A COMPARISON OF GARCH-TYPE MODELS FOR VOLATILITY MODELLING IN THREE DIFFERENT SECTORS OF MARKETS

By

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Abstract

This study examines the performance of various volatility models and distributional assumptions in modelling financial time series data from the Nigerian market. Specifically, the research evaluates the fit of different distributions, Normal, Student's t, Generalized Error Distribution (GED), and Skew-t, within volatility models, including ARCH, GARCH, and EGARCH, to capture the time-varying volatility of nine selected securities. The performance of these models is assessed using three key performance metrics: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood. The results indicate that the EGARCH model with the t-distribution provides the best fit for most securities, outperforming the other models in terms of model selection criteria. While the EGARCH model with the Skew-t distribution is slightly less effective, it still performs well in comparison to the other models. Overall, the findings highlight the superior ability of EGARCH with the t-distribution to model financial volatility in this context, making it the most robust model for forecasting and risk management in the Nigerian financial market. This study contributes to the growing literature on volatility modelling by providing empirical evidence on the effectiveness of different distributional assumptions in emerging markets.

Keywords: Volatility Models, EGARCH, GARCH, ARCH, Distributional Assumptions

1. Introduction

Modelling financial time series presents a distinct challenge due to the non-linear and often erratic behaviour of asset returns, which frequently diverge from the assumptions underpinning classical financial models. Although the log-normal distribution has been widely used to describe asset price behaviour, empirical evidence increasingly suggests that it fails to capture the heavy tails and asymmetries present in real-world financial data. This has led to a growing interest in alternative distributions, such as the logistic and generalized logistic, which offer greater flexibility in capturing the observed extremes and tail behaviour in returns. Studies by Gray and French (2008), Nidhin and Chandran (2013), and more recently, Ahmad (2018) and An and Duah (2017), support the adoption of these distributions as more suitable for representing the statistical properties of financial indices. As such, there is a compelling rationale to revisit the distributional foundations of volatility models.

Standard linear models, such as ARIMA, have traditionally been used in forecasting financial data; however, these models assume homoscedasticity, which is often violated in financial time series. The introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle (1982) addressed this limitation by allowing the conditional variance to evolve based on past forecast errors. This innovation enabled the modelling of volatility clustering, a prominent feature of financial returns, thus paving the way for more sophisticated volatility modelling techniques.

Building on this foundation, Bollerslev (1986) proposed the Generalized ARCH (GARCH) model, which incorporated lagged conditional variances in addition to lagged squared residuals, providing a more comprehensive approach to modelling volatility persistence. To further refine this framework, extensions such as the EGARCH and TGARCH models were introduced to capture asymmetries and leverage effects inherent in financial markets. The EGARCH model, for instance, proposed by Nelson (1991), allows for the modelling of asymmetric volatility responses to positive and negative shocks, a critical feature for realistic financial modelling.

Recent literature has further highlighted the utility of GARCH-type models in analysing financial volatility across diverse market environments. Marisetty (2024), in a longitudinal study of five major global indices, demonstrated the efficacy of GARCH(1,1) and its variants in capturing market-specific volatility behaviours, particularly during periods of economic disruption such as the COVID-19 pandemic. Similarly, the comparative study by Agunobi, Pam, and Dauda (2024) revealed that the volatility dynamics of developed and emerging markets, such as the UK and Nigeria respectively, differ significantly, emphasizing the need for market-specific modelling approaches. These studies reinforce the relevance of GARCH frameworks for both theoretical and applied financial research.

However, while much attention has been given to the structure of GARCH models, the role of the assumed error distribution remains underexplored, particularly in emerging markets. Financial return series often exhibit skewness and kurtosis that deviate significantly from the normal distribution, which can result in misestimation of volatility and risk. To better accommodate these characteristics, researchers have increasingly adopted alternative distributions, such as the Student's t, Generalized Error Distribution (GED), and Skewed t, which better account for heavy tails and asymmetry. Despite this, there remains limited empirical consensus on which distribution offers the best performance within GARCH-type models, especially in markets like Nigeria where structural shifts and exogenous shocks are common.

Although numerous studies have explored the application of GARCH-type models in financial volatility modelling, limited empirical evidence exists regarding the comparative performance of different distributional assumptions within these models, particularly in the context of emerging markets such as Nigeria. Traditional reliance on the normal distribution often leads to underestimation of risk and poor volatility forecasting due to its inability to capture skewness and heavy tails in return series. There is, therefore, a need to investigate which assumed error distribution provides the most accurate and reliable volatility estimates when applied within GARCH-type frameworks across different asset classes in the Nigerian financial market.

The primary objective of this study is to evaluate and compare the performance of different assumed error distributions, specifically the Normal, Student's t, Generalized Error Distribution (GED), and Skewed t, within GARCH-type models, in order to determine which distribution best models, the conditional variance of financial returns in the Nigerian financial market.

2. Literature Review

Recent empirical literature has increasingly emphasized the limitations of traditional normality assumptions in financial return modelling, particularly in the presence of extreme market movements. In this context, the logistic and generalized logistic distributions have gained attention for their ability to capture heavy-tailed behaviour and extreme return events more effectively than the normal or log-normal distributions.

Several studies have demonstrated the empirical superiority of the logistic distribution over the normal distribution in modelling financial returns, particularly due to its heavier tails, which better accommodate the observed frequency of extreme values in return series. Gray and French (2008), as well as Nidhin and Chandran (2013), show that the logistic distribution offers a significantly improved fit for empirical option prices compared to the traditional Black-Scholes model, which assumes lognormality. Their findings highlight the potential benefits of incorporating non-Gaussian distributions in financial modelling, particularly when modelling asset price behaviour under volatile conditions.

Expanding on this, the generalized logistic distribution has been applied to capture the distributional characteristics of extreme market returns. Ahmad (2018) and An and Duah (2017) provide compelling evidence that the generalized logistic distribution can more accurately model the fat tails present in the return distributions of major indices, such as the Nikkei 225. These studies underscore the inadequacy of conventional models in capturing extreme risk events and support the adoption of more flexible distributional assumptions in financial econometrics.

In terms of volatility modelling, substantial research has examined the performance of various GARCH-type models in capturing time-varying volatility and asymmetric behaviours in financial returns. Marisetty (2024) conducted an extensive study analysing the volatility dynamics of five major global stock indices over a ten-year period using GARCH(1,1), EGARCH, and TGARCH models. The study particularly focused on the impact of global economic shocks, such as the COVID-19 pandemic, on market volatility. Results indicated significant cross-market heterogeneity, with emerging markets exhibiting more persistent volatility clustering than their developed counterparts. This underscores the importance of accounting for market-specific characteristics in volatility modelling.

