Transition E-Garch Model for Modeling and Forecasting Volatility of Equity Stock Returns in Nigeria Stock Exchange

Olugbode M. A[1], Shittu O. I.[2]

[1]Federal School of Statistics, Ibadan.

[2]Department of Statistics, University of Ibadan.

DOI: https://dx.doi.org/10.47772/IJRISS.2023.7012162

Received: 26 October 2022; Accepted: 06 January 2024; Published: 24 January 2024

ABSTRACT

The mean-equations that exhibit unconditional variance do not reflect real-world data characteristics and do not always fully embrace the thick tail properties of high-frequency financial time series. However, there are cases when mean-equations exhibit conditional and unconditional variances, which conventional Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models do not accommodate with assumptions of normal error innovation. The behaviour of equity in stock returns volatility was investigated using mean-equations that reflect both conditional and unconditional variances under the variants innovation distribution.

The Nigeria Stock Exchange's, (NSE's), daily All Stock Index, (ASI) data from 3rd May 1999 to 18th March 2019 was utilized to characterize the volatility structure of equity in Nigeria Stock returns. The Transition Exponential GARCH Model (TEGM) with non-normal innovations was used to demonstrate the dynamic model performance and predictive power in modeling variances that transit between unconditional and conditional structures. Under various error innovations, the structural characteristics of the TEGM were examined, and the parameters were estimated.

The TEGM result under Student's t innovation distribution was significant for forecasting and predicting random series data. The error distribution has both the minimal and sufficient requirements for the best predictive capacity and forecasting capabilities. Over a longer period, the NSE's daily ASI showed more unconditional variance than conditional variation.

The Transition Exponential GARCH Model was found to be the best model for describing the volatility structure of financial assets in Nigerian stock returns, and is thus recommended for making informed investment decisions with better forecast performance.

Keywords: Transition parameters, volatility structural, non-normal innovation, equity and stock returns

INTRODUCTION

This paper captured the distinctive feature of volatility structure of equity in stock returns. The autocorrelation of stock returns residuals dependency, unconditional and conditional variances as well as leptokurtosis were applied. Mean-variance equations are devised to assess volatility due to the problem of

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

heteroscedasticity in financial time series data processing. The use of varieties of models to predict volatility, empirical features, theoretical framework, and asset valuation practice across time, ranging from the most basic models like random walks to the more complex Conditional Heteroscedasticity GARCH family models. Using regime switching between unconditional and conditional variances of volatile series, the distinguishing characteristics of stylized facts of financial stock returns have not been addressed.

The paper aims at dynamic model that transitions between unconditional and conditional variances in evaluating volatility and projecting equity in stock returns for risk management in random series data.

The Transition Exponential GARCH Model (TEGM) with conditional variance changes over time as a function of the transition parameter, which gives weight to unconditional variance, previous error term, and past conditional variance. The test statistic confirms the relevance of the TEGM parameter estimates with conditional variance to change overtime as a function of the transition between unconditional and conditional variances.

The study looked at the model's flexibility by switching between unconditional and conditional variances under non-normal innovations, with the goal of reflecting the volatility features of random series data. The mean-equation of conditional variance for random series data can flip between unconditional and conditional variances when modeling volatility and forecasting under non-normal error innovations.

The objective of this study is to account for the TEGM's flexibility with non-normal innovations, which may effectively represent variances with shifts in unconditional and conditional structure for superior performance and predictive forecast results of random series data. By assuming regime switching between unconditional and conditional variance as an improved volatility modeling, such as GARCH family model, TEGM, potential and empirical properties, theoretical assumptions, and asset valuation practice over time in terms of measuring, analyzing, and assessing equity in stock returns under variants innovation distributions was established as a comprehensive model for risk management that incorporates the stylized reality of skewed stock returns of random series data.

However, it has been demonstrated that developing a model that completely captures the dynamics of financial markets is difficult. Simpler models, according to some academics, provide the best forecast. For instance, Akgiray (1989) and Dimson and Marsh (1990) found that simple models like Random Walk (RW), Historical Mean (HM), Moving Average (MA), and Exponential Smoothing (ES) were the most effective in anticipating volatility. Others, on the other hand, have stressed the utility of traditional GARCH models in anticipating volatility.

The supremacy of the GARCH model is demonstrated by Emenike (2010). Also, Dumitru and Chritiana (2010) emphasized the value of the E-GARCH model, which has a reduced forecast error. The GARCH family of models has a diversity of discoveries and a shared superiority.

Olugbode (2021), compared conventional GARCH models with TEGM,, which is more flexible and capable of handling data with both symmetry and asymmetry volatility characteristics when using non-normal innovation distributions. The results show that threr is a a more robust volatility forecast that can be used for risk management, investment policy formulation, price derivation, and hedging portfolio selection. The results shows that TEGM is more accurate, satisfying the necessary and adequate conditions of the best performing and forecasting equity in stock return volatility model for risk management, investment policy formulation, price derivation, and hedging portfolio selection of the ASI of the NSE's.

LITERATURE REVIEW

Volatility is a term that defines the risk and uncertainty that come with financial investments, and it has a significant impact on financial decision-making and policy-making. Modeling stock returns for taking a free risk decision has piqued the interest of academics and investors alike, with models ranging from the simplest, such as the RW, to the more intricate GARCH family models built and applied to economic events.

