Forecasting the Volatilities of the Nigeria Stock Market Prices

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The objective of this work is to assess and forecast the volatilities of prices on the Nigeria Stock Exchange. The ARCH family (ARCH, GARCH, TGARCH, EGARCH and PGARCH) and ARIMA models are used to assess and forecast volatilities in prices on the Nigeria stock market. The EGARCH model is found to be the most efficient for forecasting volatilities and has the capability to show the asymmetric effect. The assessment of volatilities in prices for 1985 to 2014 shows clustering, over the years. The forecasting performance shows the volatility in the Nigeria stock market to be on the increase for the next four years.

Keywords: ARCH Models, ARIMA, Forecasting, Volatility

JEL Classification: E37, E44, G11

1.0 Introduction

Efficient information about volatility of the Nigeria stock market prices enables financial analysts or researchers to obtain a precise estimate of the volatility process. Volatility is a key indicator in assessing the performance of the stock market in order for both indigenous and foreign speculators to make accurate speculations and decisions on investments. Evidence derived from literature shows that ARIMA and ARCH models have been applied extensively in volatility studies {Hamzaoui and Regaieg (2016), Maana, Kamau and Kisinguh (2015), Maxwell, Omari-Sasu and Frempong (2015), Basenga, Mwita and Mung'atu (2014), Atoi (2014), Ali (2013), Cao and Tsay (1992), Lin, Mackenzie and Gulledge JR (1986)}. Therefore, it contributes to knowledge gap by comparing these frequently used models. Consequently, application of different approaches to volatility measurement provides an efficient framework for risk measurement. Interestingly, it is justifiable to proceed with the study since volatility forecast significantly adds information required for risk management applications and in general portfolio management.

The performance of the Nigeria stock market has been shedding in the recent years, as measured by the market capitalization *(WDI, 2016)*. Record shows that investors incurring loss in the equity market of the Nigeria Stock Exchange (NSE) dropped by a total of ₦2.354 billion

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between 2014 and 2015.The Nigeria Stock Exchange (NSE) market capitalization dropped from ₦9.75 trillion to ₦8.939 trillion on the 4th of January 2016. That resulted to All Share Index closing at 25,988.40 basis points from the previously recorded 28,643.67 basis points, which implies a 9.27 percent decline in the stock market value. On the 1st of April, 2016, All Share Index (ASI) lost 134.82 points to close at 25,853.58 which is equivalent to 0.52 percent of the 25,988.40 basis point recorded in January 2016. Thus, market capitalization shredded from ₦8.939 trillion (as recorded on the 4th of January 2016) to ₦8,893 trillion showing a loss of ₦46 billion as at 1st of April 2016. The Nigeria Stock Exchange (NSE) is projected to trade at 24900.00 points by the end of this quarter, 24100.00 points in the third quarter and 23400.00 points in the last quarter of 2016 *(WDI, 2016).* The market capitalization shows a record of declining performance of the Nigeria Stock Exchange (NSE). It is imperative to provide investors and policy makers with prediction on stock market index in order to prevent them from incurring loss in their future investments and thereby guiding them in trading in the Nigeria stock market.

The All Share Index (ASI) on the Nigeria Stock Exchange (NSE) is used as proxy for stock market prices in order to assess volatility by measuring the trends and thereby examining the forecasting performance of the Nigeria Stock Exchange. The trend of the NSE All Share Index (ASI) from 1985 to 2014 is presented in Figure 1;