Similarly, Setiawan et al. (2020) conducted a comparative analysis of EGARCH, TGARCH, and APARCH models to evaluate their forecasting accuracy in modelling stock return volatility. Their findings highlighted the critical role of asymmetric volatility and leverage effects, with the APARCH model emerging as the most robust in terms of predictive performance. This reinforces the growing consensus in the literature that symmetric models often fail to capture key stylized facts of financial returns, particularly in the presence of negative shocks.

Within the context of emerging markets, particularly Nigeria, empirical studies have validated the applicability and accuracy of asymmetric GARCH models. Ekong and Onye (2017) examined stock return volatility in the Nigerian stock market and concluded that the GARCH(1,1) and EGARCH(1,1) models with Generalized Error Distribution (GED) provided superior predictive accuracy. Their findings align with the broader literature, which suggests that financial markets in developing economies tend to exhibit heightened volatility persistence and clustering. Complementing this, Kuhe (2018) explored the role of structural breaks and exogenous shocks in the Nigerian equity market. The study found that incorporating such structural elements into volatility models significantly reduced the persistence of volatility and improved forecasting reliability.

Collectively, these studies emphasize the importance of using flexible volatility models and alternative distributional assumptions when analysing financial returns, particularly in the context of emerging markets. The evidence supports a paradigm shift away from conventional models toward approaches that better reflect empirical realities such as asymmetry, heavy tails, and regime shifts.

3. Material and Method

All computations are done on Jupyter Notebook using python programming language.

3.1 Data

The data that have been used were downloaded from Bloomberg. Financial instruments are chosen to cover different parts of the market (Table 1). The datasets are divided into three groups: index, currencies and stock/equity. Equities have been selected to represent some of Nigeria's largest companies.

Table 1: Security Information

	Security	Description
Index	NGSEBNK10	Banking Index
	NGSEINS10	Insurance Index
	NGSEOilG5	Oil & Gas Index
Currencies	USDNGN	Exchange rate between USD and NGN
	GBPNGN	Exchange rate between GBP and NGN
	EURNGN	Exchange rate between EUR and NGN
Stock	DANGCEM	Dangote Cement Plc
	GTCO	Guaranty Trust Holding Company Plc
	MTNN	MTN Nigeria Communications Plc

Source: Bloomberg

Each model is estimated using the adjusted closing price for each trading day for each security. The data used in the estimates are from January 2021 up to December 2024 for each dataset.

3.2 GARCH-type Models

The ARCH(q) model is defined as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{1}$$

where $\alpha_0 > 0, \alpha_i \geq 0,\ i = 1,2,3, \dots, q,$ the series is stationary if $\alpha_i < 1$. The ARCH model creates a process where today's variance depends on its own previous variance. This allows the model to capture the volatility clustering observed in financial markets. The α_i parameter explains how fast the model reacts to news on the market. The one step ahead forecast for the ARCH(1) model is done by using the equation,

$$\sigma_{t+1}^2 = \alpha_0 + \alpha_1 \varepsilon_t^2 \tag{2}$$

The GARCH(p,q) model adds a moving average term, making it similar to a regular ARMA(p,q) process. This allows a slower decay in variance from random shocks which is more coherent with observed data (Teräsvirta, 2009). The definition of the GARCH(p,q) model is

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

where $\alpha_0 > 0, \alpha_i \geq 0,\ i = 1,2,3, \ldots, q, \beta_j \geq 0,\ j = 1,2,3, \ldots, p$. The process will be stationary if $\alpha + \beta < 1$. If the stationarity condition is fulfilled the conditional variance will converge towards the unconditional variance $\frac{\alpha_0}{1-(\alpha_1+\beta_1)}$. The α_i parameter again explains how fast the model reacts to news on the market while β_j states how persistent the conditional heteroscedasticity is over time. If the β_j parameter is large, effects from economic news in the market will have a tendency to linger. The GARCH(1,1) is the most used model specification, often used as a benchmark model within this area. The one step ahead forecast for the GARCH(1,1) model is done by using the equation,

$$\sigma_{t+1}^2 = \alpha_0 + \alpha_1 \varepsilon_t^2 + \beta_1 \sigma_t^2 \tag{4}$$

The EGARCH(p,q) model captures the asymmetric effect on variance from positive and negative news (Nelson, 1991). From empirical data the market volatility seem to react differently depending on the sign of the shocks, negative shocks usually results in periods of higher volatility compared to positive news (Nelson, 1991). By including a third parameter the EGARCH allows the model to react differently depending on the different type of news. The EGARCH model is defined as

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i (|z_{t-i}| - E(|z|)) + \sum_{j=1}^{p} \beta_j \ln\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{q} \gamma_i z_{t-i} \tag{5}$$

where $z_{t-1} = \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ and $E(|z|)$ will depend on the assumed distribution, for a normal distribution $E(|z|) = \sqrt{\frac{2}{\pi}}$. If $\left(|z_{t-1}| - E(|z|)\right) < 0$ the market is returning less than expected, clearly a negative shock. If the estimation shows that $\gamma_i = 0$ it implies that the model is symmetric. However, if the estimation shows that $\gamma_i < 0$, it will imply that negative news cause a higher future volatility than a positive, hence the model is asymmetric. The EGARCH model differs from the ARCH and GARCH models because the logarithm of the variance is what is being estimated. By taking the logarithm of the conditional variance it ensures a positive value. The logarithm also relaxes the parameters constraint; they no longer need to be positive. α_i and β_j are still expected to have positive values. It is troublesome for inference and forecasting if they are negative. The γ_1 however is expected to have a negative value, which means that a negative shock in the market will increase the future volatility. The EGARCH model is stationary if $\beta < 1$. The one step ahead forecast for the EGARCH(1,1) model is done by using the equation,

$$\ln(\sigma_{t+1}^2) = \alpha_0 + \alpha_1(|z_t| - E(|z|)) + \beta_1 \ln(\varepsilon_t^2) + \gamma_1 z_t \tag{6}$$

3.3 Performance Metrics

The performance of the fitted models is evaluated using a set of well-established statistical criteria, namely: Akaike Information Criterion (AIC), Bayesian Information Criterion (SBIC), and the Log-Likelihood (LL). These metrics, defined in Equations (11) to (14), provide a rigorous framework for assessing the trade-off between model fit and complexity, which is essential for robust model selection in time series analysis.

The Akaike Information Criterion (AIC) is a widely adopted model selection tool that evaluates the goodness of fit while penalizing excessive model complexity. AIC is particularly useful for comparing non-nested models and is defined as:

$$AIC = -2\mathcal{L}(\theta) + 2k \tag{7}$$

where $L(\theta)$ is the log-likelihood of the model, and k is the number of estimated parameters. Among competing models, the one with the lowest AIC value is preferred, as it is presumed to offer the best compromise between explanatory power and parsimony.

