INVESTIGATING STOCK RETURNS VOLATILITY IN NIGERIA USING GARCH MODELS

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Abstract

Stock market volatility affects business investment and economic growth showing market inefficiency. However, the degree of volatility presence in the stock market would lead investors to demand a higher risk premium, creating higher cost of capital which impedes investment and slows economic development. Therefore this work investigates the nature and behavior of Stock Returns Volatility of the Nigerian Stock Exchange (NSE) using the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model- GARCH (1,1) Model- and the Glosten, Jagannathan and Runkle- Generalized Autoregressive Conditional Heteroskedastic GARCH Model - GJR-GARCH(1,1) model. Monthly All Share Indices of the Nigerian Stock Exchange (NSE) for the periods of 1stJanuary 1985 to 31stDecember 2011 provided the 324 time series sample data for investigating volatility persistence and asymmetric properties of the series. The results of GARCH (1,1) model indicate evidence of volatility clustering in the NSE returns series. Also, the results of the GJR-GARCH (1,1) model shows the existence of leverage effects in the series. Finally, the Generalized Error Distribution (GED) shape test reveals leptokurtic returns distribution. Overall results from this study provide evidence to show volatility persistence, fat- Tail distribution, and leverage effects for the Nigeria stock returns data. Base on the findings in this work, investors are at greater risk if the market is not modernized to improve efficiency.

Keywords: Volatility, GARCH, Stock Exchange, Nigeria

Introduction

Volatility is the standard deviation of the change in value of a financial instrument with a specific time horizon. It is often used to quantify the risk of the instrument over that time period. Volatility is considered the most accurate measure of risk and by extension, of returns, which implies that the higher the volatility, the higher the risk and the reward. Volatility of returns is a key issue for both researchers in financial economies and analysts in the financial markets. The price of stocks and other assets depend on the expected volatility (covariance structure) of returns. Banks and other financial institutions make volatility assessments as a part of monitoring their risk exposure. Numerous studies have documented evidence showing that stock returns exhibit the phenomenon of Volatility Clustering, Leptokurtosis and Asymmetry. Volatility clustering occurs when large Stock price changes are followed by large price change, of either sign, and small price changes are followed by periods of small price changes. Leptokurtosis means that the distribution of stock returns is not normal but exhibits fat-tails. In other words, Leptokurtosis signifies that high probabilities for extreme values are more frequent than the normal law predict in a series. Asymmetry, also known as leverage effects, means that a fall in return is followed by an increase in volatility greater than the volatility induced by an increase in returns. This implies that more prices wander far from the average trend in a crash than in a bubble because of higher perceived uncertainty (Mandelbrot, 1963; Fama, 1965; Black, 1976). These characteristics are perceived as indicating a rise in financial risk, which can adversely affect investors' assets and wealth. For instance, volatility clustering makes investors more averse to holding stocks due to uncertainty. Investors in turn demand a higher risk premium in order to insure against the increased uncertainty. A greater risk premium results in a higher cost of capital, which then leads to less private physical investment. Modeling volatility is an important element in pricing equity, risk management and portfolio management. Stock prices reflect all available information and the quicker they are in absorbing accurately new information, the more efficient is the stock market in allocating resources. 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. Also, detection of stock returns volatility-trends would provide insight for designing investment strategies and for portfolio management. Hence, it is important to understand the behavior of the NSE returns volatility. 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. Concerning the effectiveness of the ARCH family models in capturing volatility of financial time series, Hsieh (1989) found that GARCH (1,1) model worked well to capture most of the stochastic dependencies in the times series. Based on tests of the standardized squared residuals, he found that the simple GARCH (1,1) model did better at describing data than a previous ARCH(1,2) model also estimated by Hsieh (1989). Similar conclusions were reached by Taylor (1994), Brook and Burke (2003) and Olowe (2009).

Methodology

Source of Data

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 1985 and ends on December 2011. 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. Market returns are proxies by the log difference change in ASI of the NSE thus:

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

Where, Rmt is monthly returns for period *Pt* and *Pt-1* are the All Share 1ndices 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.

Stylized Facts about Stock Returns Volatility

A number of stylized facts about volatility of financial asset prices have emerged over the years, and been confirmed in numerous studies. A good volatility model, then, must be able to capture and reflect these stylized facts. In this, we document some of the common features of stock asset price volatility process.

