Modelling Stock Market Return Volatility: GARCH Evidence from Nigerian Stock Exchange

Kolade Sunday Adesina*

Abstract

This paper uses symmetric and asymmetric GARCH models to estimate the stock return volatility and the persistence of shocks to volatility of the Nigerian Stock Exchange (NSE). There is substantial evidence for the GARCH modelling through Lagrange Multiplier Test, Correlogram and Ljung-Box Statistics before the estimation of the GARCH models. The study uses 324 monthly data from January 1985 to December 2011 of the NSE all share-index. The result reveals high persistent volatility for the NSE return series. In addition, there is no asymmetric shock phenomenon (leverage effect) for the return series.

Keywords: Stock Returns, Volatility, ARCH Effects, GARCH Models

1. Introduction

The study of volatility is important in risk management. The level of volatility in a financial market provides a measure of risk exposure to investors on their investments. Most investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance (Alexander, 1999). Hence, high volatility may create barrier for investing.

The study on GARCH modelling of stock return volatility and the persistence of shocks to volatility from West African markets is few. The same, however, does not hold true for developed markets. In an attempt to fill this gap, the research of modelling the behaviour of stock market volatility in West Africa has been considered by various researchers in recent time; see Olowe (2009) for E-GARCH-in-Mean, Njimanted (2012) for GARCH-in-Mean, Frimpong and Oteng-Abayie (2006) for four volatility models, Emenike (2010) for GARCH (1,1) and GJR-GARCH (1,1) models. However, it is necessary to exhibit more evidence on the NSE volatility by using other models of the GARCH family. Hence, the main objective of this paper is to model stock return volatility and the persistence of shocks to volatility for Nigerian Stock Exchange (NSE), by using symmetric [GARCH (1,1) and GARCH-M (1,1)] and asymmetric [EGARCH(1,1) and TGARCH(1,1)] models for monthly Nigeria Stock Exchange all share index spanning from January 1986 to December 2011.

This paper is organised as follows: after this introductory section, Section 2 provides the Overview of the Nigerian Stock Market, while Section 3 is devoted to the Literature Review. Properties of the data used are presented in Section 4. Section 5 presents the methodology, while Section 6 is based on the discussion of the empirical results. Finally, Section 7 concludes the findings. I adopt the approach of Suliman (2012) in arranging the methodology, with slight modification.

2. Overview of the Nigerian Stock Market

The Nigerian Stock Exchange was established in 1960 as the Lagos Stock Exchange. In December 1977 it was named The Nigerian Stock Exchange. The Nigerian Stock Exchange (NSE) is the only registered securities exchange in Nigeria. The NSE maintains an All-Share

* Department of Banking and Finance, School of Management and Business Studies, Yaba College of Technology, Yaba, Lagos, Nigeria. E-mail: mastersunny2study@yahoo.com

Table 1: Nigerian Stock Exchange Snapshot (2007 - 2011)

	2007	2008	2009	2010	2011
Number of Listed Securities	309	299	266	264	250
Volume of Stocks Traded (Turnover Volume) (Billion)	138.1	193.1	102.9	93.3	82.3
Value of Stocks Traded (Turnover Value) (Billion Naira)	2,100.0	2,400.00	685.70	797.60	622.60
Value of Stocks/GDP (%)	8.9	10.0	10.0	0.3	1.7
Total Market Capitalization (Billion Naira)	13,294.6	9,535.80	7,032.10	9,918.20	10,282.20
Of which: Banking Sector (Billion Naira)	6,432.2	3,715.5	2,238.1	2,710.2	1,839.3
Total Market Capitalization / GDP (%)	56.0	39.7	28.5	33.6	28.1
Of which: Banking Sector/GDP (%)	27.1	15.5	9.1	9.2	5.0
Banking Sec. Cap./Market Cap. (%)	41.8	39.0	31.8	27.3	17.5
Annual Turnover Volume / Value of Stock (%)	6.6	8.0	15.0	15.0	13.2
Annual Turnover Value/ Total Market Capitalization (%)	15.8	25.2	9.8	8.0	6.1
NSE Value Index (1984=100)	57,990.22	31,450.78	20,827.17	24,770.5	20,730.63
Growth (In percent)					
Number of Listed Securities	7.6	-2.6	-11.0	-0.8	-5.3
Volume of Stocks	278.4	39.8	-46.9	-9.3	-3.2
Value of Stocks	346.5	14.3	-71.4	16.3	-20.1
Total Market Capitalisation	159.6	-27.8	26.3	41.0	4.0
Of which: Banking Sector	200.2	-42.2	-39.8	21.1	-32.1
Annual Turnover Value	346.5	14.3	-71.4	16.3	-21.9
NSE Value Index	74.7	-45.8	-33.8	18.9	-17
Share of Banks in the 20 Most Capitalized Stocks in the NSE (%)	65.0	70	59	80.0	40.0

