilizing stock price fluctuations within the consumer staple sector.

Keywords: Consumer Staple Goods, Component GARCH, Power GARCH, Economic Crisis, Nigeria.

INTRODUCTION
Given that consumer staple goods are essential for daily consumption, fluctuations in their prices can have significant implications for household spending, investment decisions, and macroeconomic stability. In Nigeria, the consumer staples sector is vital due to its contribution to the economy and its role in ensuring food security and basic needs (Mohammed *et al*., (2022). The sector's stability, coupled with periodic volatility driven by external and internal factors, makes it an interesting subject for financial analysis. Nestle Nigeria Plc and Presco Plc are two prominent companies within this sector, each playing a crucial role in their respective industries (Mohammed *et al*., 2022). Nestle Nigeria Plc is a subsidiary of Nestle S.A., a global food and beverage leader, established in Nigeria in 1961. Nestle Nigeria has grown to become one of the largest food companies in the country. It produces a wide range of products, including dairy products, beverages, culinary products, infant nutrition, and bottled water. Nestle Nigeria's brands, such as Milo, Maggi, and Nescafe, are household names and enjoy strong brand loyalty (Atobatele, 2023). On the other hand, Presco Plc is an agro-industrial company specializing in the cultivation, processing, and refining of palm oil and its derivatives. Established in 1991, Presco operates plantations in Edo and Delta states and has a fully integrated production process from the plantation to the finished product. The company is a key player in Nigeria's agricultural sector, contributing significantly to the country's palm oil production (Presco Plc, 2023).Despite the importance of volatility modelling, there is a paucity of research focusing specifically on consumer staples stocks in Nigeria. Most studies on volatility in the Nigerian stock market have concentrated on broader market indices or other sectors such as banking and telecommunications. The unique characteristics of consumer staples stocks, such as their relatively stable demand and resilience to economic cycles, warrant a dedicated study to understand their volatility patterns better (Tanimu & Yahaya, 2024). The period from 2012 to 2024 encompasses significant economic events and policy changes in Nigeria, including fluctuations in oil prices, changes in government policies, currency devaluations, and the impact of global events such as the COVID-19 pandemic (Central Bank of Nigeria, 2024). These factors have likely influenced the volatility of Nestle and Presco stocks, making it crucial to study this period comprehensively. The Nigerian stock market exhibits volatility clustering, with two distinct regimes identified between 1985-1999 and 2000-2018, the latter being more volatile (Salami & Olasehinde, 2021; Ayanlowo et al; 2025). GARCH models demonstrate high persistence in stock returns, though shocks have only temporary impacts (Sokpo et al., 2017; Emenike, 2010). Evidence of leverage effects and leptokurtic return distributions has been found (Emenike, 2010). However, inflation does not significantly explain stock market return volatility (Sokpo et al., 2017). Recent studies on consumer goods companies show that volatility predicts stock prices for some firms, and past prices predict current prices, suggesting the market does not follow a random walk (Onunaka&Okezie, 2024). Studies found that the global financial crisis reduced stock prices but did not significantly impact price volatility in Nigeria (Adeyeye et al., 2018). The Nigerian stock market exhibited two regimes of volatility clustering, with the period from 2000 to 2018 being more volatile (Salami &Olasehinde, 2021). Research on consumer staples stocks revealed volatility clustering, high shock persistence, and mean-reverting behavior, with asymmetry and leverage effects varying between companies (Jatau et al., 2018). Skewed error distributions were explored in volatility modeling, with skewed normal distribution often outperforming other distributions in terms of fitness and forecasting ability (Samson et al., 2020). Čermák*et al.,* (2017) employed a GARCH (1,1) model to analyze wheat price volatility from

2005 to 2015, utilizing 2,770 daily observations from the CME. The findings indicate that wheat prices exhibit volatility clustering and leptokurtic distribution, with a tendency for long-term mean reversion. Key events influencing price fluctuations include the 2008 financial crisis and rising grain demand. The model's predictive capabilities suggest that agricultural producers can effectively hedge against price variability through short-term futures contracts. The research underscores the importance of focusing on short-term structural events in the wheat market for better risk management.

Setiawati*et al.,* (2021) analyzed price volatility of staple foods rice, chicken, and sugar in Kebumen Regency, Central Java, using the ARCH-GARCH econometric model on weekly data from January 2018 to August 2020. The findings reveal significant price fluctuations, with over 50% of household expenditure on food, exacerbating poverty in the region (16.82% poverty rate). The ARCH-GARCH model effectively captures the heteroscedasticity in price data, indicating that volatility is influenced by supply and demand shocks. The research underscores the need for local governments to implement effective price stabilization policies to mitigate inflation risks and enhance food security for low-income populations.

Ajibade*et al.,* (2020) analyzed food price volatility in Nigeria from 1970 to 2019 using the GARCH model, revealing persistent volatility linked to factors such as insurgency, political stability, trade liberalization, GDP per capita, inflation, government effectiveness, crop production, crude oil prices, and exchange rates. The findings indicate that domestic food prices are relatively insulated from international market fluctuations. Recommendations include fostering political stability to enhance agricultural production and revisiting price stabilization policies. The research underscores the critical need for mechanisms to improve food affordability, particularly for low-income earners, amid rising food insecurity exacerbated by the COVID-19 pandemic.

The article by Mohammed *et al.,* (2022) investigated the volatility of stock returns for Nigeria Breweries and Guinness Nigeria Plc using a range of ARCH/GARCH models over the period 2012–2021. The study stands out for its methodological depth, applying various volatility models including GARCH(1,1), EGARCH, CGARCH, and others while also accounting for different error distributions such as the Student's t and Generalized Error Distribution (GED). The findings reveal significant volatility clustering and asymmetry in stock return behavior, with the EGARCH model best fitting Nigeria Breweries and the CGARCH model suited for Guinness. While the econometric execution is robust, the study lacks depth in contextual economic interpretation, such as how macroeconomic events (see, for example; COVID-19 or exchange rate shifts) influenced the observed patterns. Moreover, the analysis remains univariate, overlooking potential interactions between the stocks or broader market indices. The study also mentions forecast evaluation criteria like RMSE and TIC but offers little insight into their implications. The paper contributes meaningfully to volatility modeling in emerging markets and offers policy-relevant insights on the importance of inflation control and foreign investment for stock market stability in Nigeria.