Volatility Clustering

The clustering of large moves and small moves (of either sign) in the price process was one of the first documented features of the volatility process of asset prices. Mandelbrot (1963) and Fama (1965) both reported evidence that large changes in the price of an asset are often followed by other large changes and small changes are often followed by small changes. This behavior has been reported by numerous other studies, such as Baillie *et al*. (1996) and Schwert (1989). The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future.

Persistence Characteristics of Volatility

Volatility is said to be persistent if today's return has a large effect on the forecast variance many periods in the future. A further measure of persistence in a volatility model is the half life of volatility. This is defined as the time taken for the volatility to move half way back towards its unconditional mean following deviation from it. Engle et al. (2001).To make a precise definition of volatility persistence, let the expected value of the variance of returns k periods in the future be defined as

$$h_{t+k/t} = E_t(r_{t+k} - m_{t+k})^2 \qquad (2)$$

The forecast of future volatility then will depend upon information in today's information set such as today's returns. Volatility is said to be persistent if today's return has a large effect on the forecast variance many periods in the future.

Taking partial derivatives, the forward persistence is: $\theta_{t+k/t} = \frac{\partial h_{t+k/t}}{\partial r_t^2}$ (3)

This is dimensionless number as squared returns and conditional variance are in the same units.

For many volatility models this declines geometrically but may be important even a year in the future. A closely related measure is the cumulative persistence, which is the impact of a return shock on the average variance of the asset return over the period from t to $t+k$. It is defined as:

$$\phi_{t+k/t} = \frac{\partial\left(\frac{1}{2}\left(h_{t+k/t} + h_{t+k-1/t} \cdots + h_{t+1}\right)\right)}{\partial r_t^2} = \frac{1}{2}\left(\theta_{t+k/t} + \theta_{t+k-1/t} + \ldots + \theta_{t+1/t}\right)$$
(4)

The response of long – term option prices to volatility shocks suggests that volatility models should have significant cumulative persistence a year in the future.

Mean Reverting Nature of Volatility

Volatility clustering implies that volatility comes and goes. Thus a period of high volatility will eventually give way to more normal volatility and similarly, a period of low volatility will be followed by a rise. Mean reversion in volatility is generally interpreted as meaning there is a normal level of volatility to which volatility will eventually return. Very long run forecasts of volatility should all converge to this same normal level of volatility, no matter when they are made. While most practitioners believe this is a characteristic of volatility, they might differ on the normal level of volatility and whether it is constant over all time or its institutional changes. More precisely, mean reversion in volatility implies that current information has no effect on the long run forecast. Hence

$p \lim_{k \to \infty} \theta_{t+k/t} = 0,$ for all t.
(5)

Which is more commonly expressed as

$p \lim_{k \to \infty} h_{t+k/t} = \sigma^2 < \infty,$ for all t.
(6)

Options prices are generally viewed as consistent with mean reversion. Under simple assumptions on option pricing, the implied volatilities of long maturity options are less volatile than those of short maturity options. They usually are closer to the long run average volatility of the asset than short maturity options.

Possibility of Asymmetric Impact of Innovations on Volatility

Many proposed volatility models impose the assumption that conditional volatility of the asset is affected symmetrically by positive and negative innovations. The GARCH (1,1) model, for example, allows the variance to be affected only by the square of lagged innovation; completely disregarding the sign of that innovation. For equity returns it is particularly unlikely that positive and negative shocks have the same impact on volatility. This asymmetry is sometimes ascribed to *leverage effect* and sometimes to a *risk Premium effect.* As the price of stock falls, its debt – to – equity ratio rises, increasing the volatility of returns to equity holders. In the latter story, news of increasing volatility reduces the demand for a stock because of risk aversion. The consequent decline in stock value is followed by the increased volatility as forecast by the news. Black (1976), Chritie (1982), Nelson (1991), Glosten et al. (1993) and Engle and Ng (1993) all find evidence of volatility being negatively related to equity returns. In general, such evidence has not been found for exchange rates. For interest rates a similar asymmetry arises from the boundary of zero interest rates. When rates fall, (prices increase) they become less volatile in many models and in most empirical estimates, see Engle Ng and Rothschild, Chan et al. (1990) and Brenner et al. (1996). In diffusion models with stochastic volatility, this phenomenon is associated with correlation between the stock to returns and the shock to volatility. The asymmetric structure of volatility generates skewed distributions of forecast prices and under simple derivative pricing assumptions; this gives option implied volatility surfaces which have a skew. That is, the implied volatilities of out – of – the money put options are higher than those of at – the – money options, which in turn are higher than the implies of in the money puts.