Source: Central Bank of Nigeria Annual Report - 2011

Index formulated in January 1984 (January 3, 1984 = 100). Only common stocks (ordinary shares) are included in the computation of the index. The index and other indicators of the NSE are shown in Table 1.

The period 2007 – 2011 is a period of volatility in the NSE. The number of listed securities reduced on yearly basis from 309 of 2007 to 250 of 2011. The volume of the stock traded 138.1 billion with a value of ₦2,100 billion in 2007 reduced drastically when compared with the volume of the stock traded 82.3 billion with a value of ₦622.6billion in 2011.

The value of stocks as a percentage of GDP started with 8.9% in 2007 and stood at 1.7% in 2011. The total market capitalization representing 56% of the GDP in 2007closed at ₦13,294.6 billion, but a lower value of ₦10,282.2 billion was recorded for 2011.

The NSE Value Index declined from 57,990.22 in 2007 to close at 20,730.63 in 2011. The development indicates the fall in share prices of most of the listed stocks on the NSE. In terms of market capitalization, 2007 closed with a total market capitalization of ₦13,294.6 billion, and in 2008, total market capitalization experienced a drop to ₦9,535.8 billion. In terms of the total market capitalization, the banking has declining proportions from 41.8% in 2007 to 17.5% in 2011.

3. Literature Review

GARCH modelling of stock market volatility has just received attention in the past few years in West Africa while there have been a lot of the study in developed economies over the past decades. One of the most important studies of stock market volatility in West Africa is the study by Olowe (2009). Using daily returns, he investigated the relation between stock returns and volatility in Nigeria using E-GARCH-in-Mean model in the light of banking reforms, insurance reform, stock market crash and the

Figure 1: Line Graph of Monthly Index for NSE (Jan.1985 – Dec. 2011)