Emenike (2010) used the GARCH (1,1) and GJR-GARCH (1,1) models to analyze the behavior of stock return volatility on the Nigerian Stock Exchange returns, assuming the Generalized Error Distribution. The NSE's monthly All Share Indices provided the empirical sample for examining the series' volatility persistence and asymmetry properties from May 1999 to December 2008. The findings of the study show that volatility clustering does exist. The GARCH (1,1) model suggests that the NSE return sequence's volatility is persistent. The GJR-GARCH (1,1) model, Emenike, also revealed the presence of leverage effects in the series. The ARCH/GARCH models were utilized by Goudarazi and Ramamarryaman (2011) and Akgul and Sayyan (2005) to estimate and forecast stock market volatility in India.

Dana Al-Najjar (2016) investigated the influence of Jordan's capital market volatility on clustering, leptokurtosis, and leverage. His findings show that symmetric ARCH/GARCH models match the characteristics of the Amman Stock Exchange (ASE) and provide additional evidence for both volatility clustering and leptokurtic, but the E-GARCH performance shows no evidence of leverage impact in ASE stock returns. The overall GARCH (1,1) and E-GARCH (1,1) results for the top performing GARCH family model in analyzing Nigerian stock returns have been changed, indicating that of the substantial likelihood of a negative investment return.

To explain the volatility clustering and unconditional variance with high tail distribution observed in financial time series, Omorogbe et al. (2017) applied the ARCH and GARCH models. They also stressed the homoscedasticity assumption, which permits regression equation predictions to be used to anticipate the dependent variable. The homoscedasticity assumption is invalidated by the fact that virtually all financial time series have varying variance. As a result, a mechanism that allows the variance to be influenced by its prior history and has variations that transit between conditional and unconditional structures are necessary. The parameters of the innovation distributions are estimated using the maximum-likelihood estimation (MLE) method. The best fitting distribution was used to show the method for obtaining the model's parameters.

Christopher and Kenneth (2017) propose alternative error distributions to Generalized Error Doistribution (GED) based on lowest Root Mean Square Error, (RMSE) and Thiel's Inequality coefficient for modeling Nigerian stock returns in order to provide robust volatility forecasting for wise policy decisions and optimal investment portfolios.

According to Lin (2018), securities markets, in general, have significant concerns with fluctuation. Understanding how to compute pricing, risk management, and portfolio selection, he argued, was necessary for anticipating volatility. He went on to say that financial series are inherently stochastic, and that stock price volatility, particularly return, is not constant. He also believes that the markets have quiet moments and others when they are characterized by high frequency, moderate, or low fluctuations. This is referred to as a heteroskedastic quality in statistics, because it demonstrates that volatility is not constant. Because of the variances, a flexible model capable of capturing the series' unique attribute of unpredictability is needed. He went on to say that there are two ways to quantify volatility: historical volatility (based on historical data) and implied volatility (derived from the market price of a traded security). He investigated the forecasting effectiveness of various extensions of GARCH models of (MSE) with composite index in his research. The findings show that the Shanghai composite index's volatility has significant time-varying and volatility clustering characteristics. Good estimates were found in both symmetric and asymmetric models. The most effective model was identified to be the E-GARCH model.

Awalludin et al. (2018), modelled the stock price return volatility in the Indonesian stock market. The volatility was calculated using GARCH (1, 1), and it revealed indications of volatility clustering in a few stocks. The GARCH (1, 1) linear model captures volatility clustering well. The natural cubic spline function was used to fit the volatility series, and the parameters were obtained using the Maximum Likelihood method.

Wellington and Bonga (2019), used GARCH family models to analyse Zimbabwe Stock Exchange volatility. The results of their study shows ARCH effect in which E-GARCH (1, 1), turned out to be the best model using both Achaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The study concluded that both positive and negative have different effects on the shocks market returns series.

Khera and Yadav, (2020) predict stock market volatility in emerging economies. The adjusted daily closing price of eleven countries is evaluated over a five-year period. The volatility and stock return of these countries were forecasted using various GARCH orders. It was discovered that the volatility of every stock return may be predicted. The terms ARCH and GARCH are crucial in every situation. The sum of their coefficients is significant enough to indicate the persistence of the volatility. The overall persistency of shock is highest in China's stock return and lowest in Chile's stock exchange because the sum of their parameters is highest in China and lowest in Chile. When the total is less than one, the mean reverting GARCH model is implied where refers to a first order ARCH term (i.e., news about volatility from the previous period) and a first order GARCH term (i.e., persistent coefficient) respectively.

When the results of short and long run shock persistence are examined, it is shown that long run shock is more persistent than short run shock because their is larger than their. Michael (2020), used GARCH to model and predict EUR/USD and GBP/USB currency and found out that a drop in volatility for the last 30 days in a visual inspection of actual 5 days.

Olugbode, (2021), compared TEGM with the conventional GARCH volatility models, his results show that TEGM is more accurate and converges quickly to the global limit with a more robust estimate, satisfying the necessary and adequate conditions of the best performing and forecasting stock return volatility model for risk management, investment policy formulation, price derivation, and hedging portfolio selection of the ASI of the NSE. He further stressed that, the TEGM has a better volatility modeling potential resistant to violations of empirical and theoretical assumptions when modeling random series data.

METHODOLOGY

The study used fourteen (14) years data of the Daily All Stock Index of the Nigeria Stock Exchange (ASI of NSE's) from 3rd May 2006 to 18th March 2019.

The statistical hypothesis of autocorrelation in square returns and or ARCH effect for effective prediction of Standard GARCH model was examined. The sample series test, p-values for asymmetry rule of 'NO ARCH EFFECT' for the mean-equation was also to be considered appropriate for modeling Nigeria Stock Exchange.