Fat Tails Probabilities

It is well established that the unconditional distribution of asset returns has heavy tails. Typical kurtosis estimates range from 4 to 50 indicating very extreme non – normality. This is a feature that should be incorporated in any volatility model. The relation between the conditional densities is Gaussian, and then the unconditional density partially reveals the source of the heavy tails. If the conditional density is Gaussian, then the unconditional density will have excess kurtosis due simply to the mixture of Gaussian densities with different volatilities. However, there is no reason to assume that the conditional density itself is Gaussian, and many volatility models assume that the conditional density is itself fat tailed, generating still greater kurtosis in the unconditional density. Depending on the dependence structure of the volatility process, the returns may still satisfy standard extreme value theorems.

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:

$$r_t = \mu + \varepsilon_t - \quad (7a)$$

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

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

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 = \alpha_0 + \alpha(L) \varepsilon_{t-1}^2 \qquad ($$

Where,

$\varepsilon_{t=}$ is the innovation/shock at day *t* and follows heteroscedastic 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:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + --- + \alpha_p \varepsilon_{t-p}^2 + \beta_1 h_{t-1} + --- + \beta_q h_{t-q} \quad (9)$$

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

$$\varepsilon_t^2 = \alpha_0 + (\alpha(L) + \beta(L)\varepsilon_t^2 - \beta(L)\mu_t + \mu_t) \quad (10)$$

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 (p, q), 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 (10) 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:

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

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:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i}\, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^2 \quad --- (12)$$

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 is also known as the GJR model (Glosten, Jagannathan and Runkle, 1993).

Empirical Analysis

Data Characteristics

Figure 1 presents the pattern of log level data series of the NSE for the period under review (January 1985 to December 2011). The log level data show no tendency to return to its mean indicating the need for differencing.

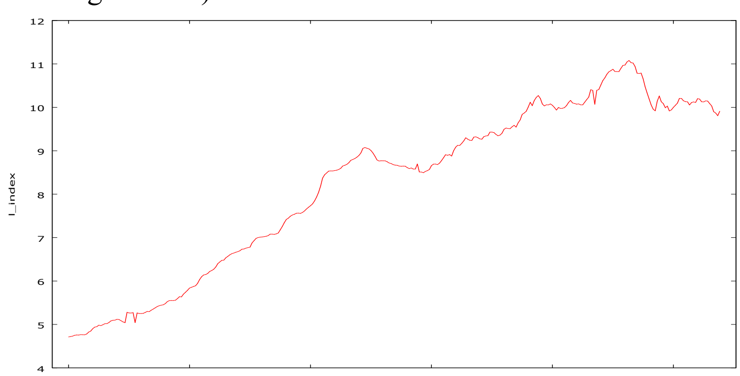

Figure1: The pattern of Log level data of NSE

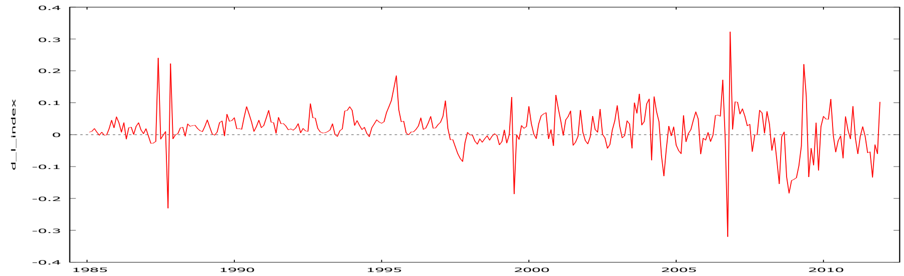

Fig. 2: plot of the first difference of the log of the data.NSE Return Series

Figure 2: shows sign of returning to its mean suggesting that the series are weakly stationary. The clustering of large moves and small moves (of either sign) in the returns process was one of the first documented features of the volatility process of asset returns. Mandelbrot (1963) and Fama (1965) both reported evidence that large changes in the price of an asset are often followed by other large changes and small changes are often followed by small changes. Also displays the monthly returns on the Nigerian Stock Exchange Index over a twenty two year period and shows evidence that the volatility of returns varies over time. The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future.

