Modelling the Risk – Return Volatility Nexus in the Nigerian Stock Exchange

Ihejirika, Peters O.
Department of Banking and Finance, Faculty of Management Sciences, Imo State University Owerri, Nigeria
Email: ihejirikap@yahoo.com

Abstract
This study estimated and analyzed the risk – return volatility nexus in the Nigerian Stock Exchange for the period January 1985 to April 2019, by applying the non-linear symmetric and asymmetric Exponential Generalized Auto Regressive Conditional Heteroscedasticity (EGARCH) model. The study results indicate that the Nigerian stock exchange all share index log relative return has a leptokurtic distribution and is negatively skewed. The ADF Unit Root Test show that the Nigerian stock exchange all share index log relative return is integrated of order zero i.e. I(0). The results also indicate that the Nigerian stock exchange index returns exhibits volatility clustering meaning that the market experience mean reversion. Another stylized fact exhibited by the Nigerian stock exchange index returns is volatility persistence (long memory) as revealed by the study. These results indicate that investors are well able to predict the future parts of return in the Nigerian stock exchange and therefore should embrace models that are capable of forecasting the risk and return relationships such as the EGARCH model in making investment decisions to avoid bearing avoidable risks.

***Keywords**: Risk–Return Volatility, EGARCH, Heteroskedasticity, Leptokurtosis, Asymmetric effect, Long-Memory, Volatility Clustering,*

1.1 Introduction

A period of intense debate, arguments and research on the importance of stock markets to economic growth and development have revealed that stock markets play significant roles in economic growth and development of nations (Acemoglu and Zillibotti, 1997). Importantly, stock markets are expected to accelerate economic growth by providing a boost to domestic savings and increasing the quantity and quality of investments (Yertey 2008). Again, notwithstanding that investments in stock markets require long-term capital, the opportunity afforded savers to liquidate their holdings at any time encourages savings and investment. Furthermore, Stock markets provide vehicles for trading, pooling and diversifying risk and according to Gurley and Shaw (1955), financial systems that allow investors to hold a diversified portfolio of risky projects will propel society to move towards investments with higher expected returns with positive impact on economic growth.

However, as stock markets provide investors with opportunity for trading, pooling and diversifying risk, it also confronts investor with the challenges of managing the portfolios of risky assets especially when stock markets enter a period of turbulence as was witnessed during the financial crisis of 2007 - 2009. The impact of that financial crisis still lingers with many investors' wealth totally wiped out leading to pessimism and lack of confidence in the stock market and funds badly needed in the economy taken away to safer markets. This situation raises issues like whether investors could have avoided the losses occasioned by the financial meltdown. Or indeed whether the financial crisis could have been predicted.

Predictions or forecasts of events is possible but mostly with some margin of error. In modelling the volatility of financial markets, the assumption of homoscedasticity is central to linear regression models. Heteroscedasticity which is the violation of homoscedasticity is present when the size of the error term differs across values of an independent variable. According to Engel (2004), instead of considering this as a problem to be corrected, ARCH and GARCH family models treat heteroskedasticity as a variance to be modeled and consequently, a prediction computed for the variance of each error term.

Paulo, David, Tiago and George (2011) observe that the gain or loss of an investment can be defined by the movement of the market. This movement can be estimated by the difference between the magnitudes of stock prices in distinct periods and this difference can be used to calculate the volatility of the markets. A highly volatile stock market may be favourable or unfavorable to investors. Thus, investors are constantly faced with uncertainty in making investment decisions.

Thus, the question here is what signs should investors watch out for in efforts to mitigate the uncertainty in the Nigerian stock exchange? Are there methods and indicators investors can use to monitor, predict, understand and manage the risk return volatility dynamics in the Nigerian stock exchange? According to Engle (2003), as well as Stavroyiannis (2012) financial time series returns have a variety of properties called stylized facts. These include leptokurtosis, heteroskedasticity, volatility clustering, leverage effect, and long memory. Also, asset prices are generally non-stationary. Returns are usually stationary. Some financial time series are fractionally integrated. Return series usually show no or little autocorrelation. Serial independence between the squared values of the series is often rejected pointing towards the existence of non-linear relationships between subsequent observations. Normality has to be rejected in favor of some thick-tailed distribution. Some series exhibit so-called leverage or asymmetric effect, i.e. changes in stock prices tend to be negatively correlated with changes in volatility. The effect of good news and bad news may have asymmetric effects on volatility.

Elsewhere, studies modeling the volatility of stock exchanges abound but very few studies have attempted to model the *volatility of volatility* in the Nigerian stock exchange. This study therefore aims to estimate and analyze the risk – return volatility relation as well as the predictability of the Nigerian stock index return by applying the non-linear symmetric and asymmetric Exponential Generalized Auto Regressive Conditional Heteroscedasticity (EGARCH) model. This may help investors in making their investment decisions.

Following the above introduction, section two covers review of related literature. The methodology adopted for this study are stated in section three while the analysis of data is handled in section four. The summary and conclusion as well as recommendations are in section five.