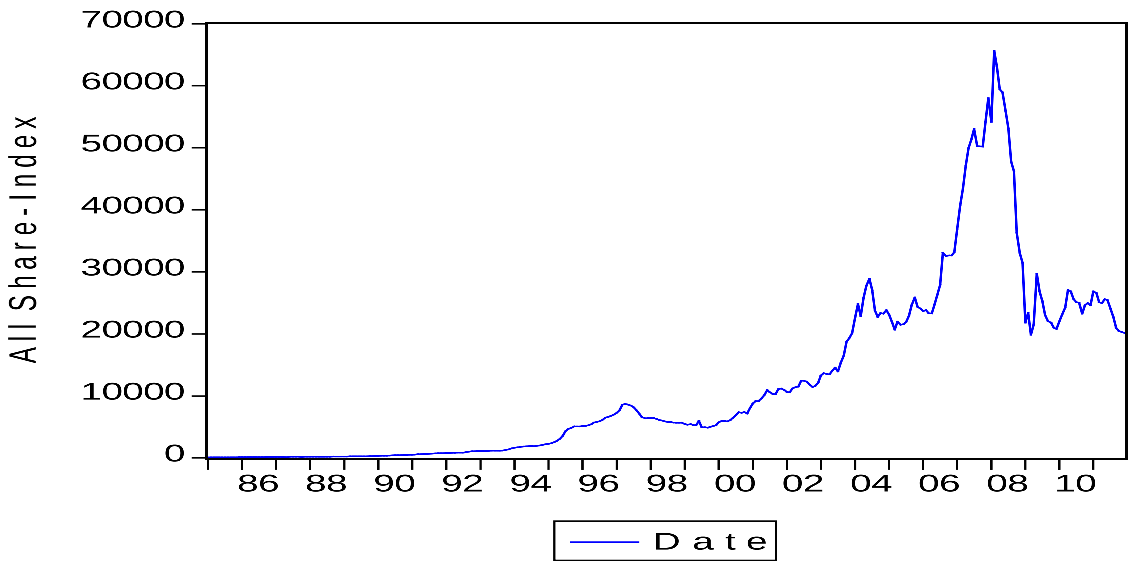
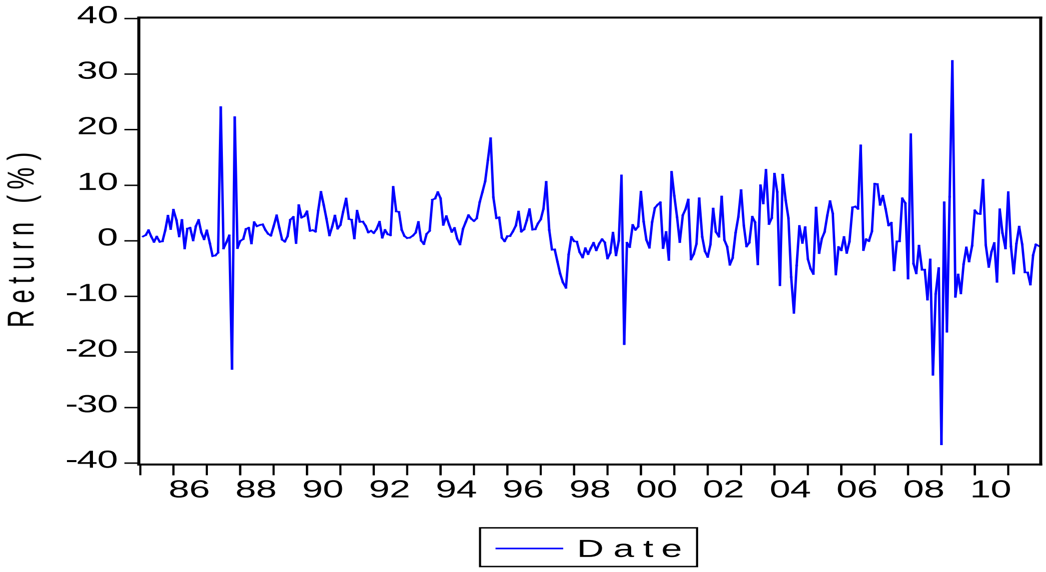


Figure 2: Line Graph of Continuously Compounded Monthly Returns for NSE (Jan.1985 – Dec. 2011)

