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Volatility Modeling of Monthly Stock Returns In Nigeria Using Garch Model

Gambo Isah Diri[1], Abubakar Bello[2], A.U Shelleng[2], Yahaya Ajiya[2] , S.O. Oladejo[2]
[1]Mathematics Department, Kebbi State Polytechnic, Dakingari
[2]Department of Mathematics (Statistics Unit), Gambe State University, Gombe, Nigeria
Corresponding auther: Gambo Isah Diri

Abstract: *Modeling volatility is an important element in pricing equity, risk management and portfolio management. Also modeling volatility will improve the usefulness of stock prices as a signal about the intrinsic value of securities, thereby, making it easier for firms to raise fund in the market. Therefore this study, study the nature and behavior of Stock Returns Volatility modeling of Nigerian for the periods of 324 months. The results ARCH effect (α_1) is at statistically significant level. This indicates that news about volatility from the previous t periods has an explanatory power on current volatility. GARCH (1,1) model is highly persists. Indicate evidence of volatility clustering in the NSE returns series. And the results of the GJR-GARCH (1,1) model shows the existence of leverage effects in the series. Finally, the parameters α_0 and α_1 are greater than 0, and β_1 is positive. Thus, the GARCH (1,1) seems quite good for explaining the behavior of stock returns volatility in Nigeria. Overall results from this study provide evidence to show volatility persistence, fat-Tail distribution, and leverage effects for the Nigeria stock returns.*

Key Words: *Stock Return, ARCH, GARCH, GJR-GARCH, Volatility, Nigeria*

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I. Introduction

The volatility modeling of price returns originated with Engle (1982) where Autoregressive Conditionally Heteroskedastic Model, ARCH Model, was used to predict the uncertainty of UK inflation rate. Engle noted that large changes tend to be followed by large changes – of either sign – and small changes tend to be followed by small changes' this phenomenon was named Volatility Clustering. He measured the clustering effects through the assumption of constant conditional mean of the returns series. However, there were some other stylized facts of volatility of equity prices in financial markets which could not be captured by the ARCH model. Bollerslev (1986), generalized the ARCH model to the Generalized Conditionally Heteroskedastic Model (GARCH Model). The model enormously extended the ability of the ARCH model to account for the stylized facts of volatility of returns. This led to a surge in research studies involving equity price returns. Among the studies that made use of GARCH models to study the stock market time series include: Bollerslev (1990) who estimated conditional correlation of GARCH model for five European currencies before and after the implementation of the European Monetary system and found out that there was an increase in the level of the conditional correlation. Others are Akgiray (1989) and Balaban (1995) whom have shown in their respective studies of the day of the week effect on returns and volatility with a GARCH model that returns of stocks vary by the day of the week effect. In similar vein, Campbell and Hentschell (1992) reported that volatility increase in the stock market would raise the expected rate of returns on common stocks. The common point of all these studies is that the report on returns (in the stock market) is time varying and conditionally heteroskedastic. The studies of Mandelbrot (1963), Fama (1965) and Black (1976) highlight volatility clustering, leptokurtosis, and leverage effects characteristics of stock returns. Engle (1982) introduced the autoregressive conditional Heteroskedasticity (ARCH) to model volatility by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. Bollerslev (1986) generalized the ARCH model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of disturbance. Since the works of Engle (1982) and Bollerslev (1986), various variants of GARCH model have been developed to model volatility. Some of the models include EGARCH originally proposed by Nelson (1991), GJR-GARCH model introduced by Glosten, Jagannathan and Runkle (1993), Threshold GARCH (TGARCH) model due to Zakoian (1994). Following the success of the ARCH family models in capturing behaviour of volatility, Stock returns volatility has received a great attention from both academies and practitioners as a measure and control of Risk both in emerging and developed financial Markets. Similar conclusions were reached by Taylor (1994), Brook and Burke (2003), Rimpong and Oteng-Abayie (2006) and