2.0 Review of related literature

*2.1 Volatility and **Volatility clustering***

Volatility has been described by Islam (2014) as the variations in the returns provided by a financial security due to percentage change in its price over a period of time. Discussing volatility, Investopedia (2018) observes that investment returns are often stated as long-term averages (mean) and assert that this practice hides short-term details. Stock market analysis and forecasting currently deal with real time data in nanoseconds such that the day-to-day, week to week or month-to-month experience of an investor might be radically different from the long-term averages. What happens in-between might have a large impact on the final wealth of an investor. The daily, quarterly and annual movements can be dramatic. Thus, Investopedia (2018) see volatility as the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time. According to Andersen, Bollerslev, Diebold and Ebens (2001), Financial market volatility is central to the theory and practice of asset pricing, asset allocation, and risk management. Although most textbook models assume volatilities and correlations to be constant, it is widely recognized among both finance academicians and practitioners that they vary importantly over time.
On the other hand, Volatility clustering refers to the observation by Mandelbrot (1963) that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." Volatility clustering has also been described by Engle (2003) to obtain in a situation where when volatility is high, it is likely to remain high, and when it is low it is likely to remain low but that these periods are time limited. Grimes (2014) assert that real market prices show at least one very serious departure from simple random walks. A random walk according to Grimes (2014) has no memory of what has happened in the past, and future steps are completely independent of past steps. However, he observed something very different in the financial data, that is, large price changes are much more likely to be followed by more large changes, and small changes are more likely to follow small changes. For practical purposes, Grimes (2014) explained that what is probably happening is that markets respond to new information with large price movements, and these high-volatility environments tend to last for a while after the initial shock. This is referred to in the literature as the persistence of volatility shocks and gives rise to the phenomenon of volatility clustering.

Furthermore, Moffatt (2017) explain that time series of financial asset returns often demonstrates volatility clustering. In time series of stock prices, for instance, it is observed that the variance of returns or log-prices is high for extended periods and then low for extended periods. As such, the variance of daily returns can be high one month (high volatility) and show low variance (low volatility) the next. This occurs to such a degree that it makes an independent and identically distributed (iid) model of log-prices or asset returns unconvincing. It is this very property of time series of prices that is called volatility clustering.

2.2 **Leverage or Asymmetric Effect**

The term leverage effect refers to the observed relationship between returns and volatility. The volatility is known to increase when the market and the stock prices experience a fall. One possible explanation for this phenomenon is based on financial leverage, where a fall in the market value of a firm's equity makes a firm more levered, resulting in an increase in the stock return volatility. The leverage effect suggests that volatility rises when the asset price falls. Thus, the effect of good news and bad news may have asymmetric effects on volatility (see Bollerslev, 1986 and Nelson, 1991).

2.3 Empirical review

Reza, Tularam and Li (2018) analyzes the stock returns and volatility of the global water Industry. Their study estimates ARMA (1, 1)-GARCH (1, 1) and EGARCH (1, 1) models on the World Water index (WOWAX), S-Network Global Water Index (S-Net), S&P Global Water Index (S&P), and MSCI ACWI Water Utilities Index (MSCI ACWI), the Asia, Europe, Latin America and US water markets, Pictet Global Water Fund (Pictet), and KBC Eco Water Fund (KBC Eco) for the period 2004–2014.they found that their EGARCH (1, 1) model results indicates the existence of persistence of volatility from four water indices, four water markets and two water funds in different periods and asymmetric volatility (leverage) for Asia and US, S-Net and Pictet in full, pre-GFC and GFC periods and for WOWAX in GFC and post-GFC periods. The WOWAX is not highly correlated with water markets and water funds, which suggests that it may provide a possible opportunity for portfolio diversification in different periods.

Sokpo, Iorember and Usar (2017) investigated the effect of inflation on stock market returns on the Nigerian stock exchange market, employing a volatility modeling approach. Using monthly data on stock market returns and consumer price index inflation rate, the paper employed GARCH and E-GARCH volatility modeling techniques for analysis. The study found that CPI inflation is not an important variable in explaining stock market return volatility in Nigeria. The E-GARCH model did not find existence of asymmetry in the stock return series; that is good news and bad news have identical impact on stock returns in Nigeria. The GARCH model show high persistence in the stock returns series, though a shock to stock returns has only a temporary impact.

Owidi and Mugo-Waweru (2016) analyze the Asymmetric and Persistence in Stock Return Volatility in the Nairobi Securities Exchange Market Phases for the NSE20 share index and 10 sampled stocks over 11 years. The asymmetric effect and volatility persistence were fitted by the Fractionally Integrated Exponential FIEGARCH (1,d,1). The study detected consistent peaks and troughs in the sampled series, obtaining in all cases two bear and three bull phases. Their result also shows persistent bullish phases than the bearish with bear phases much more frequent. Their diagnostic tests and estimates show volatility clustering and asymmetric effect with positive news impacting more during bullish and negative news during bearish. The results indicate non-systematic pattern across all stocks though a higher degree of dependence in both the level and volatility in the bull periods is detected. They assert that the results would be beneficial to investors and surveillance regime as it provides indication of behaviour of stock market volatility during the market phases.

Ivanovski, Stojanovski and Narasanov (2015) investigate the nature and dynamics of the shape of the distribution of the stock daily returns over time at Macedonian Stock Exchange (MSE) for

10 stocks and its index (2005–2014) in order to determine if they have Gaussian distribution. They use an Exponentially Weighted Moving Average and Rolling Window Moving Average Estimator to determine the level of volatility of daily stock returns, and then calculate kurtosis to test the accuracy of the assumption that the stock returns are normally distributed. Ivanovski, Stojanovski and Narasanov (2015) results show that the daily stock returns at Macedonian Stock Exchange (MSE) are characterized by high volatility and non-Gaussian behaviors as well as extremely leptokurtic distributions. They conclude that their analysis of MSE time series stock returns indicate volatility clustering and high kurtosis.