The conditional variance changes overtime as a function of the transition parameter, giving weight to unconditional variance, previous error term, and past conditional variance. TEGM is a more flexible model in improving shock assumptions.

Using a more dynamic model to capture volatility characteristics more effectively, with the goal of examining the model's versatility in terms of regime switching of the transition parameter, "ψ ". The conditional variance changes overtime as a function of the transition parameter "ψ ", is giving weight to unconditional variance, previous error term, and past conditional variance. The TEGM is a more flexible model in improving shock assumptions. This dynamic model is used to capture volatility characteristics more effectively, with the goal of examining the model's versatility in terms of regime switching of the transition parameter" ψ " between unconditional and conditional variances. The TEGM model system is a mean-variance equation for forecasting volatility under varying distributions, including normal and non-normal.

Let the equation for a linear trend model be given as:

$$Y_t = a + bX_t + e_t \quad 1$$

where Y_t is the dependent variable, X_t is the response variable, e_t is the error term and $e_t \sim N(0, \sigma_t^2)$

Let AR (1) be the mean equation of a dynamic model

$$Y_t = \phi Y_{t-1} + e_t \quad 2$$

with $e_t = \sigma_t^2 Z_t$ where $Z_t \sim N(0,1)$

The unconditional variance is given by

$$\mu_t = \frac{\omega}{1-\sum_{i=1}^{p}\alpha_i - \sum_{j=1}^{q}\beta_j} \quad 3$$

Let's describe the GARCH ("p,q") conditional variance process with the AR (p) mean equation as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i\chi_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 \quad 4$$

with i=1,2,3,....,p j=1,2,3,....,q where χ_{t-i}^2 is the lag error term, σ_{t-j}^2 is the pass conditional variance and ω, α_i and β_j are constants to be estimated.

If "p=q=1" in equation (3.4), the model is the GARCH (1,1) process with AR (1) mean equation, the conditional variance is defined as:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad 5$$

The assumed transition parameter " ψ " will allow the variance to transition from unconditional to conditional variance and back. Assume " ψ " is the transformation parameter, and $\psi+(1-\psi)=1$. The general equation for the Transition GARCH phase is then as follows:

$$\sigma_{tcv}^2 = \psi\sigma_{uv}^2 + (1-\psi)\,\sigma_t^2 \quad 6$$

where $0 < \psi < 1$,
$\sigma_{ucv}^2 = \mu_t$ is the unconditional variance, σ_t^2 is the conditional variance and σ_{tcv}^2 is the transition conditional variance.

The TEGM is given by

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

$$\sigma^2_{tEGv}=\psi\mu_t+(1-\psi)\left(\omega+\left(\alpha_1\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|-\gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)+log\beta_1\sigma^2_{t-1}\right)\right) \qquad 7$$

where $0 < \psi < 1$, ψ is the transition parameter, α_1, γ and β_1 are ARCH, GARCH and leverage effects.

Estimation of TEGM Process under Student's t-innovation.

The error term is assumed to follow student's t-distribution with the probability density Function (pdf) given as follows:

$$f(\varepsilon_t, v)=\frac{\Gamma(\frac{v+1}{2})}{\sigma_{ct}\,\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}}\left(1+\frac{\varepsilon_t^2}{\sigma^2_{ct}(v-2)}\right)^{-(v+1)/2} \qquad 8$$

Where $Y_t = \mu_t + \varepsilon_t$ and $\varepsilon_t = Y_t - \mu_t$

Taking the likelihood function of the pdf above we have

$$L(\theta)=f(\varepsilon_t, \ldots\varepsilon_N/ , \beta,\varepsilon_1, \ldots,\varepsilon_m)=\sum_{i=2}^{N}\Pi\frac{\Gamma(\frac{v+1}{2})}{\sigma_{ct}\,\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}}\left(1+\frac{\varepsilon_t^2}{\sigma^2_{ct}(v-2)}\right)^{-(v+1)/2} \qquad 9$$

The log-likelihood function of equation 9 is given as:

$$InL(\theta)=NIn\left[\frac{\pi(v-2)\,\Gamma\left(\frac{v}{2}\right)^2}{\Gamma\left(\frac{v+1}{2}\right)^2}\right]+\sum_{t=1}^{n} In\,\sigma^2_{ct}-\frac{(v+1)}{2}\sum_{t=2}^{n} In\left[1+\frac{\varepsilon_t^2}{\sigma^2_{ct}(v-2)}\right] \qquad 10$$

Put (9) into (10) we have

$$InL(\theta)=NIn\left[\frac{\pi(v-2)\,\Gamma\left(\frac{v}{2}\right)^2}{\Gamma\left(\frac{v+1}{2}\right)^2}\right]+\sum_{t=1}^{n} In\left\{\left(\psi\mu_{tE}+(1-\psi)\left(\omega+\left(\alpha_1\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|-\gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)+log\beta_1\sigma^2_{t-1}\right)\right)\right)\right\}-$$

$$\frac{(v+1)}{2}\sum_{t=1}^{n} In\left[1+\frac{\varepsilon_t^2}{\left(\psi\mu_{tE}+(1-\psi)\left(\omega+\left(\alpha_1\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|-\gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)+log\beta_1\sigma^2_{t-1}\right)\right)\right)(v-2)}\right] \qquad 11$$

Differentiating equation (11) with respect to $\mu_{tE}, \omega, \alpha_1, \gamma, \beta_1, and\ \phi_1$ to obtain their Maximum Likelihood Estimation (MLES)

Procedures for evaluating the best performing model.