The study by Egea*et al.,* (2023) presented an overview of recent advancements in dynamic modeling and simulation within food systems, highlighting the importance of mathematical models in enhancing food safety, quality, and processing efficiency. The authors categorize the contributions of the special issue into two main areas: the evolution of safety and quality indicators in unprocessed foods, and transformation and preservation processes. Key topics include microbial growth modeling, prediction of spoilage using sensors, modeling of fermentation dynamics, and the optimization of thermal processing to balance quality and safety. The study emphasized the growing relevance of predictive models and real-time control in food engineering but notes significant challenges such as lack of validation, limited integration of uncertainty analysis, and inconsistent model comparisons. While the article provided a concise summary of the included studies, it offers limited critical analysis or conceptual synthesis, missing opportunities to guide future interdisciplinary research or highlight emerging technologies like AI. Nonetheless, it serves as a valuable introduction to current modeling approaches and applications in food science.

Aborisade*et al.,* (2024) presented a rigorous empirical analysis of meat demand in Nigeria using nationally representative household panel data. A key strength lies in its comparative approach estimating demand using both consumption and expenditure datato assess whether measurement error (especially hidden consumption) significantly affects elasticity estimates. Employing the Exact Affine Stone Index (EASI) demand system and robust econometric procedures, the study finds that elasticity estimates are largely similar across both data types, suggesting that for elasticity estimation alone, collecting both data may be unnecessary. The research identifies poultry, beef, and processed seafood as luxury goods, while other meats and unprocessed seafood are necessities, and also highlights that poultry has the highest price elasticity. However, the study's limitations include potential measurement errors in both data types, reliance on unit value based prices rather than market prices, and the use of linear models despite censoring in food demand data. The study fills a critical gap in Nigerian food demand literature by using updated, nationally representative data and advanced modeling, making it a valuable contribution to food policy planning and agricultural economics in developing countries.

This study will model the volatility of Nestle Nigeria Plc and Presco Plc, in Nigeria from 2012 to 2024, analyze the historical price movements; investigate the volatility patterns of these stocks using various econometric models; compare the volatility dynamics of Nestle Nigeria Plc and Presco Plc; and evaluate the performance of these models in capturing and predicting stock price volatility.

Most studies on stock volatility in Nigeria focus on market indices or financial stocks, with little attention to consumer staples like Nestle Nigeria Plc and Presco Plc. Existing research also relies mainly on single or linear models that overlook features like volatility clustering and asymmetry. This study fills that gap by applying GARCH-family models to these key consumer staple stocks, offering fresh insights for investors and policymakers. Addressing this gap is important theoretically, as it broadens volatility modeling to essential goods; practically, as it helps investors manage risk in a defensive sector; and for policy, as it informs regulators in promoting market stability and food security.

MATERIALS AND METHODS

This study adopted an empirical, observational, quantitative time-series design using daily closing prices of Nestle Nigeria Plc and Presco Plc from the Nigerian Exchange Group (2012–2024), yielding 2,809 observations per stock. Returns were computed from price data to ensure stationarity. Volatility was modeled using GARCH (1,1), EGARCH (1,1), and TGARCH (1,1), chosen for their ability to capture volatility clustering, persistence, and asymmetric effects features.

Analysis was carried out using Microsoft excel, OxMetrics, and Eviews, and results were presented in tables and charts. Volatility, as measured by the standard deviation or variance of returns, is often used as a crude measure of the total risk of financial assets. Conditional variance models are fitted to continuously compound daily stock returns y_t.

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

Where:y_t: denotes the continuously compounded return at time t, k_t denotes the asset price at time t,k_{t-1} denotes 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:

$$y_t = k + \xi_t \quad (2)$$

Equation (2) shows that prolonged period of low volatility are followed by prolonged period of high volatility. k is a constant, ξ_t is the residual series and y_t is return series. Prior to modelling the equity return series, the study determined the order of integration of the variables. Unit root test of the stock returns is essential because any meaningful econometric time series modeling requires stationarity of the series. If the series are not stationary, the important test statistics used in the evaluation of the econometric results become unreliable. We employ the Augmented Dickey-Fuller (ADF) Test to examine the order of integration of the two equity return series.

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:

$$\Delta y_t = \varphi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \mu_t \quad (3)$$

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

Model Specification

The Power ARCH (PARCH) model of Taylor (1986) and Schwert (1989), among others introduced standard deviation GARCH model. Ding et al. (1993) further generalized standard deviation GARCH model initially proposed by Taylor (1986) and Schwert (1989) and called it Power GARCH (PGARCH). This model relates the conditional standard deviation raised to a power d (positive exponent) to a function of the lagged conditional standard deviations and the lagged absolute innovations raised to the same power. This expression becomes a standard GARCH model when the positive exponent is set at two. The provision for the switching of the power increases the flexibility of the model.In the power model, the power parameter d of standard deviation is estimated while at times imposed and the optional γ parameters are added to capture asymmetry of up to order r. The conditional variance of PGARCH (p, d, q) as

$$\sigma_t^d = \beta_0 + \sum_{i=1}^{p} \beta_i \left(|\mu_{t-i}| + \gamma_i \mu_{t-i}\right)^d + \sum_{j=1}^{q} \alpha_j \left(\sigma_{t-j}^d\right) \quad (4)$$

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) replicate 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:

$$\sigma_t^d = \beta_0 + \alpha_1 \left(|\mu_{t-1}| + \gamma_1 \mu_{t-1}\right)^d + \beta_1 \left(\sigma_{t-1}^d\right) \quad (5)$$

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.