Emenike and Opara (2014) analyze the relationship between stock returns volatility and trading volume in Nigeria using daily All-Share Index and closing trading volume of the Nigerian Stock Exchange for the period of 3 January 2000 to 21 June 2011. They apply GARCH (1,1) and GARCH-X (1,1) models and found that the relationship between trading volume and stock returns volatility is positive and statistically significant. However, their results do not support the hypothesis that persistence in volatility disappears with inclusion of trading volume in the conditional variance equation. They claim to have avoided distribution bias in the specification of GARCH (1,1) and GARCH-X (1,1) by assuming the normal distribution, the generalized error distribution and the student-t distribution and conclude that their finding is consistent irrespective of the distribution.

Osahon (2014) paper aimed at empirically testing for the presence or otherwise of volatility clustering in the Nigerian stock market. Using time series data of share prices for the period 1995 to 2009, the Autoregressive Conditional Heteroscedasticity (ARCH) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model were estimated. The estimates indicate that the market exhibits volatility clustering. The rate at which the response function decays was found to be 1.1783.

Omorokunwa and Ikponmwosa (2014) examined the relationship between stock price volatility and few macroeconomic variables such as inflation, exchange rate, GDP and interest rate. Annual time series data ranging from 1980 to 2011 was used for this study. The generalized autoregressive conditional heteroskedasticity (GARCH) model was used in the empirical analysis. The findings of the study showed that stock prices in Nigeria are volatile. And that past information in the market have effect on stock price volatility in Nigeria. In addition, the study showed that interest rate and exchange rate have weak effect on stock price volatility while inflation is the main determinant of stock price volatility in Nigeria.

Emenike and Okwuchukwu (2014) in their paper used the GARCH-X (1.1) approach to analyze the influence of macroeconomic variables on stock market return volatility. Monthly macroeconomic variables including broad money supply, inflation, credit to the private sector, exchange rate, and the net foreign assets were investigated for impact on monthly ASI from January 2000 to March 2013. Descriptive analyses of the NSE log-return series show evidence of a non-normal distribution with an average monthly return of 1.11% and a standard deviation of 7.8%. The results of benchmark GARCH (1,1) model shows evidence of volatility clustering. Results of the GARCH-X model indicates that stock market return volatility is positively influenced by changes US dollar/Naira exchange rates and credit to private sector but negatively influenced by changes broad money supply and inflation. On the other hand, changes in net foreign assets shows negative but not significant influence on changes in stock market return volatility.

The key implication of these finding is that investors should adjust their portfolio to changes in these macroeconomic variables so as to reduce stock market volatility and improve stock market returns.

Atoi1(2014) used Nigeria All Share Index from January 2, 2008 to February 11, 2013, to estimate first order symmetric and asymmetric volatility models each in Normal, Student's-t and generalized error distributions with the view to selecting the best forecasting volatility model with the most appropriate error distribution. The results suggest the presence of leverage effect meaning that volatility responds more to bad news than it does to equal magnitude of good news. The last twenty-eight days out-of-sample forecast adjudged Power-GARCH (1, 1, 1) in student's t error distribution as the best predictive model based on Root Mean Square Error and Theil Inequality Coefficient.

Ihejirika and Anyanwu (2013) examined the characteristics of volatilities in the Nigerian stock exchange (NSE) and their prospects for option trading. Also, their paper tested the information efficiency of the historical volatilities of the NSE All Share Index (ASI) and NSE30 Index equities using Variance Ratio Wild Bootstrap Joint Tests. They found that one stock in the NSE had a long left tail distribution, while others were positively skewed. They discovered three equities with kurtosis and Jarque Bera probability statistics that approximate that of a normal distribution while the rest of the stocks studied including the NSE ASI were leptokurtic and had Jarque Bera statistics that indicated strong conditional heteroscedasticity. Ihejirika and Anyanwu (2013) report that the standard deviation statistics show that the degree of volatility vary among the NSE30 index equities. While the Variance Ratio Wild Bootstrap Joint Tests based on the Chow-Denning maximum |z| statistic show that for the monthly volatilities, eight equities and the NSE ASI generally reject the null hypothesis that they are martingales. Furthermore, their study reveals that three month moving volatilities indicate that three stocks strongly reject the null of a martingale while the NSE ASI and the rest of the NSE30 Index equities failed to reject the null hypothesis. As for whether investors can rely on past volatility information on the NSE ASI and NSE30 Index equities, Ihejirika and Anyanwu conclude that the results are mixed and therefore depends on the particular asset of interest.

Krishnamurti et al. (2013) apply EGARCH (1, 1) and EGARCH-GED models to examine the relationship between intra-day volatility and trading volume by using the intra-day Shanghai A-Share Index data from 2004 to 2006. They find that the asymmetric volatility phenomenon is reversed in the Shanghai Stock Exchange during bull markets. This means that volatility increases more with good news than with bad news.

Yong Tan (2012) paper examined the effects of Stock market volatility on bank performance in China. The sample comprises a total of 11 banks (four state-owned and seven joint-stock commercial banks) listed in the Chinese Stock Exchanges. The period under consideration extends from 2003-2009. The generalized methods of moments (GMM) difference and system estimators were applied. Empirical results show that high level of stock market volatility can translate into higher return on equity (ROE) and excess return on equity (EROE).

Ajao and Wemambu's (2012) "Volatility Estimation and Stock Price Prediction in the Nigerian Stock Market" also reflect some perspectives of the present study. They use month end stock prices of four major companies from the period January 2005 to December, 2009 and made use of the

Autoregressive Conditional heteroskedasticity (ARCH) to estimate and find out the presence of volatility. Their study found the presence of volatility in all the four stock prices used. Again, their results revealed that out of the four companies, only two companies' stock prices were predicted by volatility in their stock prices, while past stock prices predicted current stock prices implying that the market does not follow a random walk.