To compare which models best represent the data set's performing abilities, we apply the knowledge of information criterion for the model comparison metrics in GARCH Modelling.

The Schwarz Bayesian Information Criterion (SBIC) obtained for the model necessary condition for the best performance.

The **SBIC** is defined as:

SBIC = -2*ln(**L**) + ln(N)*k, 12

where:

L is the likelihood of the model under the MLE parameter estimate k = k is the number of parameters in the model and
N = number of observations.

RMSE is used to assess predicting errors of different models for a single dataset rather than across datasets because it is scale-dependent. The RMSE is always positive, and a value of 0 (rarely achieved in practice) indicates that the data is properly fitted. In general, a smaller RMSE is better to a greater one. Comparisons between different types of data will be erroneous because the calculation is based on the magnitude of the numbers utilized.

RMSE is the square root of the average of squared errors. Each error's effect on RMSE is proportional to the squared error's size; consequently, larger errors have a disproportionately significant effect on RMSE. As a result, RMSE is susceptible to outliers. The square root of the mean square error is the RMSE of an estimator with respect to an estimated parameter. The MSE and RMSE formulas are equations 13 and 14 respectively:

$$MSE=\frac{1}{T}\sum_{t=1}^{T}(r_t^2-\widehat{\sigma_{ct}^2})^2 \quad 13$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t^2-\widehat{\sigma_{ct}^2})^2} \quad 14$$

where r_t^2 represents the actual observed variance value and σ_{ct}^2 the predicted variance value of the model estimator. The RMSE is the square root of the variance, also known as the standard deviation, for an unbiased estimator.

RESULTS AND DISCUSSION

The plot is a popular approach to examine the normality of a dataset. Leptokurtosis is indicated by the data plot. The non-normal innovation distribution, the presence of leptokurtosis and second-order dependency, and the kurtosis and skewedness coefficients were all validated.

In addition, the graph shows a proxy for predicting the likelihood of volatility clustering in the dataset. The statistical hypothesis, on the other hand, looks at auto correlation in square returns and/or the ARCH effect to see if volatility is uniform or significantly different.

TABLE 1: Descriptive Statistics of Real-Life Data and Its Returns of ASI of NSE from 3rd May 1999 to 18th March, 2019.

STATISTICS	Daily Close Index of ASI of NSE	Daily Stock Returns of ASI of NSE
Mean	32633.36	0.0000345
Median	30195.56	-0.00000127
Maximum	66371.20	0.052762
Minimum	19732.34	-0.076558
Standard Deviation	10089.64	0.005147
Skewness	1.123188	-0.0221102
Kurtosis	3.827403	27.78674
Jarque-Bera	771.5091***	82737.57***
Observation	3231	3231

Source: Output of descriptive statistics of close index and stock returns of ASI of NSE

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

Figures 1 – 4 showing the Nigeria Stock Exchange's All Stock Index from May 1999 to March 2019