The Bayesian Information Criterion (BIC), also referred to as the Bayesian Information Criterion (BIC), imposes a stricter penalty on model complexity than AIC, making it a more conservative criterion, especially useful in large-sample contexts or when overfitting is a concern. It is defined as:

$$SBIC = -2\mathcal{L}(\theta) + k\ln(n) \tag{8}$$

where n denotes the sample size. Similar to AIC, a lower BIC value indicates a better-fitting model, though the heavier penalty on complexity often favours more parsimonious models.

The Log-Likelihood (LL) function measures the probability of observing the given sample under the specified model. For GARCH-type models, it is derived from the conditional variance and residuals, as shown below:

$$\mathcal{L}(\theta) = -\frac{n}{2} log(2\pi) - \frac{1}{2}\sum_{t=1}^{n} \log(h_t) - \frac{1}{2}\sum_{t=1}^{n} \frac{e_t^2}{h_t} \tag{9}$$

Where:

$\mathcal{L}(\theta)$ is the log-likelihood;

n the number of observations;

h_t is the conditional variance at time t (calculated from the GARCH model).

e_t is the residual at time t

θ are the parameters of the GARCH model.

These criteria collectively provide a comprehensive basis for comparing alternative model specifications. While a higher log-likelihood implies a better fit, information criteria like AIC, SBIC, and HQIC adjust for model complexity, discouraging overfitting. When used in conjunction, these metrics enable the selection of models that are both statistically sound and practically applicable for forecasting and inference in financial time series.

4. Result and Discussion

4.1 Descriptive statistics

The table below display the summary statistics of the price of nine (9) securities.

Table 2: Price Summary for the Nine Securities

Security	Mean	Std	Min	Max	Skewness	Kurtosis
NGSEBNK10	572.97	227.56	336.46	1105.61	0.78	-0.93
NGSEINS10	257.65	103.21	150.60	718.00	1.23	0.87
NGSEOilG5	802.74	583.64	226.35	2715.72	1.48	1.54
USDNGN	735.38	460.48	380.55	1681.39	1.08	-0.53
GBPNGN	940.98	588.73	465.91	2232.18	1.11	-0.43
EURNGN	769.28	475.18	412.17	1863.16	1.27	-0.05
DANGCEM	349.84	150.53	204.00	763.00	1.35	0.42
GTCO	32.07	9.65	16.85	58.75	0.66	-0.44
MTNN	210.76	35.03	157.00	295.00	0.42	-0.80

Source: Author’s Computation, 2025

The price summary for the nine securities shown above indicate that the exchange rates and the oil and gas index are the most volatile. It reviewed that all assets exhibit positive skewness, implying a greater chance of large upward price movements. Also, it showed that most assets are either normally distributed or platykurtic, with a few showing signs of fat tails, suggesting the importance of using models that can accommodate asymmetry and non-normality in financial time series, such as GARCH-type models with non-normal error distributions.

The figure below presents a comparative time-series analysis of price levels and returns for a selection of financial assets and exchange rates in Nigeria over the period January 2021 to December 2024. Each row comprises two subplots: the left panel illustrates the temporal evolution of asset prices, while the right panel depicts the corresponding daily returns, computed as the logarithmic differences in consecutive price levels.

The exchange rate series (USD/NGN, GBP/NGN, and EUR/NGN) remain relatively stable until mid-2023, after which a sharp devaluation of the Nigerian naira is observed. This abrupt change aligns with a significant policy shift toward exchange rate liberalization. Prior to this devaluation, return volatility is notably subdued, but it escalates markedly in the post-liberalization period, highlighting heightened exchange rate uncertainty and increased market sensitivity to macroeconomic developments..