Okpara and Nwezeaku (2009) employed two-step estimation procedures, namely the time series procedure to determine the beta and idiosyncratic risk of companies and the cross-sectional estimation procedure used on EGARCH model to investigate whether idiosyncratic risks can be priced in the Nigerian stock market**.** Their study reveals that systematic risk is priced while the idiosyncratic risk is not priced. The study also found that volatility clustering is not quite persistent but there exists asymmetric effect in the stock market. That is unexpected drop in price (bad news) increases volatility more than unexpected increase in price (good news) of similar magnitude.

3.0 Methodology

3.1 Analytical Procedure

To capture the property of time-varying volatility, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model. Bollerslev's (1986) extended the ARCH model to the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model which has gained widespread acceptance in the literature and is often used for modelling stochastic volatility in financial time series. However, the ARCH and GARCH models according to Engle and Ng (1993) are not able to capture the "leverage or asymmetric effect" discovered by Black in 1976. Nelson (1991) introduced the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model in order to model asymmetric variance effects.

Important limitations of ARCH and GARCH models as recounted in the literature are the non-negativity constraints of the alpha and $beta$ which ensure positive conditional variances. Moreover, GARCH models assume that the impact of news on the conditional volatility depends only on the magnitude, but not on the sign of the innovation. However, it is now known that changes in stock prices are negatively correlated with changes in volatility. To overcome these drawbacks, Nelson (1991) introduced the exponential GARCH (EGARCH) model in which the logarithm of conditional variance is generally specified in E-views as:

$$(log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}$$

Where:

$log(\sigma_t^2)$ = the logarithm of conditional variance

ω = a constant term

ϵ_{t-1}^2= news about volatility from the previous period, measured as the lag of the squared residual from the mean equation: (the ARCH term).

σ_{t-1}^2 last period's forecast variance: (the GARCH term).

This paper models the conditional variance using EGARCH (1,1) model, which is specified as:

$$log(\sigma_t^2) = \omega + \alpha_1 \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_1 \frac{\epsilon_{t-i}}{\sigma_{t-i}} + \beta_1 \log(\sigma_{t-j}^2)$$

The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$.

The parameter β_j captures the leverage effect. For "good news" $\left(\frac{\epsilon_{t-i}}{\sigma_{t-i}} > 0\right)$ the impact of the innovation ϵ_{t-i}, is $\left(\boldsymbol{\beta_j} + \alpha_i\right) * \frac{\epsilon_{t-i}}{\sigma_{t-i}}$ and for "bad news" $\left(\frac{\epsilon_{t-i}}{\sigma_{t-i}} < 0\right)$ the impact of the innovation is $\left(\boldsymbol{\beta_j} - \alpha_i\right) * \frac{\epsilon_{t-i}}{\sigma_{t-i}}$. If $\alpha_i = 0$, $In\sigma_t^2$ responds symmetrically to $\frac{\epsilon_{t-i}}{\sigma_{t-i}}$. To produce a leverage effect, α_i, must be negative. The fact that the EGARCH process is specified in terms of log-volatility implies that σ_t^2 is always positive and, consequently, there are no restrictions on the sign of the model parameters.

For GARCH and EGARCH models the starting point in the estimation is usually the specifications for the conditional mean equation, the conditional variance and the conditional error distribution. These specifications are well laid out in e-views 10 manual.

3.2 Data

Monthly historical closing prices of the Nigerian stock exchange all share index (NSE ASI) which cover the period January 1985 to April 2019 sourced from the central bank of Nigeria's statistical data base was used. To arrive at the data for the analysis, the monthly log relative returns of the NSE ASI was calculated. Ihejirika and Anyanwu (2013) report that Black & Scholes (1973) assumed that financial asset prices are random variables that are log normally distributed. Therefore, returns to financial assets, the relative price changes are usually measured by taking the differences between the logarithmic prices. The log relative returns are mathematically defined by the equation:

$$y_t = In(S_i) - In(S_{i-1}) = In(\frac{S_i}{S_{i-1}})$$

Where y_t is the current period stock returns, $In(S_i)$ is the natural logarithm of current NSE ASI and $\ln(S_{i-1})$ is the natural logarithm of the previous NSE ASI.

3.3 Estimation procedures

Preliminary investigations include descriptive statistics, the test for unit root using the Dickey and Fuller (1979) and the estimation of the mean equation from where the plot of residuals is used to establish the existence of volatility clustering in the monthly stock index returns. The presence of Heteroscedasticity or Arch effect was also checked using the Lagrange Multiplier (LM) test for ARCH in the residuals to satisfy the condition for running the EGARCH model.

4.0 Results and Discussion of findings

4.1 Descriptive statistics

Table 4.1 descriptive statistics of the Nigerian stock exchange all share index log relative return

variable	Mean	Median	Max	Min	Std. dev.	Skewness	Kurtosis	J-Bera	Prob.
NSE ASI	0.005876	0.006418	0.140501	-0.1589	0.026663	-0.43752	9.583246	757.1326	0.000

Table 4.1 above show the descriptive statistics of the Nigerian stock exchange all share index log relative return. The Nigerian stock exchange all share index log relative return has a leptokurtic distribution and is negatively skewed. On the other hand, the ADF Unit Root Test in table 4.2 below show that the Nigerian stock exchange all share index log relative return is integrated of order zero i.e. I(0).

ADF Unit Root Test

Null Hypothesis: ASIRETURN has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.910614	0.0000
Test critical values:	1% level	-3.446201	
	5% level	-2.868422	
	10% level	-2.570501	

*MacKinnon (1996) one-sided p-values.