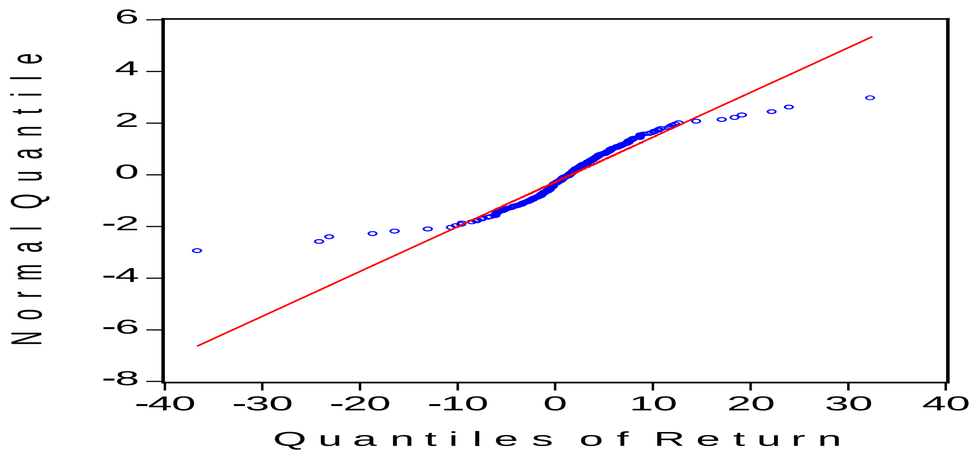


global financial crisis. On the same Nigerian stock market, Emenike and Aleke (2012) examine the response of volatility to negative and positive news using daily closing prices of the Nigerian Stock Exchange (NSE). They find strong evidence supporting asymmetric effects in the NSE stock returns but with absence of leverage effect.

Elsayeda (2011) employed EGARCH and TGARCH models to examine the existence of asymmetric volatility and leverage effect for the Egyptian stock market index. The results indicate the existence of the leverage effect for daily EGX30 index returns.

Ahmed and Suliman (2011) used different univariate GARCH models to estimate volatility in the daily returns of the Khartoum Stock Exchange (KSE) over the period from January 2006 to November 2010. The empirical results show that the conditional variance process is highly persistent (explosive process), and provide evidence on

Figure 3: **Quantile-Quantile Plot for the Continuously Compounded Monthly Returns (Jan. 1985-Dec. 2011)**



the existence of risk premium for the KSE index return series which support the positive correlation hypothesis between volatility and the expected stock returns in Sudan.

Hojatallah and Ramanarayanan (2010) used the BSE500 index of Mumbai stock exchange to evaluate the volatility of the Indian stock markets and its related stylized facts using ARCH models. The results suggest that the volatility in the Indian stock market exhibits the persistence of volatility and mean reverting behaviour.

This paper is a continuation of previously mentioned Nigerian authors' study of the volatility of the Nigerian Stock Exchange by employing both symmetric and asymmetric GARCH models.

4. Preliminary Analysis

4.1 Data for Analysis

The data employed in this paper are the monthly All Share Index (ASI) of the Nigerian Stock Exchange (NSE) from January 1985 to December 2011, resulting in 324 observations excluding public holidays. The ASI is a weighted index of the listed equities on the NSE.

The monthly ASI series are used to generate the continuously compounded returns used in the GARCH modelling, which are achieved as follows:

$$R_t = 100 * \log\left(\frac{P_t}{P_{t-1}}\right) = 100[\mathrm{Log}(P_t) - \mathrm{Log}(P_{t-1})] \qquad (1)$$

where R_t represents the continuously compounded monthly percentage return of the ASI for period t and P_t and P_{t-1} represent ASI for current month and previous month, respectively. The monthly ASI and the continuously compounded returns for the period under study are shown in Figure 1 and Figure 2, respectively. The return series (Figure 2) depicts the characteristic of periods of high volatility followed by periods of low volatility, also it can be observed that the highest volatility is in 2008-2009 when the financial crisis hit the market.

4.2 Properties of NSE Monthly Return Series

4.2.1 Descriptive Statistics

Panel A of Table 2 presents the descriptive statistics of the NSE continuously compounded monthly return series over the period under study. The series ranged between -36.59 and 32.35 with a mean of 1.61. The computed Jarque-Bera is 940.6019 with probability value of 0.000000. Since the probability-value of the Jarque-Bera is smaller than 0.01, it is concluded (with 99% confidence) that the distributed population of the return series are not normal. The negative skewness -0.540624 implies that the distribution of the variable has a long left tail (mean < median < mode). In other words, the distribution is negatively skewed to the normal distribution. The kurtosis 11.28980 means that the distribution is peaked (leptokurtic) relative to kurtosis 3.