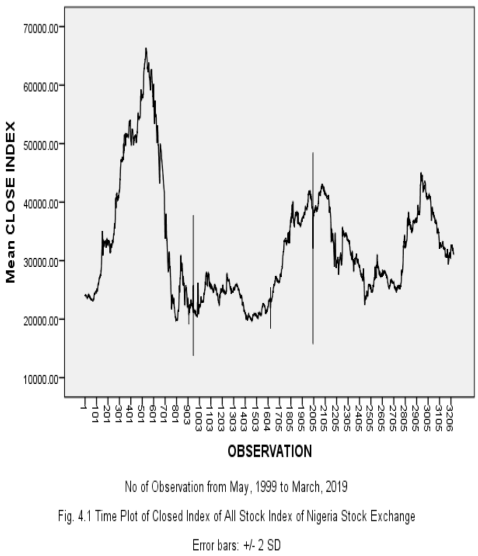

Figure 1

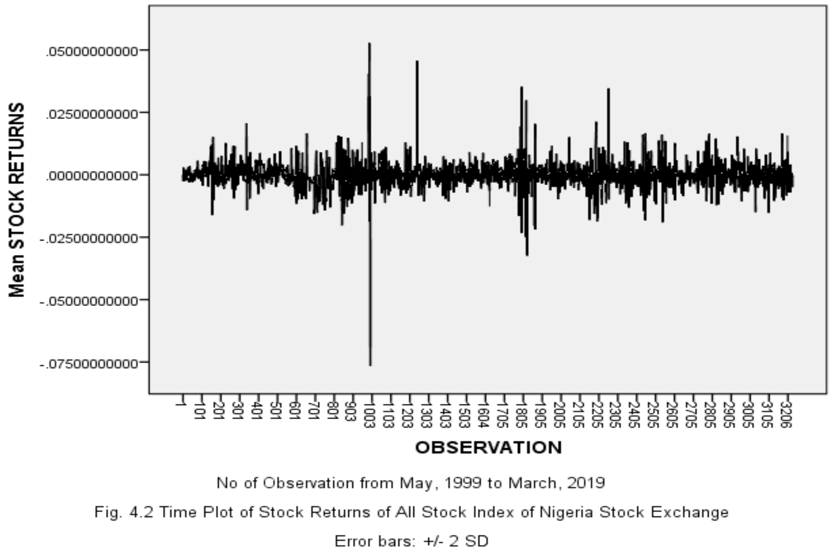

Figure 2

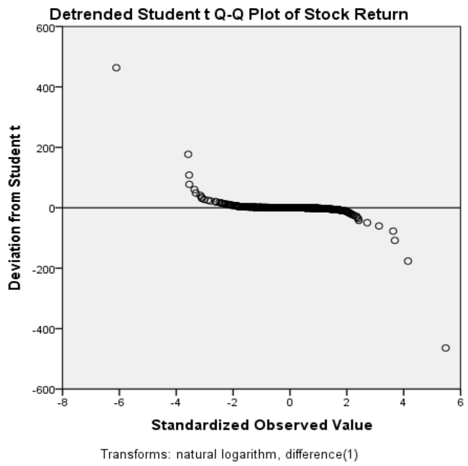

Figure 3

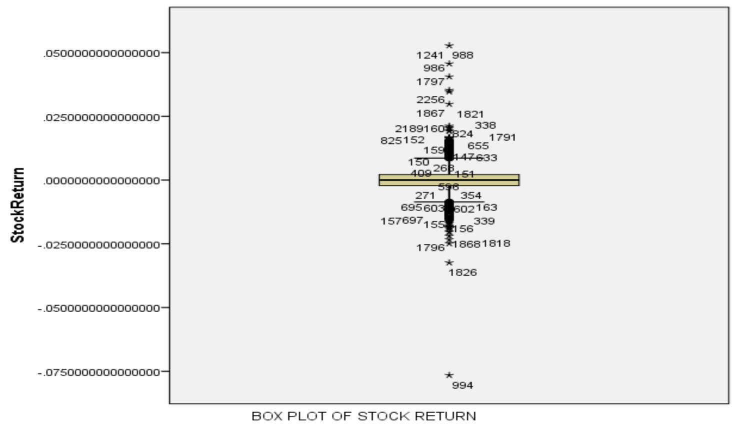

Figure 4

In Figure 1, the Nigeria Stock Exchange's All Stock Index closure indices from May 1999 to March 2019. There is evidence of volatility clustering, with periods of narrower volatility followed by periods of larger volatility. This shows that ASI variance in NSE does not remain consistent throughout time. As a result, there were periods when the market fluctuated a lot, periods when it fluctuated less, and periods when it fluctuated a lot. As a result, we looked for the most effective Standard GARCH model for predicting volatility clustering.

The time plots of daily stock returns, graph, Figure 2, also aid in examining the swings in the Nigeria Stock Exchange's All Stock Index stock returns from May 1999 to March 2019.

The proxy was found to be able to predict the likelihood of stock return volatility clustering. As a result, evidence of volatility clustering has been found, demonstrating that variance does not remain constant across time. There have been periods of great volatility, as well as periods of fluctuation that were smaller and less dramatic.

The Detrended Student t Q-Q Plot can also be used to check for symmetrical distribution of data points. The stock returns data includes outliers since some data points are above and below the line in Figures 3. As a result, the information is skewed.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

The box plot is a graphical representation of a data set's behavior at both the centre and tails of the distributions. It facilitates in the analysis of the data's overall shape, as well as key aspects such deviations from symmetry assumptions. Outlier points, sometimes known as "whiskers," are data points that arelocated outside the boxplot's gates. Figure 4 indicates that the stock returns data includes outliers since somedata points fall outside the box's outer barrier. This shows that the stock return sequence is skewed.

TABLE 2: Box-Ljung Statistic of ASI of NSE autocorrelations

Lag	Autocorrelation	Std. Error a	Box-Ljung Statistic		
			Value	Df	Sig.[b]
1	-0.213	0.026	66.306	1	0.000
2	-0.036	0.021	69.329	2	0.000
3	-0.003	0.020	69.354	3	0.000
4	0.002	0.019	69.370	4	0.000
5	-0.008	0.018	69.539	5	0.000
6	0.020	0.018	70.721	6	0.000
7	-0.023	0.018	72.297	7	0.000
8	0.001	0.018	72.301	8	0.000
9	-0.018	0.018	73.277	9	0.000
10	-0.021	0.019	74.548	10	0.000
11	0.002	0.019	74.556	11	0.000
12	-0.004	0.019	74.609	12	0.000
13	-0.008	0.019	74.790	13	0.000
14	-0.008	0.018	74.964	14	0.000
15	-0.005	0.018	75.032	15	0.000
16	0.013	0.018	75.590	16	0.000

Source: Output of stock return autocorrelations

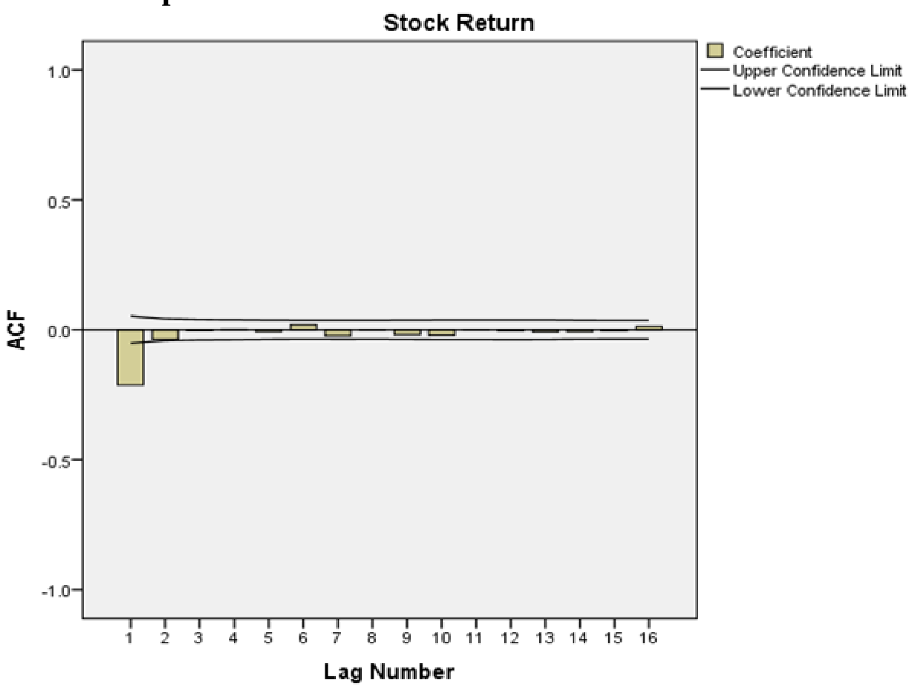

Figure 5

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

ASI of NSE's autocorrelations (Figure 5)