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

$$\sigma_t^2 - q_t = \beta_1 \left(\mu_{t-1}^2 - q_{t-1}\right) + \alpha_1 \left(\sigma_{t-1}^2 - q_{t-1}\right) \quad (6)$$

$$q_t = \beta_0 + \rho\left(q_{t-1} - \beta_0\right) + \emptyset\left(\mu_{t-1}^2 - \sigma_{t-1}^2\right) \quad (7)$$

Combining the transitory and permanent equation above, we have

$$\sigma_t^2 = (1 - \beta_i - \alpha_j)(1 - \rho)\beta_0 + (\beta_i + \emptyset)\mu_{t-1}^2 - (\beta_i \rho + (\beta_i + \alpha_j)\emptyset)(\alpha_j \emptyset)\mu_{t-2}^2 + (\alpha_j + \emptyset)\mu_{t-1}^2 - (\alpha_j \rho - (\beta_i + \alpha_j)\emptyset)\sigma_{t-2}^2 \quad (8)$$

Equation (8) shows that the component model is a restricted GARCH (2, 2) model. It introduces asymmetric effects in the transitory equation and estimates model of the form:

$$q_t = \beta_0 + \rho \left(q_{t-1} - \beta_0\right) + \emptyset\left(\mu_{t-1}^2 - \sigma_{t-1}^2\right) + \psi_2 z_{1t} \quad (9)$$

$$\sigma_t^2 - q_t = \beta_i \left(\mu_{t-1}^2 - q_{t-1}\right) + \gamma\left(\mu_{t-1}^2 - q_{t-1}\right)d_{t-1} + \alpha_j\left(\sigma_{t-j}^2 - q_{t-1}\right) + \psi_2 z_{2t} \quad (10)$$

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

γ > 0 indicates presence of transitory leverage effects in the conditional variance.

The best model for each stock return is selected based on the following criteria: Akaike information Criterion (AIC), Bayesian information criterion (BIC), and Schwarz information criterion (SIC). Comparison of the stock returns volatility of the selected equities is based on estimated coefficients of the best conditional variance models, and the model with the least value for these criteria across the error distributions is adjudged the best fitted. This selection produces the best fitted conditional variance models for stock returns.

AIC is:

$$2\text{k} + nln\left(\frac{RSS}{n}\right) \quad (11)$$

$$\text{BIC is:} nln\left(\frac{RSS}{n}\right) + \frac{2(k+2)n\sigma^2}{RSS} + \frac{2n^2\sigma^4}{RSS^2} \quad (12)$$

$$\text{(SIC)is: } nln\left(\frac{RSS}{n}\right) + k\ logn \quad (13)$$

The constant k denotes the number of estimated parameters in the fitted model, n is the sample size, RSS= $\sum_{i-1}^{n} \hat{e}^2$ is the residual sum of squares, while σ^2 denotes the pure error variance fitting the full model.

RESULTS AND DISCUSSION

We present the result from the analysis and discuss findings in this section.

Preliminary Analysis

Table 1 shows the descriptive statistics of the stock returns

Table 1: Descriptive Statistics of Nestle Nigeria Plc and Presco Plc Stocks Returns in Nigeria from 2012 to 2024

	Nestle Stock Returns	Presco Stock Returns
Mean	0.000271	0.001213
Median	0.000000	0.000000
Maximum	0.097574	0.097023
Minimum	-0.105361	-0.105361
Std. Dev.	0.020553	0.027072

Skewness	0.019104	0.111221
Kurtosis	11.03394	6.932545
Jarque-Bera	7554.529	1815.831
Probability	0.000000	0.000000
Sum	0.761355	3.407093
Sum Sq. Dev.	1.186164	2.058030
Observations	2809	2809

The descriptive statistics of Nestle Nigeria Plc and Presco Plc stock returns from 2012 to 2024 reveal differences in their performance and risk profiles within the Nigerian market. Nestle Nigeria Plc recorded a modest average daily return of 0.0271%, with extreme fluctuations ranging from a 9.76% gain to a -10.54% loss, a nearly symmetric return distribution (skewness = 0.0191), and high kurtosis (11.03), indicating frequent extreme values. Its Jarque-Bera statistic (7554.53) confirms significant deviation from normality. Meanwhile, Presco Plc had a higher average daily return of 0.1213% and greater return variability (standard deviation = 2.71%), alongside a positively skewed (0.1112) and leptokurtic (6.93) distribution, with a Jarque-Bera value of 1815.83 also confirming non-normality. Both stocks, with 2809 observations each, offer valuable insights for evaluating volatility and informing investment decisions in Nigeria's consumer staples sector. Figures 1(a) and 1(b) show the historical trend and return series of Nestle and Presco respectively.