4.2.2 A Quantile-Quantile (Q-Q) Plot

In addition to the Descriptive Statistics, a Quantile-Quantile (Q-Q) Plot is used to check whether the return series is normally distributed. The Q-Q plot is an

Table 2: Descriptive Statistics and Stationarity Test

Panel A: Descriptive Statistics			
Mean	1.609275	Skewness	-0.540624
Median	1.607086	Kurtosis	11.28980
Maximum	32.35158	Jarque-Bera	940.6019
Minimum	-36.58828	Prob. of Jarque Bera	0.000000
Std. Dev.	6.145353	Observations	323

Panel B: Stationary Tests		
Test	Augmented Dickey-Fuller Test	Philips-Perron Test
Test statistic	-5.821335	-16.18429
Test critical values at level:		
1%	-3.450747	-3.450474
5%	-2.870416	-2.870302
10%	-2.571569	-2.571508

Source: Author's Computation Using EViews 5.0

exploratory graphical device used to check the validity of a distributional assumption for a data set. If the returns are normally distributed, the Q-Q plot should lie on straight line and will have an s-shape if there are more extremes. Figures 3 shows the Q-Q plot of the monthly returns series of the NSE. The result indicates departures from normality.

4.2.3 A Stationarity Test

The results of the stationary tests for the return series are shown in Panel B of Table 2. The test statistic is less than the critical values for both Augmented Dickey-Fuller test and Phillips-Perron tests; hence the null hypothesis of a unit root convincingly rejected.

4.2.4 Testing for ARCH Effects

Before estimating a GARCH-type model, it is important first to identify whether there is substantial evidence of heteroskedasticity (ARCH effects), which determine whether or not it is necessary to apply the ARCH estimation methods instead of the OLS. In order to test for the presence of ARCH effects in the return series, this paper employed Lagrange Multiplier Test, Correlogram and Ljung-Box Statistics methods to check the correlation in residuals.

4.2.4.1 Lagrange Multiplier Test

The Lagrange Multiplier (LM) is a test for autoregressive conditional heteroskedasticity (ARCH) in the residuals. The ARCH-LM test statistic is computed from an auxiliary test regression. The test procedure is performed by first obtaining the residuals e_t from the ordinary least squares regression of the conditional mean equation which might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes; (ARMA) process (Suliman, 2012).

In this study, an autoregressive moving average ARMA (1,1) model for the conditional mean in the return series as an auxiliary regression is employed. The conditional mean equation is as:

$$R_t = \emptyset_1 R_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad (2)$$

The essence of estimating the mean return equation with Ordinary Least Square is to obtain the residuals **(ε)** from the regression with which to test the null hypothesis that there is no ARCH up to order q in the residuals.

To test the null hypothesis that there is no ARCH up to order q in the residuals, the following regression is run:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \cdots + \alpha_q e_{t-q}^2 + V_t \quad (3)$$

The null hypothesis that all q lags of the squared residuals have coefficient values that are not significantly different from zero.

The null and alternative hypotheses are

H_0: = 0 and = 0 and = 0 and ... and = 0 (4)

H_1: ≠ 0 and ≠ 0 and ≠ 0 and ... and ≠ 0 (5)

If the value of the test statistic is greater than the critical value from the $\chi 2$ distribution, then the null hypothesis would be rejected.

After the first step of obtaining the residuals e_t from the ARMA process, ARCH-LM test was applied to test for the presence of heteroskedasticity (ARCH effect) in the residuals by regressing the squared residuals on a constant and 5 lags. The output in Table 3 depicts the test results. From Table 3, it can be seen that the F statistic is significantly high (13.11838), suggesting the rejection of the null hypothesis that there exists no ARCH effects in the NSE returns. In other word, variance of the errors is non-constant for the period under study.

4.2.4.2 Correlogram and Ljung-Box Q-statistics for Heteroskedasticity

The Ljung-Box Q-statistics is used to check the validity of autoregressive conditional heteroskedasticity (ARCH) in the residuals. If there is no ARCH in the residuals, the autocorrelations and partial autocorrelations should be zero at all lags and the Q-statistics should not be significant. Looking at Table 4, there is clear evidence that the return series exhibit ARCH effect.