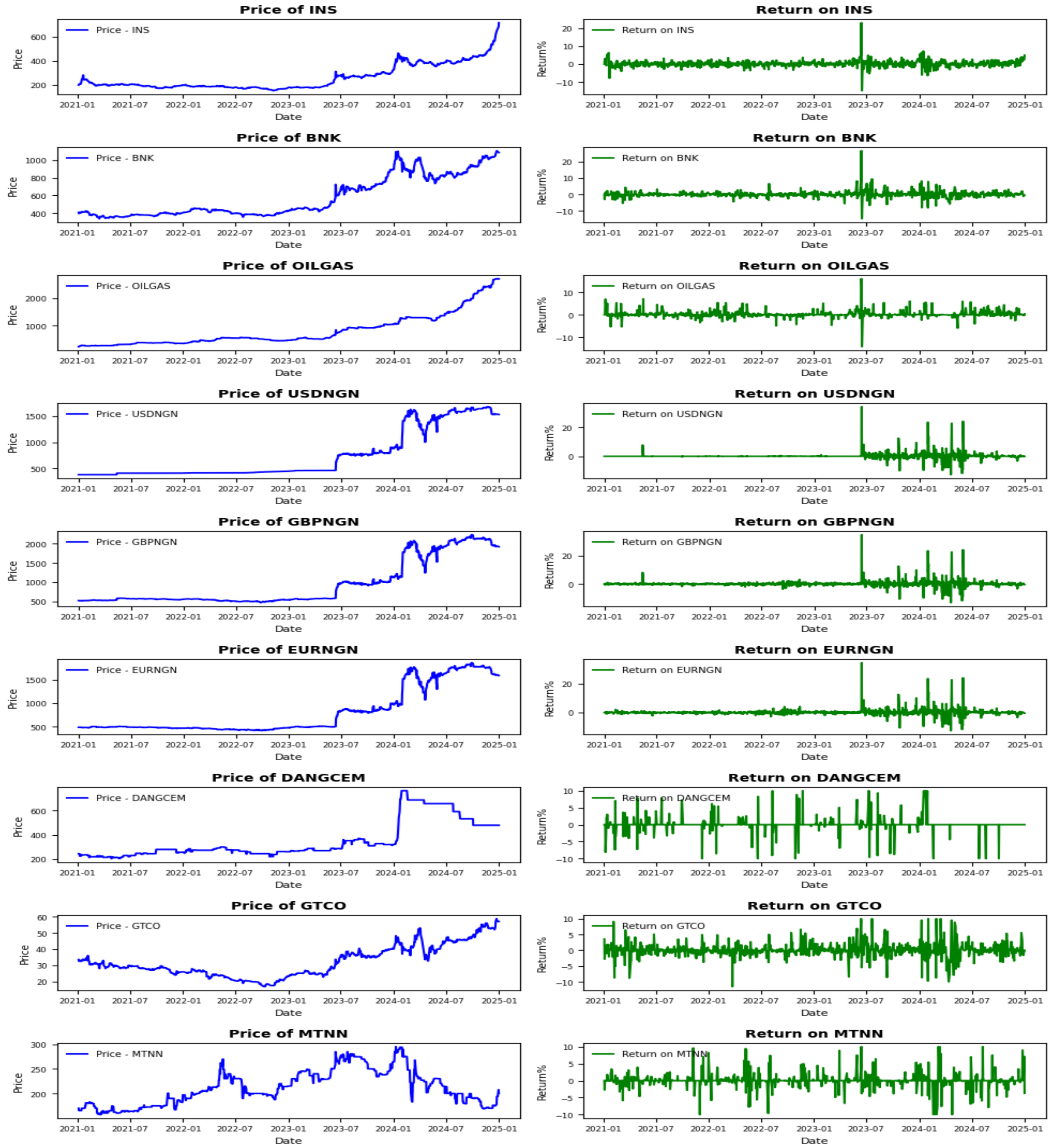

Figure 1: Line chart of price & return of the nine securities

The Insurance Sector Index (NGSEINS10) and the Banking Sector Index (NGSEBNK10) exhibit relatively flat price trends until early 2023, followed by a notable upward trajectory from mid-2023 through 2024. This pattern likely reflects a structural regime shift, possibly driven by sectoral reforms or improving investor sentiment. Return volatility for both indices remains moderate, with episodic spikes coinciding with key inflection points in price dynamics.

For the Oil and Gas Sector Index (NGSEOilG5), the analysis reveals a steady and consistent price increase throughout the observation period. This trend may indicate greater alignment with global energy market dynamics or ongoing reforms within the domestic energy sector. Return volatility is relatively contained, reinforcing the impression of sectoral stability.

A pronounced structural break is evident in the price of DANGCEM stock in early 2024, characterized by a rapid appreciation followed by a plateau. The corresponding return series displays heightened dispersion during this period, consistent with the presence of a price discontinuity. GTCO stock prices exhibit cyclical fluctuations, with a discernible upward trend beginning in 2023. This movement may reflect improved financial performance or strengthened investor confidence. Return spikes are sporadic but remain within a moderate volatility band. In contrast, MTNN exhibits more volatile price behaviour, with pronounced peaks and troughs particularly evident from mid-2022 onwards. The associated return series is more dispersed, suggesting a higher-risk profile relative to GTCO.

Overall, the assets and exchange rates analysed display heterogeneous temporal dynamics. The exchange rate series demonstrate a structural break around mid-2023, reflective of a macroeconomic policy shift. Sector indices (NGSEINS10, NGSEBNK10, NGSEOilG5) experience gradual gains, whereas individual equities such as DANGCEM and MTNN exhibit more idiosyncratic and abrupt movements. The corresponding return plots highlight periods of volatility clustering, particularly during episodes of structural or policy-driven price adjustments. These findings are consistent with established financial market theories, particularly those relating to market efficiency, volatility transmission, and structural breaks in emerging economies.

4.2 Presentation of Results

Table 3: Stationarity test for various securities

Security	ADF Test – No differencing	
	Statistic	p-value
NGSEBNK10	-8.7819	0.00000
NGSEINS10	-6.5088	0.00000
NGSEOilG5	-12.5186	0.00000
USDNGN	-6.9983	0.00000
GBPNGN	-6.8241	0.00000
EURNGN	-7.2154	0.00000
DANGCEM	-8.6277	0.00000
GTCO	-22.7115	0.00000
MTNN	-13.0585	0.00000

Source: Author's computation, 2025

To test for stationarity, the Augmented Dickey-Fuller (ADF) test was done. For all the securities, the ADF test results strongly suggest that the null hypothesis of a unit root can be rejected at 1% significance level, as evidenced by the highly negative t-statistics and p-values of 0.0000. This indicates that the returns of these securities are stationary without requiring differencing, and they are well-suited for modelling and forecasting, as their statistical properties do not change over time.

Table 4 summarizes the results of ARCH effect tests across various Nigerian financial securities. The F-statistics and corresponding p-values indicate whether each time series exhibits significant autoregressive conditional heteroskedasticity (ARCH effects). All NGSErelated assets (BNK10, INS10, OilG5, DANGCEM, GTCO, MTNN) show strong evidence of ARCH effects with very high F-statistics and p-values of 0.0000, indicating statistically significant volatility clustering. Among the currency series, USDNGN and GBPNGN also display significant ARCH effects (p-values < 0.05), while EURNGN has a borderline p-value of 0.0527, suggesting weak or marginal evidence. Overall, most of the series exhibit time-varying volatility, justifying the use of ARCH or GARCH models for better modelling and forecasting.

Table 4: ARCH Effects

ARCH Effects	NGSE BNK10	NGSE INS10	NGSE OilG5	USDNGN	GBPNGN	EURNGN	DANGCEM	GTCO	MTNN
F-statistic	85.0638	146.4021	270.5070	12.3839	12.0598	10.9344	118.0020	111.5971	54.8595
p-value	0.0000	0.0000	0.0000	0.0299	0.0340	0.0527	0.0000	0.0000	0.0000

Source: Author's computation

Table 5: Performance Metrics of Fitted Models for various Securities

	Security	Model	Distribution	LL	AIC	BIC
	Banking	ARCH	Normal	-1799.34	3604.67	3619.36
			t	-1637.24**	3282.47**	3302.06**
			GED	-1645.78	3299.56	3319.15
			Skewt	-1637.21**	3284.43**	3308.92**
		GARCH	Normal	-1734.97	3477.95	3497.54
			t	-1607.02	3224.03	3248.52
			GED	-1612.86	3235.72	3260.21
			Skewt	-1606.57**	3225.15**	3254.53**
		EGARCH	Normal	-1737.46	3484.92	3509.41
			t	-1604.51	3221.03	3250.41
			GED	-1612.34	3236.68	3266.07
			Skewt	-1604.35	3222.71	3256.99
	Insurance	ARCH	Normal	-1831.26	3668.52	3683.21
			t	-1733.06	3474.12	3493.71
			GED	-1741.28	3490.56	3510.15
			Skewt	-1733.06	3476.12	3500.61
		GARCH	Normal	-1727.29	3462.58	3482.17
			t	-1706.19	3422.39	3446.88
			GED	-1704.92	3419.85	3444.34
			Skewt	-1706.17	3424.33	3453.72
		EGARCH	Normal	-1718.54	3447.07	3471.56
			t	-1695.97	3403.95	3433.33
			GED	-1696.38	3404.76	3434.15
			Skewt	-1695.94	3405.88	3440.16
	Oil&Gas	ARCH	Normal	-1725.94	3457.87	3472.56
			t	-1194.42**	2396.83**	2416.42**
			GED	-1292.03	2592.05	2611.64
			Skewt	-1181.95**	2373.91**	2398.40**
		GARCH	Normal	-1714.91	3437.82	3457.41
			t	-1188.16	2386.32	2410.81
			GED	-1280.77	2571.55	2596.04
			Skewt	-1173.17	2358.35	2387.73
		EGARCH	Normal	-1670.38	3350.75	3375.24
			t	-1154.57	2321.14	2350.53