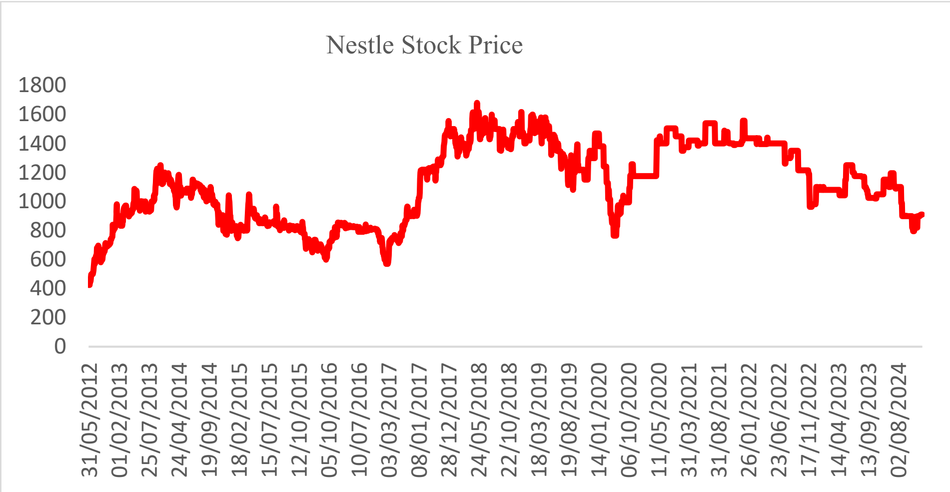

Figure 1a: Daily Time Plot of Nestle Stock Price in Nigeria from 2012 to 2024

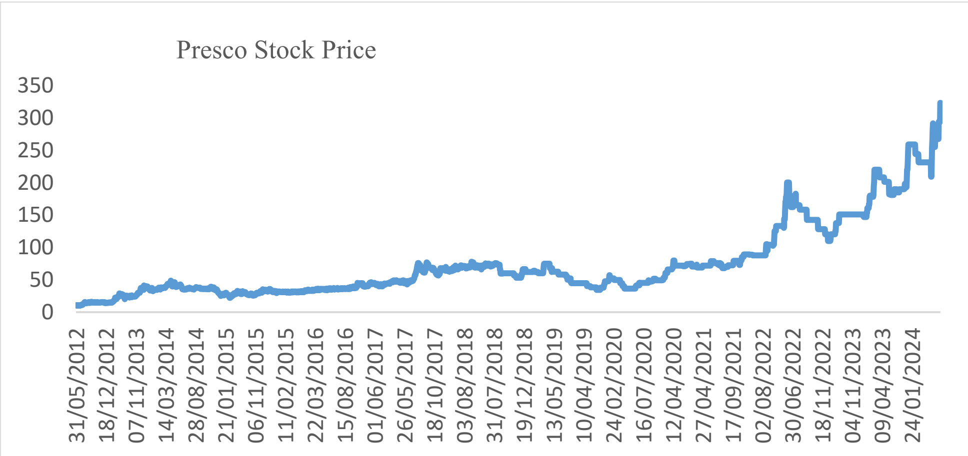

Figure 1b: Daily Time Plot of Presco Stock Price in Nigeria from 2012 to 2024

Figures 1(a) and 1(b), Presco stock price reveals an upward trend over the study period while Nestle Nigeria Plc stock experienced cyclical movement.

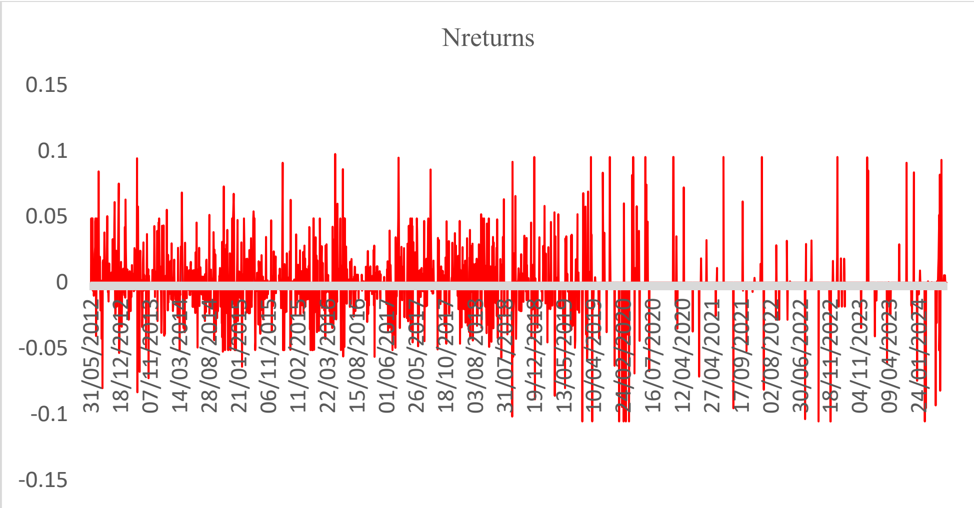

Figure 2a: Daily Return Plot of Nestle Nigeria Plc from 2012 to 2024

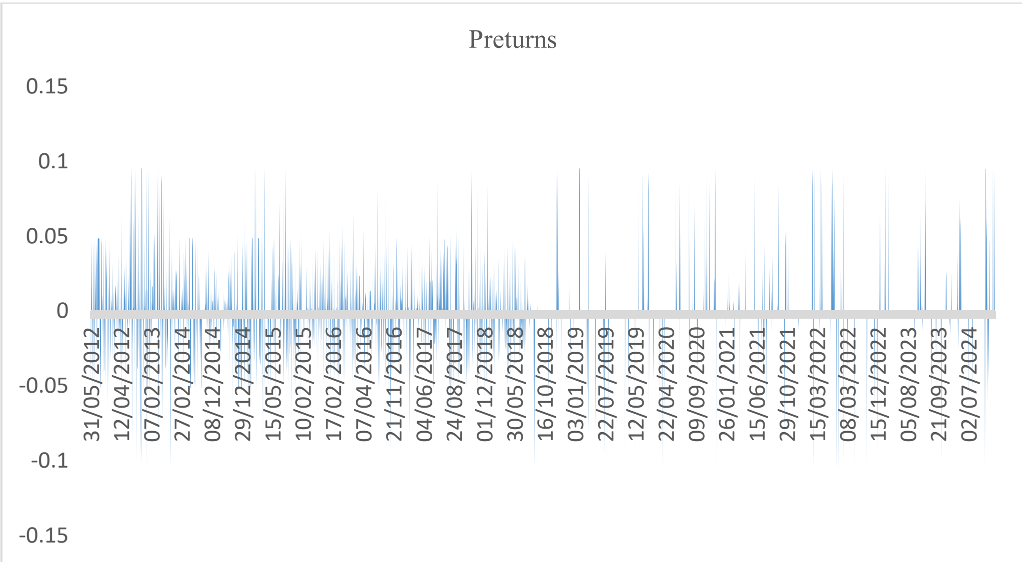

Figure 2b: Daily Return Plot of Presco Nigeria Plc from 2012 to 2024

In Figures 2(a) and 2(b), both stocks show evidence of volatility clustering. This indicates the presence of ARCH effects on the residuals of the time series. Table 3 confirms the presence of ARCH effects with the heteroskedasticity test.