Table 3: ARCH-LM Test for Heteroskedasticity

ARCH Test:				
F-statistic	13.11838	Probability		0.000000
Obs*R-squared	55.21263	Probability		0.000000
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Date: 01/31/13 Time: 15:27				
Sample (adjusted): 1985M08 2011M12				
Included observations: 317 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.26447	6.785149	2.249688	0.0252
RESID^2(-1)	0.143473	0.056707	2.530079	0.0119
RESID^2(-2)	-0.003287	0.054448	-0.060365	0.9519
RESID^2(-3)	0.134492	0.053910	2.494783	0.0131
RESID^2(-4)	0.314098	0.054450	5.768560	0.0000
RESID^2(-5)	-0.012274	0.056704	-0.216452	0.8288
R-squared	0.174172	Mean dependent var		35.92720
Adjusted R-squared	0.160895	S.D. dependent var		117.0665
S.E. of regression	107.2360	Akaike info criterion		12.20669
Sum squared resid	3576364.	Schwarz criterion		12.27783
Log likelihood	-1928.760	F-statistic		13.11838
Durbin-Watson stat	2.000967	Prob(F-statistic)		0.000000

Table 4: Correlogram and Ljung-Box Q-statistics Test for Heteroskedasticity

Autocorrelation	*Partial Correlation*		*AC*	*PAC*	*Q-Stat*	*Prob*
.|. |	.|. |	1	-0.022	-0.022	0.1635	
.|. |	.|. |	2	0.051	0.051	1.0247	
.|* |	.|* |	3	0.067	0.070	2.5006	0.114
**|. |	**|. |	4	-0.220	-0.221	18.382	0.000
.|* |	.|* |	5	0.145	0.138	25.292	0.000

Since heteroskedasticity is a pre-condition for applying the GARCH models to a financial time series, the result provides justification for the next stage in the analysis which involves volatility modelling using the GARCH models.

5. Methodology

Autoregressive Conditional Heteroskedasticity (ARCH) and its generalization (GARCH) models are the most widely used to deal with time series heteroskedasticity. The GARCH models can be divided into two main categories: symmetric models [which include GARCH (1,1) and GARCH-M (1,1)] and asymmetric models [EGARCH(1,1), and TGARCH(1,1)]. For all these different models, there are two distinct equations, the first one for the conditional mean and the second one for the conditional variance.

In view of the heteroskedastic nature of the NSE returns, the GARCH models mentioned above are employed in this study to model NSE returns.

5.1 Symmetric GARCH Models

5.1.1 GARCH (1,1) Model

The GARCH (1,1) model was developed independently by Bollerslev (1986) and Taylor (1986). The model involves the joint estimation of the mean equation and the conditional variance equation. The mean equation is specified as follows:

Mean equation: $R_t = \mu + \varepsilon_t$ (6)

where

R_t is return at time

μ is the mean of the returns

ε is the residual return at time t

The return for a month will depend on returns in previous periods (autoregressive component) and the innovation terms in previous periods (moving order component). The GARCH (1,1) version of the model is:

Conditional variance equations: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$ (7)

where

σ_t^2 is the conditional variance at time

α_0 is the mean of unconditional variance (long-run average variance)

ε^2_{t-1} is the squared error at time t-1 from the mean equation (ARCH term)

σ^2_{t-1} is the last period's forecast variance (GARCH term)

α_1 is the first (lag 1) ARCH parameter

β_1 is the first (lag 1) GARCH parameter

For this model to be well defined and conditional variance to be positive, the parameters must satisfy the following constraints:

$\alpha_0 > 0, \alpha_1 \geq 0, \beta \geq 0$ (8)

5.1.2 GARCH-M (1,1) Model

The GARCH-in-Mean model was developed by Engle, Lilien and Robins (1987); it is based on the GARCH model. The mean and the variance of the GARCH-M (1,1) are specified:

the mean equation: $R_t = \mu + \lambda 1\sigma_t^2 + \varepsilon_t$ (9)

the variance equation: $\sigma_t^2 = \alpha_0 + \alpha_1\sigma_{t-1}^2 + \beta\sigma_{t-1}^2$ (10)

The parameter λ is called the risk premium parameter. This is based on the assertion that an asset with a higher perceived risk would pay a higher return on average. Then, the model allows the conditional mean to depend on its own conditional variance.