	Security	Model	Distribution	LL	AIC	BIC
			GED	-1253.10	2518.19	2547.58
			Skewt	-1149.93	2313.87	2348.15
Currency	USDNGN	ARCH	Normal	-2189.90**	4385.80**	4400.65**
			t	22.43*	-36.85*	-17.06*
			GED	-1001.96	2011.92**	2031.72**
			Skewt	29.40*	-48.81*	-24.06*
		GARCH	Normal	-2091.01**	4190.02**	4209.82**
			t	-2.21*	14.42*	39.17*
			GED	-424.06*	858.115*	858.87*
			Skewt	-35038.10	70088.10	70117.80
		EGARCH	Normal	-2014.97	4039.94	4064.69
			t	476.314*	-940.628*	-910.929*
			GED	-717.504	1447.01	1476.71
			Skewt	545.240*	-1076.48*	-1041.83*
	GBPNGN	ARCH	Normal	-2248.92**	4503.83**	4518.68**
			t	-1484.00**	2976.00**	2995.80**
			GED	-1622.88**	3253.76**	3273.56**
			Skewt	-1483.96**	2977.96**	3002.71**
		GARCH	Normal	-2170.69	4349.37	4369.17
			t	-1408.43**	2826.85**	2851.60**
			GED	-1495.56	3001.12	3025.87
			Skewt	-1408.37**	2828.74**	2858.44**
		EGARCH	Normal	-2099.30	4208.60	4233.35
			t	-1394.20	2800.41	2830.10
			GED	-1498.69	3009.38	3039.08
			Skewt	-1393.39	2800.78	2835.43
	EURNGN	ARCH	Normal	-2465.15	4936.30	4951.50
			t	-1551.15**	3110.31**	3130.57**
			GED	-1705.08	3418.16	3438.42
			Skewt	-1550.90**	3111.79**	3137.13**
		GARCH	Normal	-2355.43	4718.87	4739.14
			t	-1458.13	2926.26	2951.60
			GED	-1539.82	3089.65	3114.99
			Skewt	-1458.13	2928.26	2958.66
		EGARCH	Normal	-949819*	0.0000*	0.0000*
			t	-1445.58	2903.16	2933.56
			GED	-1580.60	3173.20	3203.60
			Skewt	-1445.56	2905.11	2940.59
Stock	DANGCEM	ARCH	Normal	-1982.19*	3970.39*	3985.08*
			t	1735.40*	-3462.80*	-3443.21*
			GED	-1023.19	2054.37	2073.96
			Skewt	463.494*	-916.987*	-892.499*
		GARCH	Normal	-1976.30	3960.60	3980.19
			t	-1047.30	2104.60	2129.09
			GED	-1010.38	2030.76	2055.25
			Skewt	-1672.48	3356.97	3386.35
		EGARCH	Normal	-1984.85	3979.69	4004.18
			t	3007.86*	-6003.71*	-5974.32*
			GED	-1020.32	2052.63	2082.02
			Skewt	-3045.10	6104.19	6138.48
	GTCO	ARCH	Normal	-2073.77	4153.54	4168.22
			t	-1842.90**	3693.80**	3713.37**
			GED	-1848.14	3704.28	3723.85
			Skewt	-1840.49**	3690.98**	3715.45**
		GARCH	Normal	-2027.71	4063.42	4082.99
			t	-1818.80**	3647.59**	3672.06**
			GED	-1816.28	3642.55	3667.02

	Security	Model	Distribution	LL	AIC	BIC
			Skewt	-1817.37**	3646.74**	3676.10**
		EGARCH	Normal	-2026.66	4063.32	4087.79
			t	-1810.28	3632.56	3661.92
			GED	-1814.16	3640.32	3669.68
			Skewt	-1809.80	3633.60	3667.86
	MTNN	ARCH	Normal	-2082.32	4170.64	4185.34
			t	-1113.82	2235.64	2255.23
			GED	-1476.32	2960.64	2980.23
			Skewt	-1113.53	2237.06	2261.55
		GARCH	Normal	-2001.24	4010.48	4030.07
			t	-1034.18	2078.35	2102.84
			GED	-1402.39	2814.79	2839.28
			Skewt	-1034.17	2080.34	2109.72
		EGARCH	Normal	-2022.82	4055.65	4080.14
			t	-6467.68	12947.40	12976.70
			GED	-1415.39	2842.79	2872.18
			Skewt	-1062.57	2139.14	2173.42

AIC is Akaike Information Criterion, BIC – Bayesian Information Criterion, LL is Log Likelihood
GED is Generalized Error Distribution, t is Students-t, Skewt is Skewstudent-t,
* No convergence
** Sum of parameters is >= 1.0

The above table provides performance metrics for different GARCH-type models applied to various securities. The key metrics to evaluate the models are the Log-Likelihood (LL), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

The EGARCH (t) model has the lowest AIC indicating the best performance for the Banking index. GARCH (t) and EGARCH (Skew-t) models also performed well but slightly worse than EGARCH (t). For the Insurance Index, the EGARCH (t) model has the lowest AIC (3403.95), indicating the best performance for the index. EGARCH (GED) and EGARCH (Skew-t) models also performed well but slightly worse than EGARCH (t). For the Oil & Gas Index, the EGARCH (Skew-t) has the lowest AIC (2313.87) and BIC (2348.15), indicating it is the best-performing model. GARCH (Skew-t) and EGARCH (t) also performed well. Since EGARCH allows for asymmetry in volatility, its superior performance suggests that volatility in the three (3) index reacts differently to positive and negative shocks. The preference for the t and Skew-t distributions further accounts for heavy tails and skewness in return distributions, meaning large price movements are more common than a normal distribution would predict.

The EGARCH (GED) provide the best fit for USD/NGN currency pair. ARCH (GED) also performed well but slightly worse than EGARCH (GED) for this pair. For GBP/NGN and EUR/NGN currency pairs, the EGARCH (t) model best fit the data, the EGARCH (Skew-t) also performed well but it was slightly worse than the EGARCH (t) for both pairs. Also, the GARCH (Skew-t) also performed well for EUR/NGN pair. Currency markets often exhibit extreme movements (jumps and crashes), making heavy-tailed distributions (t and Skew-t) better suited for modelling exchange rate volatility.