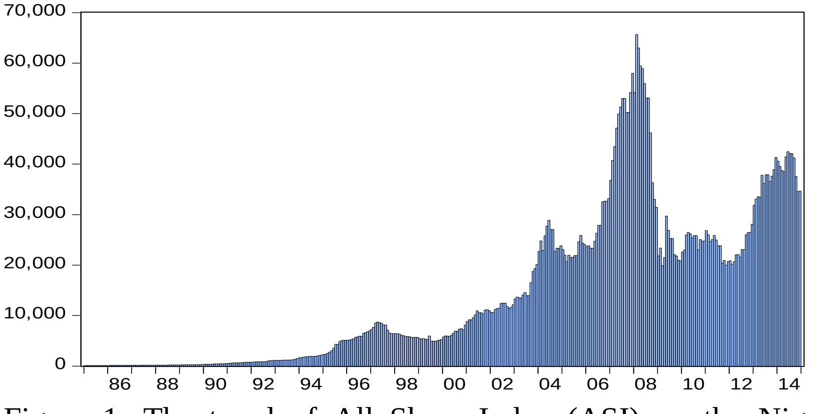

Figure 1: The trend of All Share Index (ASI) on the Nigeria Stock Exchange (NSE): January 1985 to December 2014

Volatility in the Nigeria stock exchange has been experiencing instability over the years as presented in Figure 1. Clearly, Figure 1 depicts trend in the NSE All Share Index series from 1985 to 2014. In the series, the prices were below 5,000 from 1985 to around 1994; it went up and became stable within 5,000 and 10,000 around 1995 to 2001. Again it went beyond 10,000 in 2002 and kept going on an increase at a steady rate until in 2006 when it increased explosively up till the peak around 60,000, and declined explosively to 20,000 in 2008. Again it became stable when the prices were within 20,000 and 30,000 from 2008 until around 2013 when it started going on an increase beyond 30,000.

The issue with volatility of stock market price refers to the fluctuations that may be observed in stock market prices over time. The major reason for the ups and downs in the stock market may be traced to macroeconomic instability. Since the stock market operate in a macroeconomic environment, it is therefore necessary that the environment must be an enabling one in order to realize its full potentials.

The problem with forecasting the stock market price is that the return distribution can change considerably over time. Volatility is an extremely complex thing to forecast because of the inherent instability of the variable (variability of the random). Volatility forecast sometimes may be uncertain, since it is just a mere projection based on some econometric technique in most cases.

ARCH models and ARIMA models are adopted because they are capable of controlling for dynamism in variances. Mostly in the empirical findings, researchers have applied extensively several models such as the series of ARCH models and ARIMA models, differently to develop a model for volatility forecasting in the Nigerian stock market prices. However in existing literature reviewed (see section 2), it is not proven which of these modeling techniques is superior in developing a model to forecast volatility in the Nigeria stock market prices. Therefore, this study contributes to existing knowledge by comparing these most frequently used methods (ARCH models and ARIMA models) in order to derive the best method out of them, and hence choosing the most efficient model for volatility forecast of the Nigerian stock market prices.

Volatility forecast in the Nigeria stock market prices is highly imperative to investors and policy makers. Since, forecasting performance of the volatility in the Nigeria stock market prices may be helpful to prevent investors from being exposed to future income loss. It also provides investors and policy makers with information on investment risk in the stock market so as to make optimal investment decisions and policies respectively.

Monthly data on All Share Index (ASI) series was extracted from the Central Bank of Nigeria statistical bulletin (*CBN, 2014)*, and computed graphically in order to depict the trend of the Nigeria Stock Market performance over the years.

The broad objective of this study is to assess the volatility performance of the Nigeria Stock Market in order to determine the basis for examining its forecast. In this study, volatility assessment and forecast are carried out on All Share Index (ASI) of the Nigeria Stock Exchange (NSE) in order to examine the performance of the Nigeria Stock Market Exchange. The out of sample volatility forecast is generated which will further serve as a guide to investors and policy makers on the performance of the Nigeria Stock Exchange.

The subsequent sections of this study are organized into literature review which shows other previous related work on this study, the methodology describing the method of analysis adopted for the study, Section 4 which is analysis and discussion of results showing the empirical findings from econometric estimations on the study, and finally section 5 shows the conclusion of the study.

2.0 Literature Review

In this section, the concept of stock market prices, volatility and forecasting with some of their theoretical and previous empirical findings are discussed. The objective is to establish a knowledge gap by using previous empirical findings on volatility forecast of stock market prices as basis for further findings on Nigeria stock market prices.