The estimated mean equation (not shown) with all share index monthly log relative returns as the dependent variable and a constant parameter as the only independent variable produced the residuals as shown below in figure 4.1

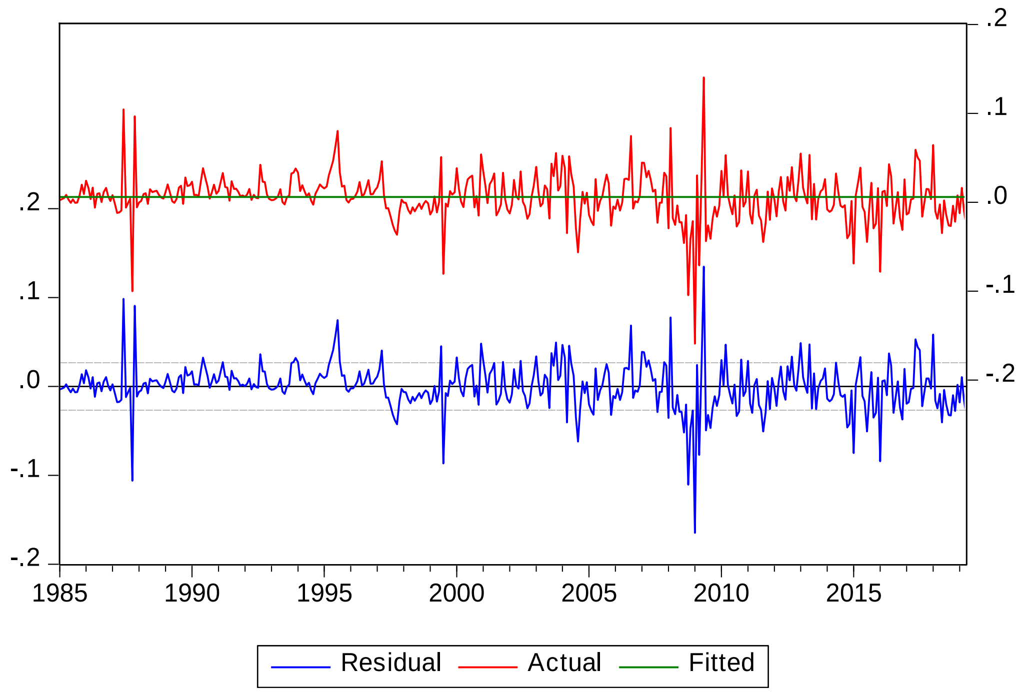

Figure 4.1: graph of residuals of the estimated mean equation

Figure 4.1 clearly show that there is evidence that the Nigerian stock exchange index returns exhibits volatility clustering with periods of high volatility followed by periods of low volatility indicating mean reversion exists in the market. This phenomenon supports the application of EGARCH model. This is further supported by the results of the Heteroskedasticity Test which show the presence of ARCH effect in the estimated mean equation (see table 4.3 below).

Table 4.3 Heteroskedasticity Test: ARCH

F-statistic	4.041306	Prob. F(1,409)	0.0451
Obs*R-squared	4.021334	Prob. Chi-Square(1)	0.0449

Estimation of the conditional variance equation

Table 4.4: estimated conditional variance results (**EGARCH MODEL**)

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009960	0.000786	12.66554	0.0000
		Variance Equation		
C(2)	-1.174091	0.177023	-6.632434	0.0000
C(3)	0.632496	0.076628	8.254107	0.0000
C(4)	-0.053347	0.035282	-1.512043	0.1305
C(5)	0.908345	0.021338	42.56852	0.0000

From table 4.4 above, C3 - the Arch term which corresponds to News about volatility from the previous period, measured as the lag of the squared residual from the mean equation show a positive and significant relationship with the conditional variance. C4- the asymmetric coefficient presents a scenario of no significant leverage effect. While C5- Last period's forecast variance (the GARCH term) indicate long memory in other words there is volatility persistence in the Nigerian stock exchange index return

Diagnostic tests

The estimated model was evaluated for serial correlation, normality as well as heteroscedasticity test to show whether there are any remaining ARCH effects in the residuals**.**

The Q-Statistic in table 4.5 below show that there is no serial correlation in the estimated model at the 5% level of significance indicating the model is good. Furthermore, the heteroscedasticity test (table 4.6 below) to show whether there are any remaining ARCH effects in the residuals indicate no further arch effect in the residuals of the model**.**

Table 4.5 Autocorrelation test
Date: 05/30/19 Time: 01:42
Sample: 1985M01 2019M04
Included observations: 412