5.2 Asymmetric GARCH Models

In financial markets, if "bad news" has a more pronounced effect on volatility than "good news" of the same magnitude, then a symmetric specification such as GARCH or GARCH-M is not appropriate, since only squared residuals ε^2_{t-1} enter the equation, the signs of the residuals or shocks have no effects (in other words, by squaring the lagged error in GARCH, the sign is lost) on conditional volatility. In other word, the model assumes good and bad news have the same effect. However, a stylized fact of financial volatility is that bad news (negative shocks) tends to have a larger impact on volatility than good news (positive shocks). In the case of equity returns, such asymmetries are typically attributed to leverage effects, whereby negative shocks cause the value of the firm to fall which raises the debt-equity ratio thereby increasing the risk of bankruptcy (debt-equity ratios are a key predictor of the probability of default in credit scoring models). This makes shareholders, who bear the residual risk of the firm, to perceive their future cash flow stream as being relatively more risky.

In order to account for the leverage effects observed in stock returns, the asymmetric models which include: [EGARCH (1,1) and TGARCH(1,1)] are employed.

5.2.1 EGARCH (1,1) Model

To capture the leverage effects, Nelson (1991) proposed the Exponential GARCH (EGARCH) model where the logarithm of the conditional variance is modelled as:

$$\mathrm{Log}(\sigma_t^2) = \alpha_0 + \mathrm{BLog}(\sigma_{t-1}^2) + \alpha_1\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (11)$$

The leverage effect term (γ) is denoted as 'RESID(−1)/@SQRT(GARCH(−1))' in the output of EViews. The term γ, accounts for the presence of the leverage effects, which makes the model asymmetric. If $\gamma = 0$, then the model is symmetric. If γ is negative and statistically different from zero, it indicates the existence of the leverage effect.

5.2.2 TGARCH (1,1) Model

The Threshold-GARCH (TGARCH) model was introduced by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993). The specification of the conditional variance for the TGARCH (1,1) model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2 \quad (12)$$

where d_t is a dummy variable, that is, $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 0$ if $\varepsilon_t \geq 0$. The coefficient γ in the model captures the asymmetric effect if $\gamma > 0$. The α_0, α_1, and β are the parameters of the conditional variance equation that will be estimated.

In the model, good news ($\varepsilon_t \geq 0$) and bad news ($\varepsilon_t < 0$) have different effects on the conditional variance; good news has an impact of α_1, while bad news has an impact of $\alpha_1 + \gamma$. If $\gamma > 0$, bad news increases volatility, and we say that there is a leverage effect. If $\gamma \neq 0$ the news impact is asymmetric.

The criteria to accept the null hypothesis of no leverage effect in TGARCH model is that γ coefficient must be negative. In other words, if the γ coefficient is not negative there is evidence of leverage effects in the series.

6. Empirical Results and Discussion

Table 5 presents the parameter estimates of different GARCH models defined in the previous section for the monthly NSE returns, and the diagnostic test result to know whether there are remaining ARCH effects in the residuals of the estimated models.

It is important to mention that the Heteroskedasticity Consistent Covariance option is used to compute the quasi-maximum likelihood (QML) covariances and standard errors using the methods described by Bollerslev and Wooldridge (1992), since the residuals are not conditionally normally distributed.

The findings that can be drawn from the table are following.

6.1 Results of GARCH (1,1)

The estimates of the GARCH (1, 1) model are shown in second column of Table 5. The coefficient (0.644298) of the ARCH effect () is significantly positive at 1% showing that news about previous volatility (past square residual terms) has an explanatory power on current volatility. The GARCH effect coefficient (0.503110) is also significantly positive at 1% level, which shows that past volatility of stock market return is significantly, influencing current volatility. The sum of ARCH and GARCH coefficients (1.147408) is a measure of the persistence of variance, and that its value is greater than 1 implies that there is significant high persistence in volatility. As suggested by Engle and Bollerslev (1986), if $\alpha_1 + \beta = 1$, a current shock persists indefinitely in conditioning the future variance. Since the sum of $\alpha_1 + \beta$ represents the change in response function of shocks to volatility persistence, a value greater than unity implies that response function of volatility increases with time and a value less than unity implies that shocks decay with time (Chou, 1988). Therefore, the above result indicates that memory of shocks is remembered in the NSE.