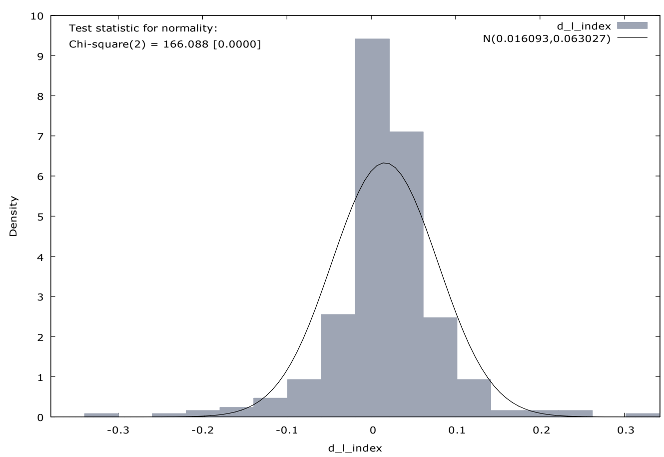

Fig 3: Histogram of the series

From Figure 3, we see that the NSE stock returns distribution is peaked confirming the evidence of non-normal distribution. 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 that 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. Table 1 describes the ADF and KPSS test result of the critical levels and the test statistic.

Table 1: ADF and KPSS Test Results

	CRITICAL LEVEL (ADF)			CRITICAL LEVEL (KPSS)		
STOCK RETURNS	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 ADF statistic test the null hypothesis for 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 for 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 shows that the stock returns are stationary.

Table 2 Portmanteau Test

TEST	RETURNS	SQUARED RETURNS
LJUNGBOX	64.9384	58.8013
P-VALUE	0.0002	0.0013

The null hypothesis of no autocorrelation cannot be accepted and that we conclude that there is low autocorrelation in the returns. The autocrrelation for the returns are much higher than those of squared return which is consistence with the literature for the characteristics of financial data suggesting the presence of conditional heteroskedasticity. We conclude that there are weak autocorrelation in the returns.

Jaque Bera Test for Normality

To achieve the first objective of the research, we examine the characteristics of unconditional distribution of stock returns. This will enable us to explore and explain some stylized facts embedded in the financial returns. Jaque Bera normality test is used to demonstrate this and the results are given in Table 4 and 5.

Table 3: Jaque - Bera Test for Normality

Mean	0.0160928
Maximum	0.322212
Minimum	-0.319822
Std. Dev.	0.0630272
Skewness	-0.33044
Kurtosis	5.67811
Jaque Berra Test	343.0862
P value	0.0000

The results in Table 3 shows that small positive average returns of about one – thousandth of a percent will be recorded for stock return. The skewness coefficient indicates that the returns distribution is negatively skewed; a common feature of equity returns. Finally, the kurtosis coefficient, which is a measure of the thickness of the tails of the distribution, is very high.

This is one of the stylized facts known in the early days of volatility modeling, and also from Jaque – Berra test, the hypothesis of normality is strongly rejected.

Model Checking

Table 4 Result for no Remaining ARCH Effect test Residuals

F-TEST	P-VALUE
1.6683	0.1974

In Table 4, the null hypothesis that there is no ARCH effects remaining at lag is accepted since the p – value is greater than 0.05. Therefore, the models are adequate.

Table 5: Results of ARCH LM Test for GARCH (1, 1) Residuals

LAGS	T-STATISTICS	P-VALUES
Lag 1	0.3435	0.5578
Lag 2	0.5387	0.7639
Lag 3	0.5418	0.9096

In Table 5 indicate that, the null hypothesis of no GARCH (1,1) effects remaining at lag 1, lag 2 and lag 3 are accepted. Since the p- values are greater than 0.05. Therefore we concluded that the models are adequate. The model is adequate, and then the standardized squared residuals should be serially uncorrelated.