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.018	-0.018	0.1340	0.714
*|. |	*|. |	2	-0.072	-0.072	2.2923	0.318
.|. |	.|. |	3	0.003	0.000	2.2954	0.513
.|* |	.|* |	4	0.107	0.103	7.1129	0.130
.|. |	.|. |	5	-0.047	-0.043	8.0350	0.154
.|. |	.|. |	6	0.026	0.039	8.3154	0.216
.|. |	.|. |	7	-0.010	-0.015	8.3549	0.302
.|. |	.|. |	8	-0.035	-0.043	8.8795	0.353
.|. |	.|. |	9	-0.052	-0.047	10.043	0.347
.|. |	*|. |	10	-0.057	-0.075	11.432	0.325
*|. |	*|. |	11	-0.076	-0.081	13.873	0.240
.|. |	.|. |	12	0.002	-0.004	13.876	0.309
*|. |	*|. |	13	-0.071	-0.077	16.037	0.247
.|. |	.|. |	14	-0.020	-0.012	16.212	0.301
.|. |	.|. |	15	-0.017	-0.016	16.333	0.360
.|. |	.|. |	16	-0.029	-0.040	16.693	0.406
.|* |	.|* |	17	0.083	0.098	19.661	0.292
.|. |	.|. |	18	0.004	-0.010	19.669	0.352
.|. |	.|. |	19	-0.048	-0.043	20.648	0.357
.|. |	.|. |	20	-0.049	-0.060	21.713	0.356
.|. |	.|. |	21	-0.002	-0.054	21.714	0.416
.|. |	.|. |	22	-0.007	-0.023	21.733	0.476
.|. |	.|. |	23	-0.027	-0.046	22.060	0.517
.|* |	.|* |	24	0.085	0.075	25.267	0.391
.|. |	.|. |	25	-0.035	-0.036	25.817	0.417
.|. |	.|. |	26	0.016	0.027	25.923	0.467
.|. |	.|. |	27	-0.028	-0.027	26.266	0.504
.|. |	.|. |	28	0.032	0.017	26.723	0.533
.|. |	.|. |	29	0.019	0.014	26.890	0.578
.|. |	.|. |	30	-0.035	-0.056	27.448	0.600
.|. |	.|. |	31	0.055	0.056	28.810	0.579
.|. |	.|. |	32	0.010	-0.016	28.854	0.627
.|. |	.|. |	33	-0.021	-0.021	29.062	0.664
.|. |	.|. |	34	0.020	0.018	29.245	0.700
.|. |	.|. |	35	-0.021	-0.043	29.452	0.733
.|. |	.|* |	36	0.062	0.074	31.181	0.697

*Probabilities may not be valid for this equation specification.

Table 4.6: Heteroskedasticity Test: ARCH

F-statistic	0.132268	Prob. F(1,409)	0.7163
Obs*R-squared	0.132872	Prob. Chi-Square(1)	0.7155

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 05/30/19 Time: 01:43
Sample (adjusted): 1985M02 2019M04
Included observations: 411 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.016196	0.104265	9.746328	0.0000
WGT_RESID^2(-1)	-0.017993	0.049473	-0.363687	0.7163

R-squared	0.000323	Mean dependent var	0.998299
Adjusted R-squared	-0.002121	S.D. dependent var	1.861541
S.E. of regression	1.863514	Akaike info criterion	4.087660
Sum squared resid	1420.328	Schwarz criterion	4.107215
Log likelihood	-838.0140	Hannan-Quinn criter.	4.095395
F-statistic	0.132268	Durbin-Watson stat	2.001080
Prob(F-statistic)	0.716280		

For the normality test, both the quantile-quantile plot and the Jarque-Bera statistics indicate that the residuals of the estimated model failed the normality test. The plot indicates that it is primarily large negative shocks that are driving the departure from normality