2.1 Conceptual Issues

The volatility of stock market prices can be regarded as the variability changes of stock price that could arise often referred to as market shock which is considered by investors as a measure of risk. Volatility clustering occurs when periods of large price change are followed by periods of large price change for a long period, and periods of little price change are followed by periods of little price change for a long period.

Masoud *(2013*) defined stock market as a very sophisticated market place where stocks and shares are the traded commodities. At the same time, it is central to the creation and development of a strong and competitive economy. Information on stock market provides investors with the status of the market value of their assets, and this serve as guide to businessmen on their investments. Since people are rational, they would rather invest in gainers than losers. The transaction activities in the stock market are extremely imperative for the generation of capital within the economy. Stock market is important for decisions on business investment, because financing investment spending is affected by share prices. According to Bodie, Kane and Marcus (1998), stock market indexes provide guidance concerning the performance of the overall stock market.

Stock market volatility is a measure for variation of price of a financial asset over time. Volatility measures the tendency of stock price to rise and fall sharply within a period of time. Volatility clustering is evident when large variation tend to be followed by large variation regardless the sign (positive or negative), and small variation tend to be followed by small variation for a long period. Aas and Dimakos (2004), define volatility clustering as a strong autocorrelation in the absolute values of returns. They further stated that a simple method for detecting volatility clustering is calculating the autocorrelation function of the absolute values of returns.

2.2 Theoretical Framework

The autoregressive conditional heteroskedasticity (ARCH) model was developed by Engel in 1982, and the literature assumes autoregressive structure, which means modeling conditional variance by its past values. ARCH is a form of heteroskedasticity that can be encountered in time-series models. It is usually adopted when modeling time-dependent conditional variance (Vogelvang, 2005). Bollerslev *(1986),* introduced the generalized autoregressive conditional heteroskedasticity (GARCH) in order to capture the dynamic pattern of conditional variance. He assumed modeling squared volatility by relating it to its previous values and previous errors in order to keep the parameters to be estimated short. However, GARCH model fails to account for asymmetric effect that may occur when modeling financial time series. This led to the extension of GARCH models into TGARCH, EGARCH and PGARCH models in order to account for asymmetric effects.

TGARCH, EGARCH and PGARCH have their distinguished methods of capturing asymmetric effect, but their uniform objective is to capture the asymmetric effect. Zakoian developed the Threshold GARCH (TGARCH) in 1991, Nelson developed the Exponential GARCH (EGARCH) in 1991, and Glosten, Jagannathan, and Runkle *(1993)* did something similar that assume conditional variance as a linear piecewise function. Ali (2013) discussed the Power GARCH model as another class of ARCH extensive model which is capable of forecasting volatility index.

Box and Jenkins (1970), introduced the autoregressive integrated moving average models (ARIMA) purposely to develop a forecasting model. The autoregressive integrated moving average models (ARIMA) is basically the combination of the techniques of AR and MA models. The autoregressive models (AR) are used to model the value of a variable using its past values. While the moving average models (MA) are used to model the value of a variable using its past errors. In other words, ARIMA models are capable of modeling the value of a variable by using its previous values and past residuals. Just like in GARCH model, the main advantage of combining AR and MA is simply to keep the parameters minimal enough. ARIMAX is a derivative of ARIMA, in a situation when it includes other time series variables as regressors. According to Tsay *(2002)*, the concept of ARIMA model is highly relevant in volatility modeling, and also regarded the generalized autoregressive conditional heteroskedaticity (GARCH) model as ARIMA model.

2.3 Empirical Literature

Empirical evidences show that ARCH and ARIMA models were employed frequently for volatility forecasting. However, despite the similar features shared by ARCH and ARIMA models, none of the authors from the several literatures reviewed showed their comparisons. Consequently, this raises a research question on the most efficient model out of ARCH and ARIMA models. It may be argued that ARIMA is superior to ARCH models because of its capability to decompose variable into seasons. In the same vein, it may be argued that ARCH models are superior to ARIMA because they are capable of showing leverage effect. Logically, comparing the two classes of model with in-depth econometric ingredients may be helpful in determining the most efficient model to be adopted for volatility forecast in this study.