Table 2: Augmented Dickey-Fuller Test for Stationarity

		Nestle Stock Price	**Presco Stock Price**
		t-Statistic	**t-Statistic**
Augmented Dickey-Fuller test statistic		-52.31426	-45.28762
Test critical values:	-3.432488	-3.432488	-3.432488
	-2.862370	-2.862370	-2.862370
	-2.567256	-2.567256	-2.567256
	Prob.*	0.0001	0.0000

The Augmented Dickey-Fuller (ADF) test results in Table 2 indicate that the stock prices of both Nestle Nigeria Plc and Presco Plc are stationary at their first differences, suggesting suitability for further time series modeling. For Nestle, the test statistic of -52.31426 with a p-value of 0.0001 strongly rejects the null hypothesis of a unit root, supported by a significantly negative lagged difference coefficient, an R-squared of approximately 49.38%, and a Durbin-Watson statistic close to 2, indicating no residual autocorrelation. Similarly, Presco's test statistic of -45.28762 and identical p-value also confirm stationarity, with regression results showing a meaningful negative coefficient, a significant intercept, an R-squared of 42.23%, and no signs of autocorrelation. These findings affirm the reliability of the stationarity assumption for both stock series. Table 3 presents the ARCH effect test.

Table 3: Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH			
Nestle Nig. Plc			
F-statistic	49.01073	Prob. F(1,2806)	0.0000
Obs*R-squared	48.20372	Prob. Chi-Square(1)	0.0000
Presco Plc			
F-statistic	60.55456	Prob. F(1,2806)	0.0000
Obs*R-squared	59.31762	Prob. Chi-Square(1)	0.0000

The ARCH test results in Table 3 provide strong evidence of autoregressive conditional heteroskedasticity (ARCH) effects in the stock returns of both Nestle Nigeria Plc and Presco Plc. For Nestle, the F-statistic of 49.01073 and ObsR-squared value of 48.20372, both with p-values of 0.0000, confirm the presence of ARCH effects, supported by a significant coefficient (0.131021) on the lagged squared residuals despite a low R-squared of 1.72%. Similarly, Presco Plc shows significant ARCH behaviour, with an F-statistic of 60.55456 and ObsR-squared of 59.31762, also with p-values of 0.0000, indicating time-varying volatility driven by past residual variances in both stocks.

Model Estimation Results

The result of the parameter estimates for the various GARCH-type models are presented in tables 4 and 5.

Table 4: Parameter estimates for ARCH/GARCH Models for Nestle Plc. Stock Returns

Parameter	ARCH	GARCH	EGARCH	TGRACH	PARCH	CGARCG	IGARCH
Constant (C)	-1.65E-05 (0.000374)	-8.95E-05 (0.000373)	0.000228 (0.000384)	9.98E-05 (0.000378)	0.000105 (0.000382)	-8.55E-05 (0.000371)	8.68E-05 (0.000348)
Intercept (β_o)	0.000348 (3.95E-06)	0.000104 (5.88E-06)	-2.751453 (0.149839)	0.000125 (6.95E-06)	0.000573 (0.000268)	0.000435 (1.44E-05)	
ARCH term (β_1)	0.196105 (0.020823)	0.123542 (0.010515)	0.257856 (0.015110)	0.216511 (0.021359)	0.142956 (0.011976)	0.857117 (0.010778)	0.005038 (0.000128)
GARCH term (α_1)		0.635611 (0.018764)	0.096355 (0.012569)	0.571917 (0.022012)	-0.311982 (0.037929)	0.072809 (0.008096)	0.994962 (0.000128)
Γ			0.664787 (0.018520)	-0.150097 (0.021232)	0.597817 (0.021606)	0.112512 (0.015667)	
d					1.0000		
Ø						-0.330115 (0.064266)	
ρ							
$\beta_1 + \alpha_1$		0.759153	0.354211	0.788428	-0.169026	0.929926	1.000
μ	0.000271	0.000271	0.000271	0.000271	0.000271	0.000271	0.000271
Log L	7007.386	7034.323	7042.919	7046.490	7047.901	7049.663	6943.729
AIC	-4.987103	-5.005570	-5.010978	-5.013520	-5.013813	-5.015068	-4.942491
SIC	-4.980758	-4.997111	-5.000404	-5.002946	-5.001124	-5.002379	-4.938262
Observed	2809	2809	2809	2809	2809	2809	2809

Note: Numbers in parenthesis indicates standard error

The evaluation of various volatility models for Nestle Plc stock returns from 2012 to 2024 in table 4 reveals that while all models show statistically significant ARCH and GARCH components, the CGARCH model emerges as the best fit. The ARCH model confirms significant short-term volatility effects, but its relatively low persistence and model fit make it less ideal. The GARCH model improves on this with a higher volatility persistence ($\beta_1 + \alpha_1 = 0.7592$) and better fit indicators. The EGARCH and TGRACH models further capture asymmetric effects, with EGARCH showing a strong leverage effect (Γ = 0.6648) and TGRACH indicating slight asymmetry. The PARCH model incorporates a shape parameter and asymmetry, yet exhibits negative persistence, suggesting reduced volatility retention over time. In contrast, the CGARCH model not only captures both short-term shocks (ARCH) and long-term volatility components (GARCH), but also exhibits the highest persistence ($\beta_1 + \alpha_1 = 0.9299$) and the lowest AIC (-5.0151) and SIC (-5.0024) values, indicating superior model performance. Although the IGARCH model reflects full persistence, its higher AIC and SIC values make it less favorable. Based on the model selection criteria, the CGARCH model is identified as the most suitable for modeling Nestle Plc's return volatility.