The GARCH (GED) model has the lowest AIC & BIC and the largest log-likelihood indicating the best performance for the DANGCEM (Dangote Cement stock). ARCH (GED) and EGARCH (GED) models also performed well but slightly worse than GARCH (GED). For

GTCO, EGARCH (t) and EGARCH (Skew-t) are the best models with the students-t distribution slightly outperforming Skew-t distribution. Finally, the GARCH (t) distribution narrowly outperformed the GARCH (Skew-t) distribution as the best fit model with regards to the MTNN security leaving these two as the best models. The performance of Skew-t and t-distributions implies that stock price returns are characterized by fat tails and occasional large deviations from the mean. The high performance of EGARCH (t) for GTCO suggest that the stock returns exhibit asymmetric volatility patterns.

In addition, the performance metric table above highlighted that GARCH-type models with t-distributions and Skew-t distributions consistently outperform those with Normal and GED distributions, confirming the presence of heavy tails in financial return data. EGARCH models mostly provide the best performance by outperforming GARCH and ARCH models, highlighting the importance of asymmetry in volatility modelling. GARCH models occasionally outperform ARCH models, especially in the stock market, suggesting that in some cases, volatility is more persistent rather than short-lived.

Table 6: Parameter Estimates of ARCH Models with different Conditional Distributions

Security		ARCH - Normal		ARCH - Student t		ARCH - GED		ARCH – Skewstudent t	
		ω	α_1	ω	α_1	ω	α_1	ω	α_1
NGSEBNK10	Estimate	1.4645	0.6023	1.8003	1.0000	1.1587	0.6081	1.8071	1.0000
	Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
NGSEINS10	Estimate	1.5813	0.5467	1.5267	0.4808	1.5099	0.4767	1.5267	0.4817
	Prob	0.0000	0.0018	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NGSEOilG5	Estimate	1.7649	0.1109	3.5875	1.0000	0.7817	0.1294	4.7227	1.0000
	Prob	0.0000	0.0187	0.0312	0.0055	0.0000	0.0357	0.1330	0.0023
USDNGN	Estimate	3.0836	1.0000	0.0011	0.9999	0.2156	1.0000	0.0001	1.0000
	Prob	0.0939	0.4720	0.1110	0.0000	0.1030	0.0001	0.1280	0.0000
GBPNGN	Estimate	3.1955	1.0000	1.2142	1.0000	0.8354	1.0000	1.2157	1.0000
	Prob	0.1890	0.6950	0.0000	0.0000	0.0000	0.0018	0.0000	0.0000
EURNGN	Estimate	3.2252	0.6357	1.8843	1.0000	0.7864	0.7025	1.8936	1.0000
	Prob	0.0282	0.2510	0.0002	0.0000	0.0000	0.0089	0.0002	0.0000
DANGCEM	Estimate	2.8164	0.2644	0.0000	0.0009	0.4130	0.1737	0.0000	0.0002
	Prob	0.0000	0.0002	0.9990	0.8900	0.0000	0.0127	0.573	0.0214
GTCO	Estimate	3.1120	0.3224	3.7174	1.0000	1.9673	0.4341	3.7888	1.0000
	Prob	0.0000	0.0001	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000
MTNN	Estimate	3.6280	0.1132	0.1801	0.6926	1.1564	0.0826	0.1809	0.6907
	Prob	0.0000	0.0358	0.7200	0.6680	0.0000	0.0413	0.7200	0.6680

Source: Author's Computation, 2025

The estimation results from the ARCH models indicate significant variations in volatility persistence across different asset classes in the Nigerian financial market. Exchange rates, particularly USD/NGN, GBP/NGN, and EUR/NGN, exhibit high volatility persistence, as evidenced by α_1 estimates approaching unity across multiple model specifications. This finding is consistent with recent studies on exchange rate dynamics, which suggest that foreign exchange markets tend to exhibit long memory and persistent volatility due to macroeconomic shocks and speculative trading (Balcilar et al., 2023). In contrast, the sector indices, such as NGSEBNK10 and NGSEINS10, demonstrate moderate volatility persistence, with α_1 values ranging from 0.48 to 0.61, indicating a relatively faster mean-reverting process. The oil and gas index (NGSEOilG5), however, exhibits stronger volatility persistence under Student's t and Skewed Student's t distributions, aligning with findings that energy sector volatility is highly sensitive to global crude oil price fluctuations (Bouri et al., 2022).

Moreover, the choice of distributional assumptions significantly affects the estimated parameters, with Student's t and Skewed Student's t models generally yielding higher α_1 estimates than the Normal and GED specifications. This suggests that accounting for fat tails and skewness improves the model's ability to capture extreme market movements, a key characteristic of financial time series data (Choudhry & Jayasekera, 2023). Notably, the volatility of individual stocks, such as GTCO and MTNN, varies across models, reflecting firm-specific risk factors and potential structural breaks in volatility dynamics (Nelson, 1991). Additionally, the statistical insignificance of the ARCH parameters for DANGCEM under certain model specifications suggests that alternative volatility models, such as the GARCH or EGARCH frameworks, may be more appropriate for capturing its return dynamics. These results underscore the importance of selecting appropriate distributional assumptions when modeling volatility in emerging markets, as misspecified models may underestimate or overestimate risk exposure, leading to suboptimal investment and risk management decisions.

The parameter estimates from the ARCH models indicate varying levels of volatility persistence across different securities, with notable differences based on the assumed error distribution. Across models, the persistence parameter (α_1) is close to or equal to 1 for most exchange rates (USD/NGN, GBP/NGN, EUR/NGN), suggesting strong volatility clustering, consistent with findings in emerging market volatility studies (Balcilar et al., 2023). For equities, estimates vary, with financial sector stocks like GTCO exhibiting moderate volatility persistence. The selection of distributions influences parameter stability, as highlighted in recent comparative studies of volatility forecasting models (Choudhry & Jayasekera, 2023).