Olowe (2009). In a like manner, Bekaert and Harvey (1997) and Aggarwal et al.(1999) in their study of emerging markets volatility, confirm the ability of asymmetric GARCH models in capturing asymmetry in stock return volatility. Although the GARCH model has been very successful in capturing important aspect of financial data, particularly the symmetric effects of volatility, it has had far less success in capturing extreme observations and skewness in stock return series. The Traditional Portfolio Theory assumes that the (logarithmic) stock returns are independent and identically distributed (IID) normal variables which do not exhibit moment dependencies, but a vast amount of empirical evidence suggest that the frequency of large magnitude events seems much greater than is predicted by the normal distribution (see, Harvey and Siddique, 1999; Verhoeven and McAleer, 2003; diBartolomeo, 2007). In Nigeria, the few published studies on modelling volatility of stock returns, include: Ogum, Beer and Nouyrigat (2005), Jayasuriya (2002), Okpara and Nwezeaku (2009). Jayasuriya (2002) used an asymmetric GARCH methodology to examine the effect of stock market liberalization on stock return volatility for fifteen emerging markets, including Nigeria, for the period December 1984 to March 2000. The study reported, among others, that positive (negative) change in prices have been followed by negative (positive) changes indicating a cyclical type behavior in stock price changes rather than volatility clustering in Nigeria. In contrast to Jayasuriya (2002), Ogum, Beer and Nouyrigat (2005) investigated the emerging market volatility using Nigeria and Kenya stock return series. Results of the exponential GARCH model indicate that asymmetric volatility found in the U.S. and other developed markets is also present in Nigerian, but Kenya shows evidence of significant and positive asymmetric volatility, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude. Also, they showed that while the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium parameters, the NSE return series exhibit a significant and positive time-varying risk premium. Finally, they reported that the GARCH parameter (β) is statistically significant indicating volatility persistence in the two markets. Okpara and Nwezeaku (2009) examine the effect of the idiosyncratic risk and beta risk on the returns of the 41 randomly selected companies listed in the Nigerian stock exchange from 1996 to 2005. They employed a two-step estimation procedures, firstly, the time series procedure is used on the data to determine the beta and idiosyncratic risk for each of the companies; secondly, a cross – sectional estimation procedure is used employing EGARCH (1,3) model to determine the impact of these risks on the stock market returns. Their results reveal, among others, that volatility clustering is not quite persistent but there exists asymmetric effect in the Nigerian stock market. They concluded that unexpected drop in price (bad news) increases predictable volatility more than unexpected increase in price (good news) of similar magnitude in Nigeria. From the brief review of literature above, it is glaring that ARCH family of models has, extensively, been used to model volatility. While simple GARCH (1,1) is good enough to capture volatility clustering, it cannot capture fat-tails and asymmetry. Asymmetric model such as EGARCH, GJR-GARCH, have been specifically developed to capture asymmetry. Also, while there is disagreement on volatility clustering in Nigeria, all agree that leverage effects exist. This work, therefore, contributes and extends the existing literature on modelling stock returns volatility in Nigeria using more recent data.

II. Material and Method

2.1 Data Description

The time series data used in this analysis consists of the monthly average stock returns from January 2000 to December 2017 obtain from Nigeria stock exchange consisting of 324 observations. Table 1 shows the preliminary descriptive statistics results of the stock returns.

Table 1.0: Preliminary Analysis of Data

Mean	0.0160928
Median	0.0167135
Minimum	-0.319822
Maximum	0.322212
Standard deviation	0.063027
C.V.	3.91649
Skewness	-0.330440
Ex. kurtosis	5.67811
Jarque-Bera	439.7880

The table **1.0** above shows the descriptive statistics of the NSE return series. The average monthly return is 1.67%. The monthly standard deviation is 6.0%, reflecting a high level of volatility in the market. The wide gap between the maximum (0.322212) and minimum (-0.319822) returns gives support to the high variability of price change in the NSE. Under the null hypothesis of normal distribution, J-B is 0. The J-B value of 439.7880 deviated from normal distribution. Similarly, skewness and kurtosis represent the nature of departure from normality. In a normally distributed series, skewness is 0 and kurtosis is 3. Positive or negative skewness indicate asymmetry in the series and less than or greater than 3 kurtosis coefficient suggest flatness and peakedness, respectively, in the returns data. The skewness coefficient of -0.33044 is negatively skewed. Negative skewness implies that the distribution has a long left tail and a deviation from normality. The empirical distribution of the kurtosis is clearly not normal but peaked. On the whole, the NSE return series do not conform to normal distribution but display negative skewness and leptokurtic distribution. These results are, however, based on the null hypothesis of normality and provide no information for the parametric distribution of the series.