Empirically, evidences from literature reviewed show that ARCH series and ARIMA model have been applied more extensively on volatility studies than other methods; in accordance with the works of the followings; Hamzaoui and Regaieg (2016), Maana, Kamau and Kisinguh (2015), Maxwell, Omari-Sasu and Frempong (2015), Basenga, Mwita and Mung'atu (2014), Atoi (2014), Ali (2013), Cao and Tsay (1992), Lin, Mackenzie and Gulledge JR (1986). They all contribute to literatures on volatility studies that autoregressive models are capable of specifying time variation in both conditional skewness and kurtosis, and thereby taking into consideration the past behaviour in model estimation. Autoregressive models attribute the feature of controling changing variances in model estimation. The autoregressive models entail linearly unpredictable stochastic processes which are conditionally leptokurtic and conditionally heteroskedastic, thus, they possess the tendency to be more accurate for longer forecasting time-horizon.

Other volatility forecasting models in literature include Artificial Neural Network following an evidence in the work of Neenwi, Asagba and Kabari (2013), Bayesian TVC model which works efficiently on random walk model, and appears to be flexible in special cases of forecasting environment (Canova, 1993). However, this generate the research question of the best model of the most frequently used models (that is, ARCH and ARIMA models).

Objective-wise, this study attempts to fill the knowledge gap by comparing ARIMA and ARCH family models purposely to estimate the most efficient model for volatility forecasting of the Nigeria stock market prices.

3.0 Methodology

For the purpose of developing an efficient model to assess the volatility and forecasting performance of the Nigerian stock market prices, the ARCH family models will be compared with ARIMA models using the Conditional Maximum Likelihood and Box-Jenkins methods respectively in order to derive the best model to forecast the Nigeria stock market prices.

3.1 Model Specification

ARIMA models and the ARCH family models are specified in order to develop the most efficient forecasting model.

3.1.1 Autoregressive Integrated Moving Average (ARIMA) model specifications

ARIMA model (p, d, q) includes an autoregressive process AR (p) and moving average MA (q). The "p" stands for order of AR (Autoregressive) which is determined by its partial autocorrelation function (PACF), "*d*" is the number of time the data was seasonally and non-seasonally differenced purposely for stationarity which is determined by conducting unit root test, and "q" stands for order MA (Moving Average) which is determined by its autocorrelation function (ACF).

Autoregressive (AR) models are models in which the value of a variable in one period is related to its previous period values. AR is expressed as;

$$\theta_t = \alpha_0 + \alpha_1\theta_{t-1} + \alpha_2\theta_{t-2} + \alpha_3\theta_{t-3} + \cdots + \alpha_p\theta_{t-p} + \mu_t \qquad (1)$$

θ_t is the current period volatility. While θ_{t-1}, θ_{t-2}, θ_{t-3} ……. θ_{t-p} all measure the previous years' volatilities. α_0 is constant term, μ_t is disturbance term. α_1 , α_2 , α_3 , ……..α_p are parameters measuring the change of lagged years of θ_t

Moving average (MA) models accounts for the possibility of correlation between a variable and its residual in the previous periods. MA is expressed as

$$\theta_t = \alpha_0 + \beta_1\mu_{t-1} + \beta_2\mu_{t-2} + \beta_3\mu_{t-3} + \cdots + \beta_p\mu_{t-p} \qquad (2)$$

β_1, β_2, β_3 , … β_q are the parameters measuring the effect of lagged residual terms on current value (θ_t) μ_{t-1} , μ_{t-2} , μ_{t-3} … μ_{t-q} are the lagged residual terms.