Table 7a: Parameter Estimates of GARCH Models with different Conditional Distributions

Security		GARCH - Normal			GARCH - Student t		
		ω	α_1	β	ω	α_1	β
NGSEBNK10	Estimate	0.1425	0.2359	0.7435	0.1357	0.2604	0.7396
	Prob	0.0578	0.0184	0.0000	0.0295	0.0007	0.0000
NGSEINS10	Estimate	0.2255	0.2450	0.6717	0.1788	0.1676	0.7532
	Prob	0.0210	0.0132	0.0192	0.1210	0.0380	0.0000
NGSEOilG5	Estimate	0.1929	0.0623	0.8418	0.3565	0.3290	0.6710
	Prob	0.0748	0.0829	0.0000	0.2930	0.0326	0.0342
USDNGN	Estimate	0.4555	0.2381	0.7619	0.0340	0.5682	0.4210
	Prob	0.3850	0.0448	0.0000	0.0000	0.0000	0.0000
GBPNGN	Estimate	0.5185	0.2689	0.7311	0.1243	0.3200	0.6800
	Prob	0.5340	0.3870	0.0000	0.0007	0.0000	0.0000
EURNGN	Estimate	0.2990	0.1377	0.8391	0.0528	0.0722	0.9278
	Prob	0.4640	0.1010	0.0000	0.0472	0.1580	0.0000
DANGCEM	Estimate	1.5157	0.1883	0.4068	0.0014	0.0973	0.6455
	Prob	0.0066	0.0020	0.0127	0.0658	0.707	0.0211
GTCO	Estimate	0.2265	0.1404	0.8225	0.5553	0.3864	0.6136
	Prob	0.0796	0.0159	0.0000	0.0822	0.0001	0.0000
MTNN	Estimate	0.1615	0.0781	0.8888	0.0002	0.5808	0.3680
	Prob	0.0602	0.0015	0.0000	0.8850	0.7450	0.0205

Source: Author's Computation, 2025

Table 7b: Parameter Estimates of GARCH Models with different Conditional Distributions

Security		GARCH - GED			GARCH - Skewstudent t		
		ω	α_1	β	ω	α_1	β
NGSEBNK10	Estimate	0.1147	0.2284	0.7419	0.1340	0.2560	0.7440
	Prob	0.0275	0.0045	0.0000	0.0306	0.0012	0.0000
NGSEINS10	Estimate	0.2205	0.2070	0.7010	0.1763	0.1655	0.7559
	Prob	0.1380	0.0442	0.0000	0.1180	0.0386	0.0000
NGSEOilG5	Estimate	0.0966	0.0470	0.8110	0.5148	0.1663	0.8337
	Prob	0.1050	0.0591	0.0000	0.8380	0.0079	0.0000
USDNGN	Estimate	0.0045	0.3151	0.6849	0.0047	0.4371	0.5589
	Prob	0.5220	0.1520	0.0000	0.8910	0.0000	0.0730
GBPNGN	Estimate	0.0653	0.2944	0.7056	0.1241	0.3181	0.6819
	Prob	0.1260	0.0061	0.0000	0.0008	0.0001	0.0000
EURNGN	Estimate	0.0261	0.0773	0.8831	0.0527	0.0720	0.9280
	Prob	0.4330	0.5760	0.0000	0.0462	0.1560	0.0000
DANGCEM	Estimate	0.2017	0.1011	0.3892	1.0693	0.2817	0.1348
	Prob	0.0691	0.0670	0.0899	0.0002	0.0066	0.4850
GTCO	Estimate	0.2171	0.1975	0.7324	0.5679	0.3821	0.6179
	Prob	0.0428	0.0038	0.0000	0.0630	0.0000	0.0000
MTNN	Estimate	0.0624	0.0562	0.8350	0.0002	0.5807	0.3681
	Prob	0.1160	0.0074	0.0000	0.8850	0.7450	0.0204

Source: Author's Computation, 2025

The GARCH model estimates reveal significant differences in volatility persistence across various financial instruments, influenced by the choice of distributional assumptions. Across all models, the sum of α_1 (short-term volatility impact) and β (long-term persistence) is close to unity for most assets, indicating high volatility clustering, particularly in exchange rates such as USD/NGN and EUR/NGN, where β exceeds 0.90 in certain specifications. This aligns with prior research suggesting that currency markets exhibit strong volatility persistence due to macroeconomic uncertainties (Balcilar et al., 2023). Sector indices like NGSEBNK10 and NGSEINS10 show moderate volatility persistence, with β values ranging from 0.67 to 0.75, indicating that volatility shocks decay at a faster rate compared to exchange rates. Notably, oil and gas sector volatility (NGSEOilG5) exhibits lower α_1 estimates under some models, suggesting that external shocks may have less immediate impact but linger over time, consistent with studies on commodity-linked equities (Bouri et al., 2022). Additionally, the choice of distribution significantly affects parameter estimates; for instance, under the Student's t and Skewed Student's t distributions, equity volatility persistence tends to be higher, reflecting the ability of these distributions to capture heavy-tailed return characteristics (Choudhry & Jayasekera, 2023). These findings emphasize the necessity of selecting appropriate distributional assumptions when modelling volatility to ensure accurate risk assessment and forecasting in emerging markets.

Table 8a: Parameter Estimates of EGARCH Models with different Conditional Distributions

Security		EGARCH - Normal				EGARCH - Student t			
		ω	α_1	γ	β	ω	α_1	γ	β
NGSEBNK10	Estimate	0.1273	0.4618	0.0497	0.8962	0.1574	0.5265	-0.0020	0.9207
	Prob	0.0340	0.0001	0.2380	0.0000	0.0394	0.0002	0.9580	0.0000
NGSEINS10	Estimate	0.0440	0.2389	0.1109	0.9448	0.0314	0.1659	0.0960	0.9591

	Prob	0.0239	0.0027	0.0007	0.0000	0.0165	0.0017	0.0000	0.0000
NGSEOilG5	Estimate	0.0538	0.0336	0.1590	0.9003	0.3142	0.4926	0.1135	0.9513
	Prob	0.0199	0.4710	0.0002	0.0000	0.5030	0.2980	0.4940	0.0000
USDNGN	Estimate	0.0659	0.0658	-0.0451	0.9809	0.2036	0.7946	0.4685	0.9681
	Prob	0.1940	0.0795	0.2990	0.0000	0.0134	0.0000	0.0000	0.0000
GBPNGN	Estimate	0.6428	1.2986	0.4178	0.8372	0.0693	0.2281	-0.1274	0.9808
	Prob	0.1180	0.0094	0.2140	0.0000	0.1280	0.0024	0.0129	0.0000
EURNGN	Estimate	-0.0047	-0.0121	0.0301	0.9978	0.1355	0.2503	-0.0978	0.9835
	Prob	0.0029	0.0415	0.0214	0.0000	0.2320	0.0825	0.2380	0.0000
DANGCEM	Estimate	0.6482	0.3552	0.0531	0.5895	-7.8232	0.0784	0.0775	0.4733
	Prob	0.0154	0.0000	0.2680	0.0017	0.0000	0.0000	0.0000	0.0000
GTCO	Estimate	0.1537	0.3105	0.0269	0.9223	1.5891	1.8221	0.1969	0.8508
	Prob	0.0224	0.0010	0.4430	0.0000	0.3630	0.3180	0.4310	0.0000
MTNN	Estimate	0.1459	0.1967	-0.0162	0.9398	3.2824	-38.5362	14.0125	1.0000
	Prob	0.0073	0.0013	0.6470	0.0000	0.9730	0.9980	0.9850	0.9980