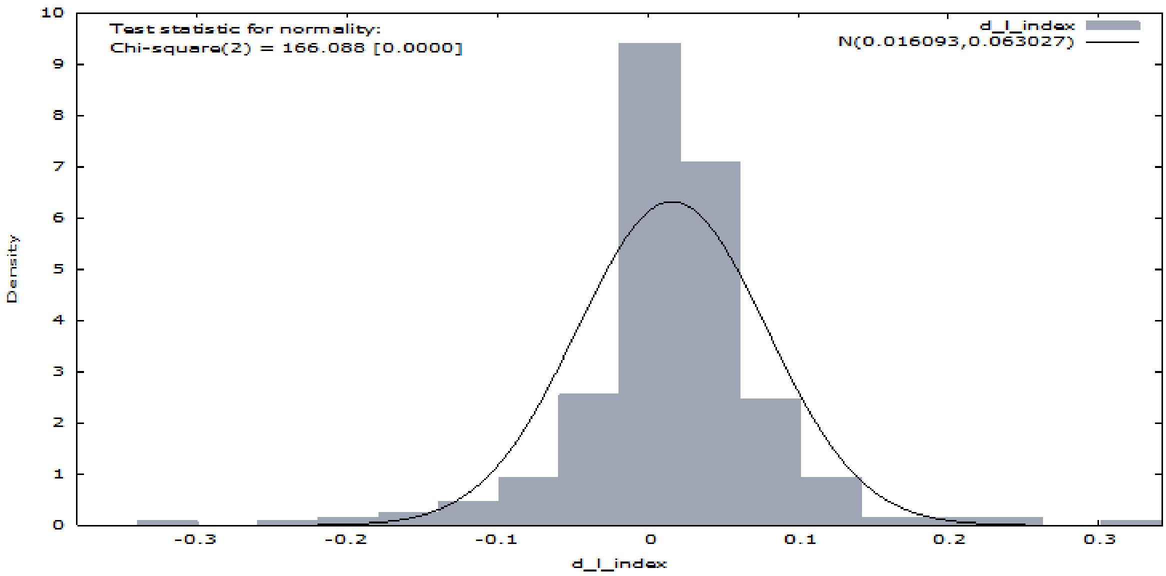

FIGURE 1.0 Histogram of the series

From Figure 1.0 above, we see that the NSE stock returns distribution is peaked confirming the evidence of non-normal distribution in Table 1.0 Peaked distribution is a sign of recurrent wide changes, which is an indication of uncertainty in the price discovery process. The visual representation above suggest the error terms may not likely be normally distributed as there are some points that are further apart, not evenly distributed or spread and this may likely resulted in high kurtosis (Kurtosis greater than 3 of normal distribution) which is another characteristics of financial returns. In other words, if the points of errors are not normally distributed, the skewness will be different from zero and the distribution will be asymmetrical. Most of the time the leverage effects of financial time series resulted from the asymmetrical effect produced from the skewness of the distribution.

Unit Root And Stationarity Test For The Stock Returns

Statistical test of the null hypothesis that a time series is non-stationary against the alternative that it is stationary are called UNIT ROOT test. The Table 2.0 below describes the ADF and KPSS test result of the critical levels and the test statistic.

Table 2.0 ADF and KPSS Test Results

STOCK RETURNS VARIABLE	**CRITICAL LEVEL (ADF)**			**CRITICAL LEVEL (KPSS)**		
	1%	5%	10%	1%	5%	10%
	-3.48	-2.89	-2.57	0.741	0.463	0.348
	TEST STATISTIC -5.83645			**TEST STATISTIC 0.0162492**		

The above table ADF statistic tests the null hypothesis of the presence of unit root against the alternative of no unit root and the decision rule is to reject the null hypothesis when the value of the test statistic is less than the critical value. The KPSS statistic test the null hypothesis of stationarity against the alternative of non-stationarity and the decision rule is to accept the null hypothesis when the value of the test statistic is less than the critical value. The result of the ADF and KPSS test show that the stock returns are stationary.