The autocorrelation coefficients of the squared returns of ASI of NSE reported in Table 2 demonstrate proof of ARCH effects due to their large autocorrelation coefficients. The significant autocorrelation in the squared returns sequence demonstrates the existence of volatility clustering. The sequence's autocorrelation dies out after 16 delays. The test p-values for autocorrelation in the sample series indicate positive asymmetry volatility. On the other hand, the "NO ARCH EFFECT" hypothesis is ruled out. This indicates that the mean-variance equation used to model ASI of NSE's stock returns is appropriate.

ARCH effects are present, as seen by the strong autocorrelation coefficients in Figure 4.5. The sequence's autocorrelation dies out after 16 delays.

Table 3: Results of Transition – GARCH Model (TEGM) under normal and non-normal Innovation

Model	Innovation	**Information Criteria**	**Model Order (1,1)**	**Log Likelihood**
TEGM	Student's t	SBIC	1.866515	2990.1803

Source: Output of R Packages for TEGM results under non-normal innovation.

Table 3 shows that the TEGM under students-t only converges very quickly to the global limit, satisfying the requisite condition for predictive capacity of the best performing model with a minimum SBIC (1.866515) less than other traditional and proposed error distribution models when modeling the Nigeria Stock Exchange. The TEGM did not approach a global limit under other variant development distributions.

Table 4 Information criteria for best performing model

Statistic	GARCH	E-GARCH	TEGM
SBIC	6.6176	6.6063	1.866515
INNOVATION	Normal	Skewed Normal	Student's t

Source: Output of R Packages for information criteria for best performing model.

In table 4 the TEGM meets the essential condition for the best performing model by having an SBIC of 1,866515, which is lower than the GARCH and E-GARCH models' SBICs of 6.1676 and 6.6063, respectively. The TEGM model performed better than the classic GARCH models in this study.

Table 5: Results of comparing Parameter Estimates of Conventional and proposed Models

Model	Innovation	Parameter Estimates	Ljung-Box Test (pv)	LM Tests (pv)
GARCH	Normal	ω =0.000009, α=0.473893, β =0.525107	8.0578 /7.240e-09	0.3591 /0.5490
E-GARCH	Skewed Normal	ω = -1.208502	8.050 /7.535e-09	2.000 /0.4855
		α = 0.067217		
		β= 0.867726		
		Υ= 0.707468		
TEGM	Student's t	ω =0.02519	NaN	NaN

		ψ=0.8450245		
		α= 0.2153		
		ϒ= 0.11681		
		β=0.0000		

Source: Output of R Packages for comparing parameter estimates of conventional and proposed models

The ARCH effect is visible in Table 5 at both the 1% and 5% relevant levels, exhibiting autocorrelation of GARCH and E-GARCH model parameter estimates under normal and distorted normal trends, respectively. The test statistic for TEGM autocorrelation of parameter estimates could not be listed due to the model's quick convergence to global maximum. As shown in this study, TEGM meets the required criteria for selection criteria based on minimum SBIC with an inherent serial nonlinearity dependence, as well as the appropriate condition for the model's best predictive potential.

Table 6: Results of best performing GARCH Model under Normal and Non-normal Innovation

Model	Innovation	**Information Criteria**	**Model Order (1,1)**	**Log Likelihood**	MSE	RMSE
GARCH	Normal	SBIC	**6.6176**	**3369.262**	**0.2246**	**0.4739**
	Skewed Normal	SBIC	6.6177	3372.753	0.2094	0.4576
	Student's t	SBIC	6.7232	3426.151	0.0538	0.2319
	Skewed Student's t	SBIC	6.7198	3427.896	0.0661	0.2570
	Generalized Error Distribution (GED)	SBIC	6.7088	3418.882	0.0906	0.3100
	Skewed Generalized Error Distribution (SGED)	SBIC	6.7056	3420.727	0.0905	0.3009
E-GARCH	Normal	SBIC	6.6093	3368.545	0.3654	0.6044
	Skewed Normal	SBIC	**6.6063**	**3370.446**	**0.3804**	**0.6168**
	Student's t	SBIC	6.7221	3429.078	0.4797	0.6926
	Skewed Student's t	SBIC	6.7194	3431.16	0.3902	0.6246
	Generalized Error Distribution (GED)	SBIC	6.7030	3419.374	0.4406	0.6638
	Skewed Generalized Error Distribution (SGED)	SBIC	6.7006	3421.63	**0.2779**	**0.5271**
TEGM	Student's t	SBIC	**1.866515**	**2990.1803**	**.0007**	**0.0257**

Source: Output of R Packages for the best performing Standard GARCH Model under Non-normal Innovation

Table 6 reveals that TEGM under Student-t innovation meets the necessary requirement for the best performing model's predictive ability with a minimum value of SBIC 1.8665. In compared to the GARCH model with SBIC 6.617, MSE 0.2246, and RMSE 0.4739, and E-GARCH with SBIC 6.6063, MSE 0.3804, and RMSE 0.6168, it likewise meets the adequate requirement with MSE 0.0007 and RMSE 0.0257. In terms of prediction and forecasting, this shows that TEGM outperforms classic GARCH models.