Table 5: Parameter Estimates for ARCH/GARCH Models for Presco Plc. Stock Returns

Parameter	ARCH	GARCH	EGARCH	TGRACH	PARCH	CGARCG	IGARCH
Constant (C)	0.000673	0.000366	0.000770	0.000745	0.000809	0.000420	0.001159
	(0.000479)	(0.000461)	(0.000468)	(0.000466)	(0.000466)	(0.000453)	(0.000446)
Intercept	0.000573	0.000120	-1.497376	8.29E-05	0.003870	0.000726	
(β_o)	(8.78E-06)	(8.07E-06)	(0.090698)	(5.55E-06)	(0.001379)	(5.01E-05)	
ARCH term	0.251926	0.145848	0.226492	0.184098	0.121990	0.991956	0.008567
(β_1)	(0.025539)	(0.012428)	(0.014187)	(0.016893)	(0.008421)	(0.001688)	(0.000354)
GARCH		0.695774	0.119681	0.776217	-0.537313	0.012063	0.991433
term (α_1)		(0.018084)	(0.012016)	(0.013289)	(0.053858)	(0.001819)	(0.000354)
Γ			0.812498	-0.146522	0.762640	0.159307	
			(0.011557)	(0.016637)	(0.013812)	(0.017107)	
D					1.0000		
Ø						0.475833	
						(0.039119)	
P							
$\beta_1 + \alpha_1$		0.841622	0.346173	0.960315	-0.415323	1.004019	1.000
μ	0.001213	0.001213	0.001213	0.001213	0.001213	0.001213	0.001213
Log L	6234.400	6307.015	6340.292	6327.834	6342.534	6327.760	6229.571
AIC	-4.436739	-4.487729	-4.510710	-4.501840	-4.511594	-4.501075	-4.434013
SIC	-4.430394	-4.479270	-4.500136	-4.491266	-4.498905	-4.488386	-4.429783
Observed	2809	2809	2809	2809	2809	2809	2809

Note: Numbers in parenthesis indicates standard error

The volatility modelling of Presco Plc stock returns from 2012 to 2024 involved evaluating several ARCH-type models, each capturing different aspects of time-varying variance. The ARCH and GARCH models in table 5 show significant ARCH and GARCH terms with high volatility persistence, particularly in the GARCH model ($\beta_1 + \alpha_1 = 0.8416$). The EGARCH model captures strong asymmetry ($\Gamma = 0.8125$) and a good model fit, indicating the presence of leverage effects, while the TGRACH model also indicates high persistence (0.9603) and slight asymmetry. The CGARCH model records the highest persistence ($\beta_1 + \alpha_1 = 1.0040$), though this may suggest overfitting or excessive sensitivity to past volatility. The IGARCH model confirms perfect persistence (sum = 1), but its relatively higher AIC and SIC values make it less desirable. Among all models, the PARCH model provides the best fit, with the lowest AIC (-4.511594) and one of the lowest SIC values (-4.498905), along with significant asymmetry ($\Gamma = 0.7626$) and flexibility in modelling the conditional variance via a shape parameter ($Ø = 0.4758$). These diagnostics confirm the PARCH model as the most appropriate for capturing Presco Plc's return volatility behavior over the study period.

According to the plots of the conditional volatilities of the fitted GARCH models, shown in Figures 3 and 4, the volatility models chosen represent the main trends as well as periods of high and low equity returns.

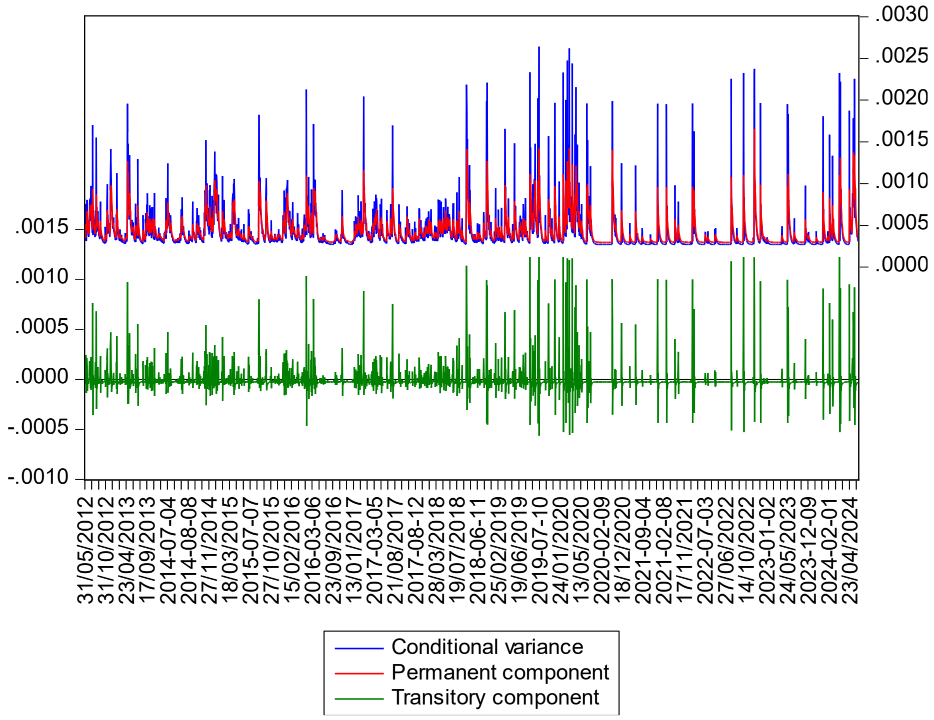

Figure 3: Conditional Volatilities from fitted CGARCH Model for Nestle Stock Returns