2.2 Methods

The data for this study consist of the Monthly All Share Index (ASI) of the NSE. The ASI is a value weighted index made up of the listed equities on the Exchange. The period under study begins from January 2000 and ends on December 2017. This yields a total of 324 time series observations. The data were obtained from the NSE and transformed to Market returns as individual time series variables. The stock returns is defined as

$$Rmt = Ln\,(Pt - Pt\text{-}1) \qquad (1)$$

Where, Rmt is monthly returns for period Pt and Pt-1 are the All Share indices for Months t and t-1. Ln is Natural Logarithm. The addictive property implies that monthly returns are equal to the sum of all daily returns during the month. As a result, statistics such as the mean and variance of lower frequency data are easier to derive from higher frequency data.

ARCH (p) MODEL AND ITS PROPERTIES

Engle (2001) specifies that a good volatility model should reflect and capture the stylized facts of asset returns. The simplest model for studying volatility in univariate time series is the Autoregressive Conditional Heteroskedastic Model of order p, denoted ARCH (p). The model was originally introduced by Engle (1982).

For time series $\{r_t\}$ the ARCH (p) model Specification is:

$$r_t = \mu + \varepsilon_t \qquad (2)$$

$$(\varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2} \dots\dots) \sim N(0, h_t)$$

$$\varepsilon_t = \sqrt{h_t \mu_t} \qquad \mu_{t,} \sim IIN(0,1) \qquad (3)$$

$$h_t = \alpha_t + \sum_{i=1}^{p} \alpha_i \; \varepsilon_{t-i}^2 = \alpha_o + \alpha(L)\; \varepsilon_{t-i}^2 \qquad (4)$$

Where,

$\varepsilon_{t=}$ is the innovation/shock at day t and fol[illegible]et error process

$r_t =$ Asset returns at day t

$\mu =$ conditional mean of $\{r_t\}$

$h_t =$ Volatility at day t i.e. Conditional variance

$\varepsilon_{t-i}^2 =$ Squared innovation at day t – i

The time varying conditional variance is postulated to be a linear function of the past squared innovations. A sufficient condition for the conditional variance to be positive is that the parameters of the model should satisfy the following constraint: $\alpha_0 > 0, \alpha_1 > 0, \dots \alpha_p > 0.$

GARCH (p,q) MODEL AND ITS PROPERTIES

In practice, it is often found that large number of lag p, and large number of parameters, are required to obtain a good model fit of ARCH (p) model. Bollerslev in 1986 proposed Generalized ARCH or GARCH (p, q) model to solve these problems with the following formulation:

$$h_t = \alpha_o + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \; h_{t-i}$$

$$h_t = \alpha_o + \alpha_1 \varepsilon_{t-1}^2 + - - - + \alpha_p \varepsilon_{t-p}^2 + \beta_1 h_{t-1} + - - - + \beta_q h_{t-q} \qquad (5)$$

Where,

h_t is the volatility at day t – i

$\alpha_0 > 0$

$\alpha_i \geq 0$ for i = 1, ----,p

$\beta_i \geq 0$ for i = 1,---, q

ε_{t-1}^2 *and* h_t are as previously defined.

Under GARCH (p,q) model, (GARCH p,q) is the generalized ARCH p,q model of order or lag p and q) the conditional variance of $\varepsilon_t, h_{t,}$ depends on the squared innovations in the previous 'p' periods, and the conditional variance in the previous 'q' periods. The GARCH models are adequate to obtain a good volatility model fit for financial time series.

Rearranging the GARCH (p,q) model by defining $\mu_t = \varepsilon_t^2 - h_t$, it follows that

$$\varepsilon_t^2 = \alpha_0 + (\alpha(L) + \beta(L)\varepsilon_t^2 - \beta(L)\mu_t + \mu_t) \qquad (6)$$

Where, L is the backshift operator and

$\alpha(L) = \alpha_1 L + \cdots + \alpha_p L^p$

$\beta(L) = \beta_1 L + \cdots + \beta_q L^q$

Which is an ARMA (max (q,p), q) model for ε_t^2. By standard argument, the model is covariance stationary if and if all the roots of $(1 - \alpha(L) - \beta(L))$ lie outside the unit circle. The ARMA representation in 6 allows for the use of time series techniques in the identification of the order of p and q. For the sake of simplicity however, we are going to examine the GARCH (1,1) model and investigate all the features of stylized facts exhibited by the model.