Table 7: The MSE and RMSE used for best predictive performance model

Statistic	GARCH	E-GARCH	TEGM
MSE	0.2246	0.2779	**0.0007**
RMSE	0.4739	0.5271	**0.0257**
INNOVATION	Normal	SGED	**Student's t**

Source: Output of R Packages for the MSE and RMSE for the best predictive performing model

Table 7 shows that TEGM meets the sufficient conditions for the best forecasting performance of ASI of NSE with MSE 0.0007 and RMSE 0.0257, when compared to GARCH model under normal distribution with MSE 0.2246 and RMSE 0.4739 and

E-GARCH under skewed standard error with MSE 0.2779 and RMSE 0.5271.

SUMMARY OF FINDINGS AND CONCLUSION.

The diagnostic tests Ljung Box, Q Statistics, and Lagranger Multiplier support the lack of the residual ARCH effect with parameter estimates of both the conventional and established models at a 5% significant level, and SBIC criteria for the best performing model were obtained. The information criteria with the lowest SBIC value represent the best performing model, whilst the Ljung Box and LM Q- Statistics Tests indicate the presence of Auto-correlation and ARCH findings, respectively. The Ljung Box Test Statistics are used to see the auto-correlation in square returns, with p-values at both the 0.01 and 0.05 relevant levels.

The GARCH and E-GARCH models are correctly defined, according to the Ljung-Box Test results. The standardized squared residuals have large Q-statistics (8.0578 /7.240e-09 and 8.050 /7.535e-09), indicating that the GARCH models are accurate in modeling the serial correlation structure of the conditional means and conditional variances.

TEGM meets the essential prerequisites for the selection criteria based on a minimum SBIC value of 0.18665 due to its intrinsic serial nonlinearity dependence. According to the TEGM with transition parameter value, ψ = 0.845, the conditional volatility of the ASI of NSE returns series exhibits 84.5 percent unconditional variance over time and 15.5 percent conditional variance mode using TEGM under Student's t error word.

The TEGM under Student's t innovation distribution meets both the required and adequate requirements, with SBIC 1.8665, MSE 0.0007, and RMSE 0.0257, indicating that the model has the best predictive capacity and forecasting capability than the GARCH model under normal innovation, which has SBIC 6.617, MSE 0.2246, and RMSE 0.473.

The results indicate that TEGM outperformed and forecasted both the GARCH and E-GARCH models, as proven by its lowest MSE and RMSE values, making it the best model for forecasting NSE.

The TEGM parameter estimations clearly reveal that volatility is persistent in the NSE's ASI, confirming with Fripong and Oteng-Abayie (2006) that stock returns are persistent. The findings also supported Ogun et al., (2005) and Nwoazaaku (2009)'s claims that stock return volatility is not persistent, as well as their proof of volatility characteristics in the NSE.

The model also shows that complex nonlinear models are not always inferior, as TEGM outperformed GARCH and E-GARCH models in forecasting conditional volatility of Nigerian Stock Exchange (NSE) returns, unlike Dimson and Marsh's (1990) findings that E-GARCH models performed the worst. As a result of our findings, we suggest that relatively complex nonlinear models are not inferior to simpler

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

parsimonious models when it comes to forecasting.

The Transition E-GARCH Model (TEGM) under student's-t only converges very quickly to the global limit, satisfying the needed condition with minimum SBIC, while modeling ASI of NSE. The TEGM model with SBIC 1,8665 outperforms the GARCH model with SBIC 6.1676 and the E-GARCH model with SBIC 6.6063.

Table 8 Predict (fit1, n. ahead=10, plot=TRUE) GARCH (1,1) "norm"

S/No	Mean Forecast	Mean Error	Standard Deviation	Lower Interval	Upper Interval
1	-0.9996096	0.01651647	0.01651647	-1.031981	-0.9672379
2	-0.9996096	0.01651719	0.01651719	-1.031983	-0.9672365
3	-0.9996096	0.01651791	0.01651791	-1.031984	-0.9672351
4	-0.9996096	0.01651862	0.01651862	-1.031985	-0.9672337
5	-0.9996096	0.01651933	0.01651933	-1.031987	-0.9672323
6	-0.9996096	0.01652004	0.01652004	-1.031988	-0.9672309
7	-0.9996096	0.01652075	0.01652075	-1.031990	-0.9672295
8	-0.9996096	0.01652146	0.01652146	-1.031991	-0.9672281
9	-0.9996096	0.01652216	0.01652216	-1.031992	-0.9672267
10	-0.9996096	0.01652286	0.01652286	-1.031994	-0.9672252

Table 9 Predict (fit2,n.ahead=10,plot=TRUE) TEGM "student's – t"

S/No	Mean Forecast	Mean Error	Standard Deviation	Lower Interval	Upper Interval
1	-0.9998794	0.01650455	0.01650455	-1.032718	-0.9680344
2	-0.9998794	0.01650503	0.01650530	-1.032720	-0.9680329
3	-0.9998794	0.01650605	0.01650605	-1.032721	-0.9680315
4	-0.9998794	0.01650680	0.01650680	-1.032723	-0.9680301
5	-0.9998794	0.01650755	0.01650755	-1.032724	-0.9680286
6	-0.9998794	0.01650829	0.01650829	-1.032726	-0.9680272
7	-0.9998794	0.01650903	0.01650903	-1.032727	-0.9680258
8	-0.9998794	0.01650977	0.01650977	-1.032729	-0.9680243
9	-0.9998794	0.01651050	0.01651050	-1.032730	-0.9680229
10	-0.9998794	0.01651124	0.01651124	-1.032732	-0.9680215

Based on the best performing and forecasting model for the 10 steps ahead predicting values as shown in Tables 8 and 9. GARCH (1,1) has a minimum mean error and standard deviation of 0.01651647 – 0.01652286, while the TEGM model has a mean error and standard deviation of less than 1% between 0.01650455 – 0.01651124.