Autocorrelation functions (ACF) measure the degree of correlation between any two elements in a series. Partial autocorrelation function (PACF) shows significant spikes at the seasonal lags. Thus, the AR (Equation 1) and MA (Equation 2) make up the ARIMA model as developed by Box and Jenkins in 1970. ARIMA model is expressed as follows;

$$\theta_t = \alpha_0 + + \alpha_1\theta_{t-1} + \alpha_2\theta_{t-2} + \alpha_3\theta_{t-3} + \cdots + \alpha_p\theta_{t-p} + \mu_t + \beta_1\mu_{t-1} + \beta_2\mu_{t-2} + \beta_3\mu_{t-3} + \cdots + \beta_p\mu_{t-p} \quad (3)$$

Here, θ_t measures the actual volatility, μ_t is the white noise, α and β are the coefficients measuring the effect of variations in past volatilities and past residuals of the current volatility respectively, p and q are the lag orders often referred to as AR and MA respectively.

3.1.2 The ARCH family model specifications

The ARCH family models consist of ARCH (q), GARCH (p, q), TGARCH (p, q), EGARCH (p, q) and PGARCH (p, q). ARCH (q) model gives the variance of a series using its past variance. The "q" stands for the order of the past variance. The GARCH (p, q) is the improvement of ARCH (q) model because it comprises of an order of past conditional variance and past residual in determining conditional variance. TGARCH (p, q), EGARCH (p, q) and PGARCH (p, q) are the improvements of GARCH (p, q) model because they account for asymmetric effects in a variance model. The "p" is the order of the past residual term while the "q" remains the order of the past conditional variance.

(a) The idea behind ARCH model is that the current value of a variable is determined by its previous value(s).

$$Y = \lambda_0 + \lambda_1 X_t + \mu_t \quad (4)$$

$$\sigma_t^2 = \propto_0 + \sum_{q=1}^{k} \propto_1 \mu_{t-q}^2 \quad (5)$$

Equation (4) is the mean equation of the volatility model, while equation (5) is the variance model. ARCH model comprises of mean and variance equations, and are estimated simultaneously. However, much concern is placed on the variance equation because of its capability to forecast volatility.
σ_t^2 is the current volatility, $\boldsymbol{\propto_1}$ is the parameter measuring the effect of its lagged value that is, $\mu_{\boldsymbol{t-q}}^{\boldsymbol{2}}$

(b) GARCH model can be specified in order (*p*, *q*) because it comprises of "*p*" ARCH term and "*q*" GARCH term.

$$\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (6)$$

σ_t^2 is the current volatility, α_i is the parameter measuring the effect of previous residual that is, ε_{t-i}^2 . β_j measures the effect of change in its lagged value, that is, σ_{t-j}^2 .

(c) TGARCH appears in the order of *p, q, d*. The *p, q* and *d* stand for the number of ARCH, GARCH and asymmetric terms respectively.

$$\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q} \alpha_i \mu_{t-1}^2 + \sum_{i=1}^{q} \gamma_i I_{t-1} \mu_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (7)$$

where $I_{t-1} = 1$if $\mu_{t-1}^2 < 0$ and 0 otherwise.

This differs from GARCH model because it accounts for degree of asymmetry, which is measured by the parameterγ_i.

(d) EGARCH measures the effect of bad news on volatility, since the effect of a shock is asymmetric, that is good news or bad news.

$$\log(\sigma_t^2) = \lambda_0 + \sum_{i=1}^{q} \left\{ \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \right\} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \qquad (8)$$

EGARCH differs from GARCH model because it accounts for degree of asymmetry, which is measured by γ_i and also differs from TGARCH because it is in exponential form symbolized by its logged form.

(e) PGARCH model also captures asymmetric effects and is specified as;

$$\sigma_t^d = \lambda_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-1}| + \gamma_i \varepsilon_{t-1})^d + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d \qquad (9)$$

If d = 2, then the PGARCH mimics a GARCH (p, q) with a leverage effect. If d = 1, the standard deviation is modeled. The PGARCH model also accounts for degree of asymmetry, just like the EGARCH and TGARCH models.

The equations (4) to (9) depict the specified ARCH family models**.**

3.3 Variable Measurement and Data

The data required for this study is the NSE All Share Index which is the variable capable of measuring the volatility performance of the Nigeria Stock Exchange. The nature of the data is secondary. The All Share Index on Nigeria Stock Exchange is used as an indicator to measure the value of the Nigeria Stock Market. The data to be used for the study is adopted from Central Bank of Nigeria (CBN) Statistical Bulletin.