The standard GARCH (1, 1) model process is specified as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (7)$$

Where, β_1 measures the extent to which a volatility shock today feeds through into the next period's volatility. $(\alpha_1 + \beta_1)$. Measures the rate at which this effect dies over time h_{t-1} is the volatility at day t -1. The conditional variance equation of GARCH (1,1) model contains a constant term and news about volatility from the previous period measured as the lag of previous term squared residuals.

GJR-GARCH MODEL

Another GARCH variant that is capable of modeling leverage effects is the threshold GARCH (GJR-GARCH) model, which has the following form:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_t \quad {}^{2}_{t-i} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (8)$$

Where, $$S_{t-i} = \begin{cases} 1 & if\, \varepsilon_{t-1} < 0 \\ 0 & if\, \varepsilon_{t-1} \geq 0 \end{cases}$$

γ_i =leverage effects coefficient. (if $\gamma_i > 0$ indicates presence of leverage effect.) that is depending on whether ε_{t-i} is above or below the threshold value zero, ε_{t-i}^2 has different effects on conditional variance σ_t^2: when ε_{t-i} is positive, the total effects are given by $\sigma_i \varepsilon_{t-i}^2$; when ε_{t-i} is negative, the total effects are given by $(\sigma_i + \gamma_i)\varepsilon_{t-i}^2$. so one would expect γ_i to be positive for bad news to have larger impacts. This model also known as the GJR model (Glosten, Jagannathan and Runkle, 1993) in this model the good and bad news had differential effects on the conditional variance. Good news have the influence of α, while the bad news have the influence of $(\alpha + \omega)$. If $\omega > 0$, we could say that the leverage effect exists while news is asymmetric when $\omega \neq 0$. The outcome of the model showed that the parameters in the variance equation were significant. The leverage term was highly significant. The assumption that positive and negative shocks have different impact on the volatility of monthly returns was reinforced. The AIC and the SIC of this model was lower compared to the GARCH (1, 1) model and also had a higher log likelihood value.

Table 3.0 Empirical Results of ARCH, GARCH (1,1), and GJR (GARCH) Models

Parameters	Coefficient	Std Error	T. Statistics	Significance
Mean	0.0210142324	0.001791231	11.73172	0.00000000
Constant ($\square_0$)	0.000178622	0.0000646324	2.7637	0.00572
ARCH ($\square_1$)	0.446621	0.0700685	6.3741	0.00048494
GARCH ($\square_1$)	0.553379	0.0464477	11.9140	0.00000000
($\square_1$ + $\square_1$)	1.000000			
GJR GARCH (γ)	0.0473161	0.0776136	0.6096	0.54216

The results presented in Table 3.0 show that the coefficient of the ARCH effect (α_1) is at statistically significant level. This indicates that news about volatility from the previous t periods has an explanatory power on current volatility. Similarly, the coefficient of the lagged conditional variance (β_1) is significantly different from zero, indicating volatility clustering in NSE return series. The sum of (α_1 + β_1) coefficients is unity, suggesting that shocks to the conditional variance are highly persistent i.e. (α_1 + β_1) = 1 implies indefinite volatility persistence to shocks over time. This implies that wide changes in returns tend to be followed by wide changes and mild changes tend to be followed by mild changes. A major economic implication of this finding for investors of the NSE is that stock returns volatility occurs in cluster and as it is predictable. We also notice that asymmetry (gamma) coefficient γ_1 is positive. The sign of the gamma reflects that a negative shock induce a larger increase in volatility greater than the positive shocks. It also implies that the distribution of the variance of the NSE returns is right skewed, implying greater chances of positive returns than negative. The positive asymmetric coefficient is indicative of leverage effects evidence in Nigeria stock returns. However, theory expects parameters α_0 and α_1 to be higher than zero (0), and β_1 to be positive to ensure that the conditional variance δ^2_t is non-negative. The parameters α_0 and α_1 are more than 0, and β_1 is positive. Thus, the GARCH (1,1) seems quite good for explaining the behavior of stock returns volatility in Nigeria.