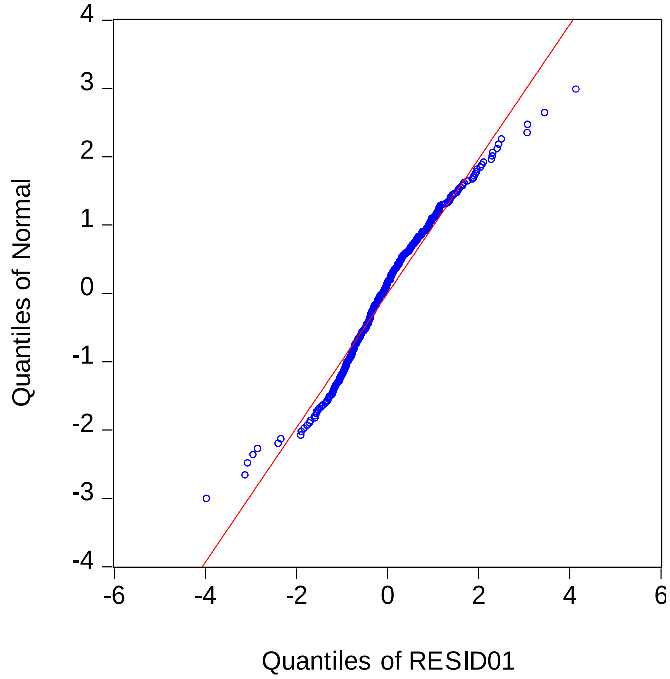

Figure 4.2: quantile – quantile theoretical graph of the residuals

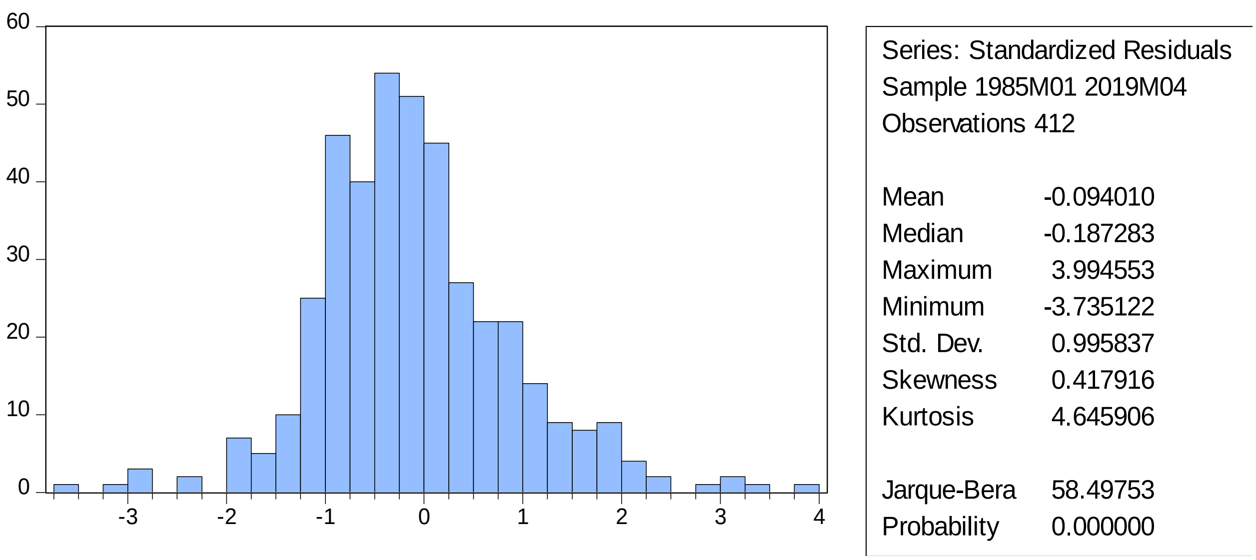

Figure 4.3: Jarque-Bera normality test

Conclusions

The empirical investigations conducted in this study have thrown up some facts about the Nigerian stock exchange index log relative returns. These include the negative skewness of returns and excess kurtosis as shown by the descriptive statistics in this study. The presence of volatility clustering was also established. Negative skewness, excess kurtosis and volatility clustering are known stylized facts associated with stock market returns and the Nigerian stock market has shown that it is not different from other stock markets in this regard. The critical point here for investors is that the returns in the Nigerian stock market are negatively biased and has the tendency to fluctuate widely in terms of magnitude and spread. Further, the assumption of constant variance of the error term is not true for the Nigerian stock market given the presence of volatility clustering and ARCH effect from the residuals of the estimated mean equation. In other words, the Nigerian stock market index return suffers from mean reversion.

The study also established that news about volatility from the previous period significantly affect future volatility- the conditional variance while last period's forecast variance (the GARCH term) indicate long memory in other words there is volatility persistence in the Nigerian stock exchange index return. These results indicate that investors are well able to predict the future parts of return in Nigerian stock exchange.

As the asymmetric coefficient presents a scenario of no significant leverage effect the study cannot categorically state that there is a leverage effect in the Nigerian stock exchange index returns even with the negative coefficient.

References

Acemoglu, D & Zilibotti, F (1997), Was Prometheus Unbound by Chance? Risk, Diversification and Growth, *Journal of Political Economy*. 105: 709-51.

Ajao, M.A & M.U. Wemambu (2012), Volatility Estimation and Stock Price Prediction in the Nigerian Stock Market, *International Journal of Financial Research Vol. 3, No. 1*

Andersen, T., Bollerslev, T., Diebold, F.X.& Ebens, H. (2001), The Distribution of Realized Stock Return Volatility," *Journal of Financial Economics, 61, 43-76.*

Atoi, N. V. (2014), Testing Volatility in Nigeria Stock Market using GARCH Models *CBN Journal of Applied Statistics Vol. 5 No.2 (December, 2014)* 65

Black, F. & Scholes, M. (1973), The Pricing of Options and Corporate Liabilities**,** *Journal of Political Economy, 637- 654*

Black, F. (1976), Studies in Stock Price Volatility Changes, Proceedings from the American Statistical Association, Business and Economics Statistics Section, 177-181.

Bollerslev, T. (1986) Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics, Vol. 31, No. 3, pp.307–327.*

Dickey, D. A., & Fuller, W. A. (1979), Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of American Statistical Association*, 74: 427-431.

Emenike K.O. & O. Odili (2014), Stock Market Return Volatility and Macroeconomic Variables in Nigeria. *International Journal of Empirical Finance Vol. 2, No. 2, 75-82*

Emenike K.O. & Opara C.C. (2014), the relationship between stock returns volatility and trading volume in Nigeria, *Business systems and Economics vol. 4 (2)*

Engle, R.F. (1982), Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica,50, 987-1007.*

Engle, R. F. (2003), Risk and Volatility: Econometric Models and Financial Practice. *Noble Lecture (December 8)*. New York: Salomon Centre.

Engle, R.F. & V.K. Ng (1993), "Measuring and Testing the Impact of News on Volatility," *Journal of Finance*, 48, 1749-1778.

E-views 10, 1994 – 2015 HIS Global Inc. Quantitative Micro Software, LLC www.eviews.

Grimes, A.H. (2014), https://adamhgrimes.com/volatility-clustering/ Aug 11,

Gurley, J & Shaw, E. (1955), Financial Aspects of Development and Growth, *American Economic Review, (September), 515-38.*

Ihejirika P.O & Anyanwu G.I. (2013), Characterization of Volatilities in the Nigerian Stock Exchange: Prospects for Options Trading, *Research Journal of Finance and Accounting Vol.4, No.16*

Investopedia, LLC (2018), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Process

Islam, M.A. (2014), Applying Generalized Autoregressive Conditional Heteroscedasticity Models to Model Univariate Volatility. *Journal of Applied Sciences, 14: 641-650.*

Ivanovski, Z., Stojanovski T. & Narasanov Z. (2015), Volatility and Kurtosis of Daily Stock Returns at Macedonian Stock Exchange, *UTMS Journal of Economics 6 (2): 209–221.*

Krishnamurti, C., Tian, G. G., Xu, M., & Li, G. (2013), No news is not good news: Evidence from the intra-day return volatility–volume relationship in Shanghai stock exchange. *Journal of the Asia Pacific Economy, 18*, 149–167. https://doi.org/10.1080/13547860.2012.742709