Source: Author's Computation, 2025

Table 8b: Parameter Estimates of EGARCH Models with different Conditional Distributions

Security		EGARCH - GED				EGARCH - Skewstudent t			
		ω	α_1	γ	β	ω	α_1	γ	β
NGSEBNK10	Estimate	0.0929	0.4696	0.0176	0.9064	0.1540	0.5200	-0.0029	0.9211
	Prob	0.0478	0.0006	0.8150	0.0000	0.0410	0.0003	0.9390	0.0000
NGSEINS10	Estimate	0.0369	0.1915	0.1025	0.9528	0.0314	0.1666	0.0967	0.9589
	Prob	0.0207	0.0019	0.0000	0.0000	0.0169	0.0016	0.0000	0.0000
NGSEOilG5	Estimate	-0.0355	0.0890	0.1123	0.9009	0.2972	0.4364	0.1070	0.9458
	Prob	0.1530	0.0241	0.0103	0.0000	0.5340	0.3420	0.5010	0.0000
USDNGN	Estimate	-0.0283	0.0710	-0.0489	0.9887	0.4675	1.2324	0.3706	0.9900
	Prob	0.5280	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GBPNGN	Estimate	0.0218	0.1345	-0.0614	0.9873	0.0784	0.2400	-0.1350	0.9792
	Prob	0.1120	0.0176	0.1520	0.0176	0.1400	0.0040	0.0157	0.0176
EURNGN	Estimate	0.0476	0.4327	-0.0380	0.8953	0.1369	0.2522	-0.0990	0.9834
	Prob	0.0825	0.0000	0.4050	0.0000	0.2350	0.0856	0.2410	0.0000
DANGCEM	Estimate	-0.1585	0.2196	0.0441	0.7163	10.4386	16.1716	-24.6011	0.9440
	Prob	0.2250	0.0040	0.1870	0.0004	0.0293	0.0145	0.0000	0.0000
GTCO	Estimate	0.1424	0.4019	0.0379	0.8900	1.5901	1.8055	0.2018	0.8485
	Prob	0.0067	0.0000	0.0263	0.0000	0.4410	0.3990	0.4780	0.0000
MTNN	Estimate	0.0331	0.1975	-0.0061	0.9252	-0.1433	0.2652	0.0290	0.9521
	Prob	0.1060	0.0000	0.8180	0.0000	0.7200	0.4160	0.4950	0.0000

Source: Author's Computation, 2025

The EGARCH model estimates provide key insights into the asymmetric nature of volatility across various financial instruments. Across all specifications, the persistence parameter (β) is consistently close to one, indicating strong volatility clustering in the time series, particularly for currency pairs such as USD/NGN and EUR/NGN, where β exceeds 0.98. This supports prior findings that exchange rates exhibit long memory in volatility due to macroeconomic and geopolitical uncertainties (Balcilar et al., 2023). The leverage effect parameter (γ) varies across assets, suggesting differential responses to positive and negative shocks. For instance, NGSEINS10 and NGSEOilG5 exhibit significant positive γ values under most distributions, implying that positive shocks increase volatility more than negative shocks, which is consistent with evidence from sectoral equity markets (Choudhry & Jayasekera, 2023). Conversely, some assets, such as GBPNGN and EURNGN, show negative or insignificant γ values, indicating that negative shocks may not necessarily amplify volatility, potentially due to market interventions or structural factors (Bouri et al., 2022). The choice of distribution plays a crucial role in the model's performance, under the Student's t and Skewed Student's t distributions, the α_1 parameter (capturing the immediate impact of shocks) is generally higher, reflecting the ability of these distributions to better capture the heavy-tailed nature of financial returns. Notably, the DANGCEM stock exhibits extreme parameter instability in the Skewed Student's t distribution, suggesting that this distribution may not be well-suited for modelling its volatility dynamics. These findings emphasize the importance of accounting for asymmetry and distributional choices when modelling volatility in emerging market assets.

5. Conclusion

This study presents a comprehensive analysis of volatility dynamics across various financial instruments in the Nigerian market, utilizing ARCH and GARCH-type models with alternative distributional assumptions. The empirical results consistently demonstrate that models incorporating asymmetry, particularly the EGARCH framework, and heavy-tailed distributions such as the Student's t and Skewed t, provide superior performance across multiple asset classes. The persistent outperformance of EGARCH models underscores the importance of accounting for asymmetric responses to market shocks, a characteristic prevalent in financial markets where negative and positive shocks exert unequal effects on volatility.

The analysis reveals notable differences in volatility persistence across asset classes. Exchange rate series such as USD/NGN, GBP/NGN, and EUR/NGN exhibit high levels of volatility clustering, with persistence parameters nearing unity, aligning with evidence that currency markets are prone to prolonged volatility due to macroeconomic and geopolitical uncertainties (Balcilar et al., 2023). In contrast, sectoral indices, particularly NGSEBNK10 and NGSEINS10, show moderate volatility persistence and a more rapid decay of shocks, indicative of a relatively mean-reverting process. The oil and gas sector index (NGSEOilG5) demonstrates stronger persistence under heavy-tailed distributions, consistent with the sector's sensitivity to global energy price shocks (Bouri et al., 2022).

Further, the leverage effect captured by the EGARCH model highlights heterogeneity in how different assets respond to shocks. Significant positive asymmetry in certain sectors, such as insurance and oil and gas, suggests that positive returns may exacerbate volatility more than negative ones, a finding consistent with sector-specific investor behaviours and structural dynamics (Choudhry & Jayasekera, 2023). Conversely, some currency pairs display minimal or negative asymmetry, potentially reflecting regulatory interventions or stabilizing mechanisms in the forex market.

From a methodological standpoint, the findings emphasize the critical role of selecting appropriate distributional assumptions. The superior performance of models using Student's t and Skewed t distributions confirms the prevalence of fat tails and non-normal return distributions in financial data. Moreover, the underperformance and instability of certain models, such as the Skewed Student's t for DANGCEM, underscore the need for asset-specific model calibration to avoid misestimation of risk.

In conclusion, this study affirms that volatility modelling in emerging markets benefits significantly from flexible model structures that incorporate asymmetry and accommodate distributional flexibility. These findings carry important implications for risk management, portfolio optimization, and policy formulation, as accurate volatility forecasts are essential for navigating the complexities of financial markets in developing economies.

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