III. Discussion of the Results

The table **1** shows the descriptive statistics of the NSE return series. The average monthly return is 1.67%. The monthly standard deviation is 6.0%, reflecting a high level of volatility in the market. The wide gap between the maximum (0.322212) and minimum (-0.319822) returns gives support to the high variability of price change in the NSE. Under the null hypothesis of normal distribution, J-B is 0. The J-B value of 439.7880 deviated from normal distribution. Similarly, skewness and kurtosis represent the nature of departure from normality. In a normally distributed series, skewness is 0 and kurtosis is 3. Positive or negative skewness indicate asymmetry in the series and less than or greater than 3 kurtosis coefficient suggest flatness and peakedness, respectively, in the returns data. The skewness coefficient of -0.33044 is negatively skewed. Negative skewness implies that the distribution has a long left tail and a deviation from normality. The empirical distribution of the kurtosis is clearly not normal but peaked. On the whole, the NSE return series do not conform to normal distribution but display negative skewness and leptokurtic distribution. These results are, however, based on the null hypothesis of normality and provide no information for the parametric distribution of the series. From Figure 1.0, we see that the NSE stock returns distribution is peaked confirming the evidence of non-normal distribution in Table 2.0 Peaked distribution is a sign of recurrent wide changes, which is an indication of uncertainty in the price discovery process. The visual representation above suggest the error terms may not likely be normally distributed as there are some points that are further apart, not evenly distributed or spread and this may likely resulted in high kurtosis (Kurtosis greater than 3 of normal distribution) which is another characteristics of financial returns. In other words, if the points of errors are not normally distributed, the skewness will be different from zero and the distribution will be asymmetrical. Most of the time the leverage effects of financial time series resulted from the asymmetrical effect produced from the skewness of the distribution. The above table ADF statistic tests the null hypothesis of the presence of unit root against the alternative of no unit root and the decision rule is to reject the null hypothesis when the value of the test statistic is less than the critical value. The KPSS statistic test the null hypothesis of stationarity against the alternative of non-stationarity and the decision rule is to accept the null hypothesis when the value of the test statistic is less than the critical value. The result of the ADF and KPSS test show that the stock returns are stationary. The results presented in Table 3.0 show that the coefficient of the ARCH effect (α_1) is at statistically significant level. This indicates that news about volatility from the previous t periods has an explanatory power on current volatility. Similarly, the coefficient of the lagged conditional variance (β_1) is significantly different from zero, indicating volatility clustering in NSE return series. The sum of ($\alpha_1 + \beta_1$) coefficients is unity, suggesting that shocks to the conditional variance are highly persistent i.e. ($\alpha_1 + \beta_1$) = 1 implies indefinite volatility persistence to shocks over time. This implies that wide changes in returns tend to be followed by wide changes and mild changes tend to be followed by mild changes. A major economic implication of this finding for investors of the NSE is that stock returns volatility occurs in cluster and as it is predictable. We also notice that asymmetry (gamma) coefficient γ_1 is positive. The sign of the gamma reflects that a negative shock induce a larger increase in volatility greater than the positive shocks. It also implies that the distribution of the variance of the NSE returns is right skewed, implying greater chances of positive returns than negative. The positive asymmetric coefficient is indicative of leverage effects evidence in Nigeria stock returns. However, theory expects parameters α_0 and α_1 to be higher than zero (0), and β_1 to be positive to ensure that the conditional variance δ^2_t is non-negative. The parameters α_0 and α_1 are more than 0, and β_1 is positive. Thus, the GARCH (1,1) seems quite good for explaining the behaviour of stock returns volatility in Nigeria.

IV. Conclusion

This work study the behaivior of volatility modeling of monthly stock market returns in Nigeria using ARCH, GARCH (1,1) and the GJR-GARCH (1,1) models. Volatility clustering, leptokurtosis and leverage effects were examined for the NSE returns series from January 2000, to December 2017. The results from GARCH (1,1) model show that volatility of stock returns is persistent in Nigeria. The result of GJR-GARCH (1,1) model shows the existence of leverage effects in Nigeria stock returns. Finally, volatility persistence in NSE return series is clearly indicated in the unity of ARCH and GARCH parameter estimates ($\alpha_1 + \beta_1$) = 1 implying indefinite volatility persistence to shocks over time. Overall results from this study provide evidence to show volatility persistence, leptokurtic distribution and leverage effects and volatility persistence for the Nigeria stock returns data. These results are in tune with international evidence of financial data exhibiting the phenomenon of volatility clustering, fat-tailed distribution and leverage effects. The results also support the evidences of volatility clustering in Nigeria provided by Ogum, et al. (2005); existence of leverage effects in Nigeria stock returns provided by Okpara and Nwezeaku (2009).

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