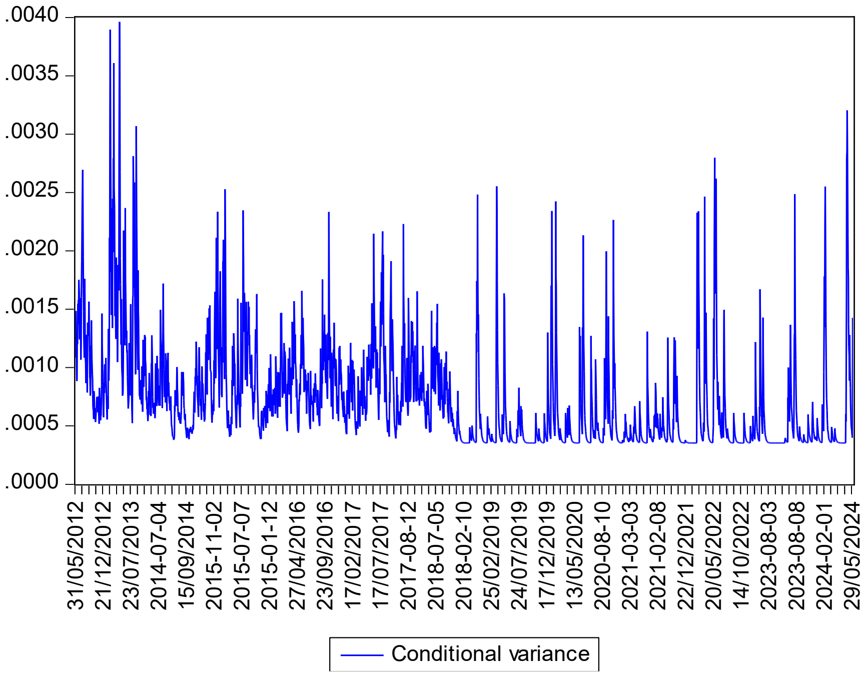

Figure 4: Conditional Volatilities from fitted PARCH Model for Presco Stock Returns

Model Diagnostic Checks

The diagnostic test carried out including Heteroskedasticity and Serial Correlation Tests are presented in tables 6 and 7

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

Heteroskedasticity Test: ARCH			
CGARCH(1,1) Nestle			
F-statistic	0.079994	Prob. F(1,2806)	0.7773
Obs*R-squared	0.080049	Prob. Chi-Square(1)	0.7772
PARCH (1,1) Presco			
F-statistic	0.081172	Prob. F(1,2806)	0.7757
Obs*R-squared	0.081228	Prob. Chi-Square(1)	0.7756

The diagnostic tests for the best-fitted GARCH family models, CGARCH(1,1) for Nestle Plc and PARCH(1,1) for Presco Plc presented in Table 6, confirm that both models are well-specified and effectively capture the volatility dynamics of their respective stock returns from 2012 to 2024. For Nestle Plc, the CGARCH model reports high p-values for both the F-statistic and the Chi-square test (0.7773 and 0.7772, respectively), indicating no significant remaining ARCH effects in the residuals and thus affirming the model's adequacy. Similarly, the PARCH model for Presco Plc yields high p-values (0.7757 and 0.7756), confirming the absence of residual ARCH effects and validating the model's specification. Furthermore, the Q-statistics for all lags, as shown in Table 7, indicate no evidence of serial correlation in the standardized residuals at the 5% significance level. This further reinforces the reliability of both models in capturing the volatility behaviour of these equities.

Table 7: Results of the Serial Correlation Tests for the Two Best Fit Volatility Models

	CGARCH (1,1) Nestle				PARCH (1,1) Presco			
Lag	**AC**	**PAC**	**Q-Stat**	**Prob***	**AC**	**PAC**	**Q-Stat**	**Prob***
1	-0.005	-0.005	0.0802	0.777	0.005	0.005	0.0809	0.776
2	-0.002	-0.002	0.0957	0.953	0.023	0.023	1.5470	0.461
3	0.017	0.017	0.9176	0.821	-0.014	-0.014	2.1151	0.549
4	-0.012	-0.012	1.3335	0.856	-0.020	-0.021	3.2558	0.516
5	-0.020	-0.020	2.4673	0.781	-0.008	-0.007	3.4244	0.635
6	0.001	0.000	2.4684	0.872	0.010	0.011	3.7022	0.717
7	-0.015	-0.014	3.0788	0.878	0.015	0.015	4.3449	0.739
8	-0.006	-0.006	3.1878	0.922	-0.017	-0.018	5.1259	0.744
9	0.001	0.001	3.1931	0.956	-0.018	-0.019	6.0809	0.732
10	-0.003	-0.003	3.2146	0.976	-0.027	-0.025	8.1263	0.616
11	0.022	0.022	4.5625	0.950	0.021	0.023	9.3852	0.586
12	-0.014	-0.014	5.1082	0.954	0.011	0.011	9.7373	0.639
13	0.023	0.023	6.6554	0.919	0.013	0.010	10.250	0.673

14	-0.015	-0.016	7.2889	0.923	-0.030	-0.032	12.821	0.541
15	0.029	0.029	9.5857	0.845	-0.020	-0.019	13.948	0.529
16	-0.007	-0.007	9.7382	0.880	0.015	0.018	14.543	0.558
17	-0.029	-0.029	12.146	0.791	0.002	0.003	14.560	0.627
18	0.006	0.006	12.260	0.834	-0.015	-0.019	15.177	0.650
19	-0.002	-0.002	12.270	0.874	-0.013	-0.014	15.621	0.682
20	-0.028	-0.026	14.530	0.803	-0.009	-0.007	15.864	0.725
21	-0.004	-0.006	14.578	0.844	0.024	0.029	17.563	0.676
22	0.002	0.001	14.591	0.879	-0.025	-0.026	19.388	0.621
23	0.025	0.027	16.356	0.840	0.007	0.003	19.537	0.670
24	0.044	0.042	21.882	0.586	-0.000	-0.002	19.537	0.723
25	-0.002	-0.001	21.893	0.642	0.000	0.002	19.538	0.771
26	-0.015	-0.018	22.502	0.661	-0.011	-0.009	19.887	0.797
27	-0.010	-0.010	22.793	0.696	0.033	0.032	22.948	0.688
28	0.001	0.002	22.798	0.743	0.026	0.024	24.932	0.632
29	-0.004	-0.001	22.834	0.784	-0.011	-0.014	25.278	0.664
30	0.032	0.033	25.795	0.686	0.001	0.002	25.282	0.711
31	-0.002	-0.000	25.803	0.731	0.021	0.026	26.528	0.696
32	0.007	0.008	25.932	0.767	0.015	0.013	27.145	0.711
33	0.049	0.048	32.763	0.479	-0.005	-0.007	27.218	0.750
34	0.013	0.012	33.274	0.503	-0.011	-0.015	27.588	0.773
35	0.037	0.039	37.167	0.369	-0.018	-0.014	28.558	0.771
36	0.042	0.041	42.133	0.223	0.021	0.024	29.810	0.757

Forecasting Performance

Figures 5 and 6 shows the forecasting performance of Nestle and Presco Stock Returns respectively.