Conclusion

GARCH model outperformed competing models in terms of characterizing ASI of NSE series.

In terms of describing ASI of NSE series, the Transition E – GARCH model outperformed competing models in modeling and forecasting conditional volatility of All Stock Index, of Nigeria Stock Exchange.

The model is highly recommended for risk management, investment policy formulation, price derivation, and hedging portfolio selection, according to the research in helping investors, regulators, and governments achieve better stock exchange policy and financial results.

It is also recommended for assessing and evaluating other random series volatility in the global economy for risk management and investment decision-making.

REFERENCES

1. Akgiray V. 1989. Conditional heteroskedasticity in time series of stock returns: Evidence and Forecasts. *Journal of Business.* 62. 55-80.
2. Akgul. I. and Sayyan H, (2005). Forecasting volatility in ISE-30 stock returns with asymmetric conditional Heteroscedasticity models. Symposium of Traditional finance, marmara Universities, Bankacilik ve Sigortacilik Yuksekokulu, Istanbul, turkey.
3. Awalludin, S.A., Ulfah, S., and Soro, S., 2018. Modeling the stock price returns volatility using GARCH (1, 1) in some Indonesia stock prices. Journal of Physics: Conference Series, Vol. 948, No. 1, January, p. 012068. IOP Publishing.
4. Christopher, N. E. and Kenneth, U. O. (2017). Application of GARCH Models to Estimate and Predict Financial Volatility of Daily Stock Returns in Nigeria
5. Dana Al-Najjar (2016). Modeling and Estimation of Volatility Using ARCH/GARCH Model in Jordan’s stock Market. Asian Journal of Finance and Accounting ISSN 194-0528 Vol. 8 No. 1 pages 152-167
6. Dimson, E. and Marsh, P. 1990. Volatility Forecasting without Data-Snooping. *Journal of Banking and Finance* 14, 399-421.
7. Dumitru, M. and Cristiana, T. (2010). Asymmetric Conditional Volatility Models. Empirical Estimation and Comparison Forecasting Accuracy. Romanian Journal of Economic Forecasting. 3(2010), pages 70-81.
8. Emenike K.O. (2010). Modeling Stock Return Volatility in Nigeria Using GARCH Models. Africa Journal of Management and Administration. 3(1), pages 83-106. http://dx.org/10.1016/0927-5398(93)90006-D.
9. Frimpong, J.M. and Oteng-Abayie, E.F. (2006),”Modelling and Forecasting Volatility of Returns on the Ghana Stock Exchange using GARCH Models”, Munich personal RePEc Archive, 593, 1-21.
10. Goudarzi, H. and Ramamarryaman, C. S. (2011). Modelling Asymmetric Volatility in the Indian stock Market. International Journal of business and management. 6(3). Pages 221-231. http://dx.doi.org/10.5539/ijbm.v6n3p221.
11. Khera, A. and Yadav, M. P (2020). Predicting the volatility in stock return of emerging economy: An empirical approach
12. Lin, Z., 2018. Modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models. Future Generation Computer Systems, 79, pp. 960-972.
13. Michel, G. (2020). Estimating Currency Volatility Using GARCH. Towards Data Science. http://towardsdatascience.com
14. Ogum, G., Beer, F. and Nouyrigat, G. 2005. Emerging Equity Market Volatility: An Empirical Investigation of Markets in Kenya and Nigeria. *Journal of African Business*. 6, (1/2). 139-154.
15. Olugbode M. A. (2021). Transition E-GARCH Model for Unconditional and Conditional Variances under Non-Normal Innovations. Unpublished PhD. Thesis. December, 2021.
16. Omorogbe, J. Asemota and Ucheoma, C. Ekejiuba. (2017). An Application of Asymmetric GARCH Models on Volatility of Banks Equity in Nigeria’s Stock Market. CBN Journal of Applied Statistics Vol. 8 No. 1 June, 2017, pages 73 – 99.
17. Weilligton and Bonga, (2019), Stock Marketing Volatility Analysis using GARCH family models: Evidence from Zimbabwe Stock Exchange. Online at httpa://upra.usun-muenchan.de/94201 MPRA paper N0 94201 posted 30 May 201 2028 UTC

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VII Issue XII December 2023

APPENDIX

RESULTS DETAILS OF THE TEGM

```
> #estimate and store as ‘mymod’:

> Congarch <- tegarch (Returns)

> #print estimates and standard errors:

> print(Congarch)
```

Message (nlminb): false convergence (8)

Coefficients:

	Estimate	Std. Error
omega	0.0251966559	0.0006614947
phi1	0.8450245	NaN
kappa1	0.2153251852	0.0008955483
kappastar	0.1168093	NaN
df	10.0031	0.029812
skew	1.944208822	0.001263854
Log-likelihood:		-2990.180344
SBIC:		1.866515