Table 5: Results GARCH Models for the NSE Returns

Parameters	GARCH (1,1)	GARCH-M (1,1)	EGARCH (1,1)	TGARCH (1,1)
Mean Equation				
μ	2.359539***	2.447960***	2.373097***	2.314525***
λ (Risk premium)	—	-0.002707	—	—
Variance Equation				
α_0 (Constant)	1.354424**	1.358834**	-0.310439**	1.381926*
α_1 (ARCH effect)	0.644298***	0.642016***	0.816229***	0.585279***
β (GARCH effect)	0.503110***	0.503852***	0.901608***	0.506330***
γ (Leverage effect)	—	—	-0.019540	0.095902
$\alpha_1 + \beta$	1.147408	1.145868	1.717837	1.091609
ARCH-LM Test for Heteroskedasticity up to 5 Lags				
F-statistic	1.399388	1.521056	1.411197	1.332925
Probability	0.224176	0.182839	0.219838	0.249971

Note: ***, ** and * respectively represents significant at the 1%, 5% and 10%.
Source: Author's Computation Using EViews 5.0

6.2 Results of GARCH-M (1,1)

The estimates of the GARCH-M (1,1) model are reported in the middle column of Table 5. The results of the GARCH-M model are similar to the GARCH (1,1) results. The only different is the risk premium parameter, which is used to capture the risk-return relationship. The coefficient of the risk premium parameter, denoted as λ, is negative but insignificant. This suggests that the risk of return (variance) is not significantly compensated in the NSE. In other words, there is no risk/return trade-off in the market.

6.3 Results of EGARCH (1,1)

The EGARCH (1,1) is an asymmetric model, which is used to investigate the existence of leverage effect in returns of the NSE. The estimates of the model are reported in the fourth column of the Table 5. The asymmetric term in the EGARCH (1, 1) model is negative and insignificant suggesting no leverage effect in returns during the study period. This implies that previous period's positive and negative shocks do not have a different effect on the conditional variance.

For the effect of the previous period's bad news to be greater than the effect of good news of the same magnitude, γ should be significant and have a negative sign. On the other hand, for the effect of the previous period's positive news to be greater than the effect of bad news of the same magnitude, γ should be significant and have a positive sign.

6.4 Results of TGARCH (1,1)

The last column reported in Table 5 are the estimates of the of the TGARCH (1,1) model. The asymmetric effect of the TGARCH (1,1), captured by the parameter estimate γ, is positive and insignificant. Again this does not support the presence of leverage effects.

6.5 Results of Remaining ARCH Effects

The result to detect possible remaining ARCH effects, after the estimation of the GARCH models, is depicted in the last section of Table 5. The ARCH-LM test results show no evidence of remaining ARCH effects. This is an indication of parsimonious models and there are no remaining ARCH effects that need to be modelled by higher-order GARCH models.

7. Conclusion

This paper examined the volatility of returns on the Nigerian Stock Exchange. The preliminary analysis of data used reveals the stationarity, non-normal distribution and strong evidence of ARCH effects in NSE return series. To capture the volatility, GARCH (1, 1), GARCH-M (1, 1), EGARCH (1, 1) and TGARCH (1, 1) models are used. The ARCH effect (α_1) is significantly positive for all the models at 1% showing that news about previous volatility has an explanatory power on current volatility. The GARCH effect (β) is also significantly positive for all the models at 1% level, which shows that past volatility of stock market return is significantly, influencing current volatility. The GARCH-M shows that there is no risk/return trade-off in the market, while the asymmetric models do not support the presence of leverage effects. After estimation of the GARCH models, ARCH-LM test is used to test whether there is any further ARCH effect in the series. The ARCH-LM test results show no evidence of remaining ARCH effects. The evidence of high volatility in the market return may create barrier for investors. Therefore, the result of this study is a signal for regulators and policy makers in the NSE.

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