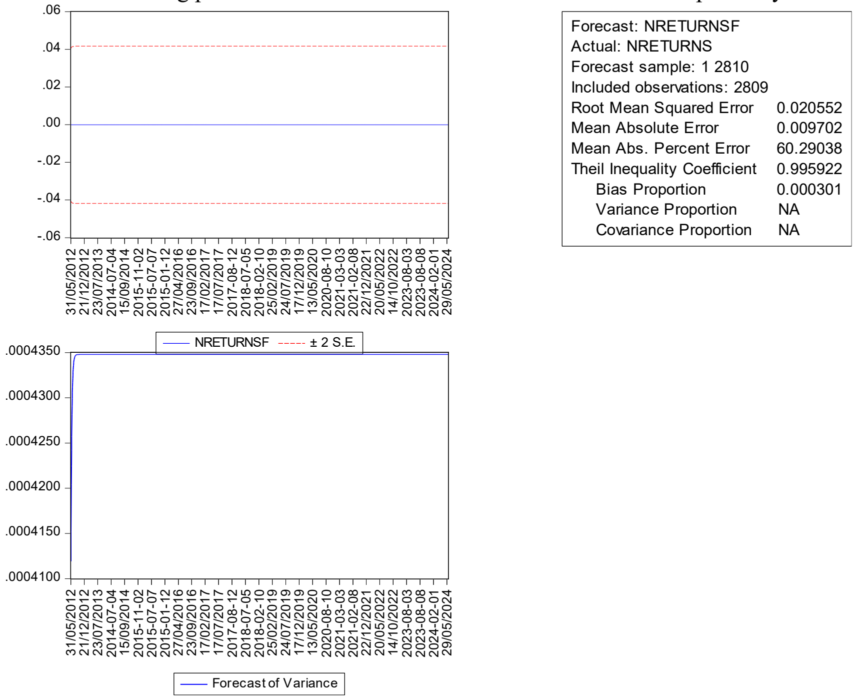

Figure 5: Forecast performance of Nestle Stock Returns

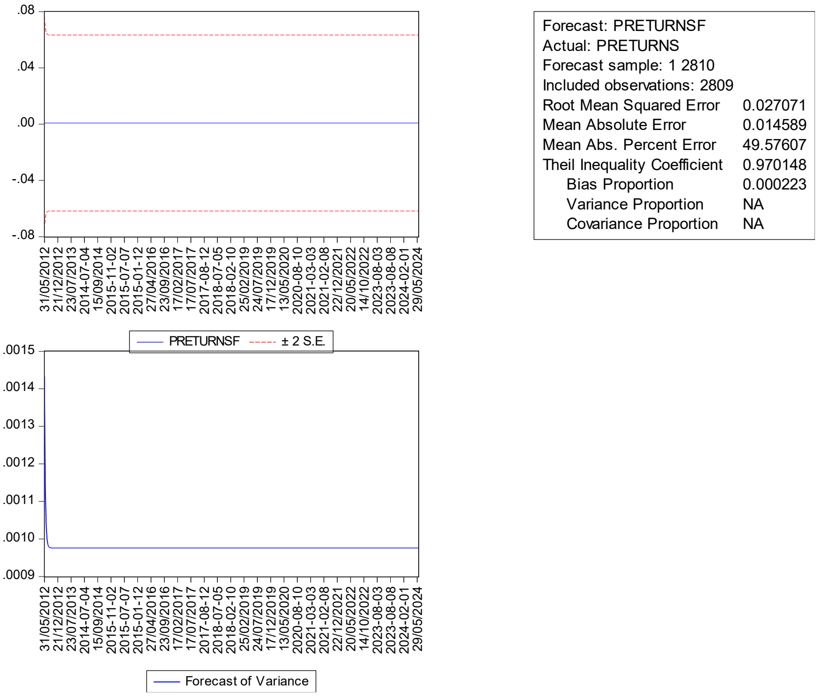

Figure 6: Forecast performance of Presco Stock Returns

The forecast evaluation of Nestle Plc and Presco Plc stock returns shows that both models produce low absolute errors and unbiased predictions. For Nestle Plc, the low RMSE (0.0206) and MAE (0.0097) indicate a strong fit in absolute terms. Although Presco Plc exhibits slightly higher absolute errors (RMSE = 0.0271, MAE = 0.0146), it demonstrates better relative performance than Nestle, reflected by a lower MAPE (49.58) and a more favorable Thiel's U statistic (0.970). Both models display very low bias proportions, suggesting that the forecast errors are largely random rather than systematically skewed.

CONCLUSION

This study finds that both Nestle Nigeria Plc and Presco Plc stocks exhibit substantial volatility, as reflected in their high standard deviations, positive skewness, and excess kurtosis, consistent with findings by Mohammed *et al.* (2022). The results reveal that Nestle Plc had an average return of 0.0271% with a standard deviation of 2.06%, indicating relative stability, while Presco Plc recorded a higher average return of 0.1213% and greater volatility with a standard deviation of 2.71%, reflecting higher risk return trade-offs. The confirmation of stationarity through the Augmented Dickey-Fuller test and the presence of significant ARCH effects justify the use of ARCH/GARCH models. Among the models evaluated, the CGARCH model best fits Nestle’s return data, while the PARCH model is most suitable for Presco, effectively capturing both short- and long-term volatility components. Forecast evaluations show mixed performance, with Nestle’s model displaying low absolute but high relative error, and Presco’s model yielding better relative accuracy. Therefore, CGARCH and PARCH models are recommended for modeling volatility in Nigeria’s consumer staple sector. These findings suggest Presco is attractive for risk-seeking investors, whereas Nestle appeals to risk-averse investors, with implications for portfolio diversification and policy interventions in consumer staples. The study’s limitations include its focus on two firms and reliance on secondary data, pointing to the need for future research using broader samples and advanced volatility models.

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