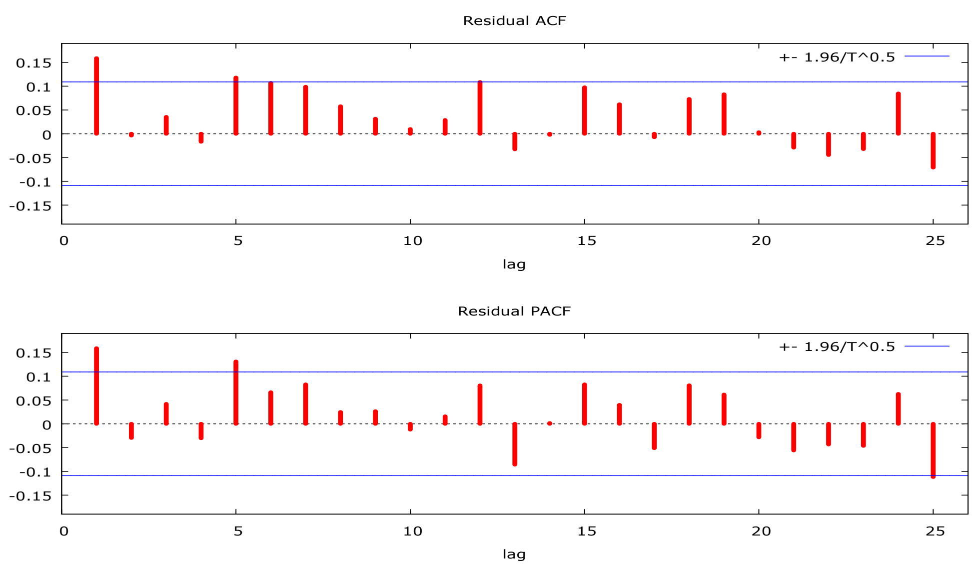

Figure 4: GARCH (1, 1) Residuals Squares of Returns

Figure 4 above shows that there is little or low correlation observed in the squared residuals of the GARCH (1, 1) returns.

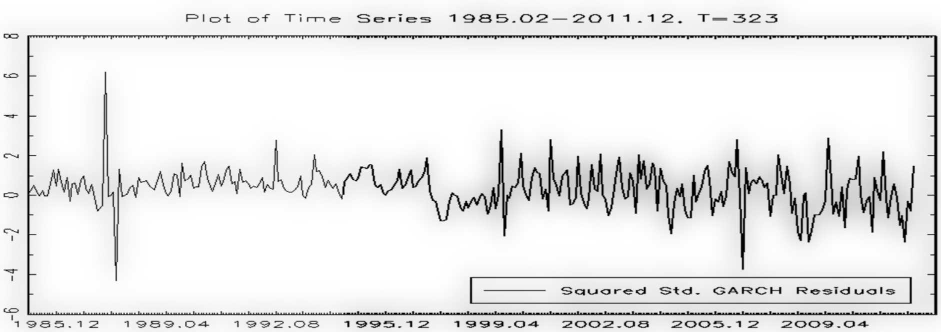

Figure 5 Estimated Conditional Volatility of the Returns Using GARCH (1, 1)

The plot of Figure 5 clearly shows that the returns series mimics the estimated conditional volatility.

Table 6 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 (α_0)	0.000178622	0.0000646324	2.7637	0.00572
ARCH (α_1)	0.446621	0.0700685	6.3741	0.00048494
GARCH (β_1)	0.553379	0.0464477	11.9140	0.00000000
($\alpha_1 + \beta_1$)	1.000000			
GJR GARCH (γ)	0.0473161	0.0776136	0.6096	0.54216

The results presented in Table 6 shows 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 the presence of 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. ($\alpha_1 + \beta_1$) = 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 in returns tend to be followed by mild changes in volatility in volatility clustering. 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.

Conclusion and Recommendation

This work investigated the behavior of volatility of stock market returns in Nigeria using 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 1985, to December 2011. 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).

Recommendation

Volatility of returns should be a key issue for both researchers in financial economics and analysts in the financial markets. Since the price of stocks and other assets depends on the expected volatility (covariance structure) of returns, Banks and other financial institutions most make volatility assessments a mandatory part of monitoring their risk exposure. Also, detection of stock returns volatility-trends would provide insight for designing investment strategies and for portfolio management.

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