Mandelbrot, B. B. (1963), The Variation of Certain Speculative Prices, *The Journal of Business 36, No. 4, 394-419*

Nelson, D.B. (1991), Conditional heteroskedasticity in asset returns: A new approach, *Econometrica,59,347-370*

Okpara, G.C & Nwezeaku, N.C. (2009), Idiosyncratic Risk and the Cross-Section of Expected Stock Returns: Evidence from Nigeria, *European Journal of Economics, Finance and Administrative Sciences Vol. 17 http://www.eurojournals.com*

Omorokunwa, O.G. & Ikponmwosa, N. (2014) Macroeconomic Variables and Stock Price Volatility in Nigeria. *Annals of the University of Petroşani, Economics, 14(1), 259-268 259*

Osahon, O.H (2014) Measuring Nigerian stock market volatility Singaporean Journal of Business Economics, and Management studies Vol.2, No.8

Owidi O.H. & Mugo-Waweru F. (2016) Analysis of Asymmetric and Persistence in Stock Return Volatility in the Nairobi Securities Exchange Market Phases. *Journal of Finance and Economics*, 4(3):63-73

Paulo S.G., David A. S., Tiago A.E.F., & George D.C.C. (2011) Market volatility modeling for short time window *Physica A 390 3444–3453 journal homepage: www.elsevier.com/locate/physa*

Reza, R., Tularam, G.A & Li, B. (2018), Returns and volatility of water investments, *Cogent Economics & Finance Vol.*6: https://doi.org/10.1080/23322039.2018.1438724

Sokpo, J.T., Iorember, T.U. & Usar, T. (2017), Inflation and Stock Market Returns Volatility: Evidence from the Nigerian Stock Exchange 1995Q1-2016Q4: An E-GARCH Approach *International Journal of Econometrics and Financial Management, Vol. 5, No. 2, 69-76* Available online at http://pubs.sciepub.com/ijefm/5/2/9 ©Science and Education Publishing DOI:10.12691/ijefm-5-2-6

Stavroyiannis, S., Makris, I., Nikolaidis, V.& Zarangas, L. (2012), Econometric modeling and value-at-risk using the Pearson type-IV distribution, *International Review of Financial Analysis, Vol. 22, pp.10–17.*

Yertey, A. C. (2008), The Determinants of stock market development in Emerging Economies: Is South Africa Different. *IMF Working Paper, WP/08/32*

Yong, T., & Christos, F. (2012), Stock market volatility and bank performance in China, Studies in Economics and Finance, Vol. 29 Issue: 3, pp.211-228, https://doi.org/10.1108/10867371211246885

Appendix 1
Null Hypothesis: ASIRETURN has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.910614	0.0000
Test critical values:	1% level	-3.446201	
	5% level	-2.868422	
	10% level	-2.570501	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ASIRETURN)
Method: Least Squares
Date: 05/31/19 Time: 00:33
Sample (adjusted): 1985M06 2019M04
Included observations: 407 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ASIRETURN(-1)	-0.586129	0.084816	-6.910614	0.0000
D(ASIRETURN(-1))	-0.264902	0.078883	-3.358160	0.0009
D(ASIRETURN(-2))	-0.131602	0.074215	-1.773252	0.0769
D(ASIRETURN(-3))	-0.007553	0.065275	-0.115703	0.9079
D(ASIRETURN(-4))	-0.159656	0.049441	-3.229183	0.0013
C	0.003417	0.001365	2.504164	0.0127

R-squared	0.468725	Mean dependent var	-7.50E-05
Adjusted R-squared	0.462101	S.D. dependent var	0.034829
S.E. of regression	0.025544	Akaike info criterion	-4.482196
Sum squared resid	0.261651	Schwarz criterion	-4.423098
Log likelihood	918.1268	Hannan-Quinn criter.	-4.458808
F-statistic	70.75762	Durbin-Watson stat	2.011256
Prob(F-statistic)	0.000000		

Heteroskedasticity Test: ARCH

F-statistic	4.041306	Prob. F(1,409)	0.0451
Obs*R-squared	4.021334	Prob. Chi-Square(1)	0.0449

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 01:38
Sample (adjusted): 1985M02 2019M04
Included observations: 411 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000641	0.000108	5.927465	0.0000
RESID^2(-1)	0.098906	0.049200	2.010300	0.0451

R-squared	0.009784	Mean dependent var	0.000711
Adjusted R-squared	0.007363	S.D. dependent var	0.002083
S.E. of regression	0.002075	Akaike info criterion	-9.513013
Sum squared resid	0.001761	Schwarz criterion	-9.493458
Log likelihood	1956.924	Hannan-Quinn criter.	-9.505277
F-statistic	4.041306	Durbin-Watson stat	2.032539
Prob(F-statistic)	0.045055		

Dependent Variable: ASIRETURN
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 05/30/19 Time: 01:40
Sample: 1985M01 2019M04
Included observations: 412
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009960	0.000786	12.66554	0.0000

Variance Equation

C(2)	-1.174091	0.177023	-6.632434	0.0000
C(3)	0.632496	0.076628	8.254107	0.0000
C(4)	-0.053347	0.035282	-1.512043	0.1305
C(5)	0.908345	0.021338	42.56852	0.0000

R-squared	-0.023527	Mean dependent var	0.005876
Adjusted R-squared	-0.023527	S.D. dependent var	0.026663
S.E. of regression	0.026975	Akaike info criterion	-4.750580
Sum squared resid	0.299063	Schwarz criterion	-4.701781
Log likelihood	983.6194	Hannan-Quinn criter.	-4.731277
Durbin-Watson stat	1.646943		