Monthly data of All Share Index on the Nigeria Stock Exchange is in unit, ranging from 1985 to 2014.

3.4 Estimation Procedures and Issues

Box-Jenkins and the conditional maximum likelihood methods will be applied to estimate the specified models in order to assess the volatility and forecasting performance of the Nigeria stock market prices.

3.4.1 Box-Jenkins method

The Box-Jenkins method was developed to estimate the autoregressive integrated moving average (ARIMA) model. The steps in building ARIMA model using Box-Jenkins approach are as follow:

i. The first step is to test for stationarity.
ii. The second stage entails the identification of the order of the ARIMA denoted by "p, d, q". This is found by examining the autocorrelation and partial correlation of the time series. The limitation is that often more than one model is entertained, thus applying some estimation criterion to select the best one.
iii. The third step is the estimation of the ARIMA model with respect to several orders of the "p, d, q" generated.
iv. The final step is the diagnostic test to determine the goodness of the model, and then compare them on the basis of estimation criterion, thus selecting the best out of them for further analysis.

3.4.2 The conditional maximum likelihood method

According to Asteriou and Hall (2007), the method used to estimate ARCH models is a special case of a general estimation strategy known as the maximum-likelihood approach. The conditional maximum likelihood method ensures the correctness of choice of error distribution, and it is adopted to estimate parameters for all the ARCH family models. The series of ARCH comprises of ARCH, GARCH, TGARCH, EGARCH and PGARCH. The steps in building models on the ARCH family series;

i. The first step is to ensure stationarity in the time series variable to be estimated.
ii. The second step is to test for ARCH effect and clustering volatility.

iii. The third step is to proceed in estimating the ARCH family models one after the other along with their respective error distribution.

iv. The final step is to conduct diagnostic check.

3.4.3 Test strategy

The evaluation methods adopted in this study are Akaike Information Criteria (AIC) developed by Akaike (1977), and Schwartz Information Criteria (SIC) developed by Schwarz (1978). The AIC and SIC take into account how well the model fits the observed series and the number of parameters to be used. The minimum AIC and SIC criterion is hopefully closer to the best possible choice, by assuming to describe the adequacy of the model. For the level of significance, 5 percent is adopted for all estimations with probability values. Test is significant if p-value is less than the specified level of significance (5 percent), and insignificant if otherwise.

4.0 Analysis and Discussion of Results

In this section, findings from statistical estimation are analyzed and discussed.

4.1 Stationarity Test and Volatility Presence

Stationarity test was conducted using Augmented Dickey Fuller (ADF) method, and the result shows the series of the NSE All Share Index to be stationary (with P-Value at 0.000) only after converting it to first difference, unlike when estimated at level (P-Value at 0.3918). The next activity is to assess volatility in the series after ascertaining that the variable is stationary.

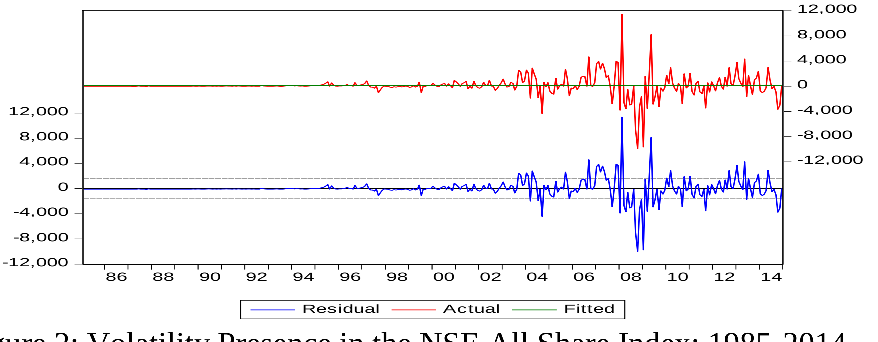

Figure 2: Volatility Presence in the NSE All Share Index: 1985-2014.

The series was stable over some years from 1985 up until 1995 when the dimension of the volatility changed and went up until around 2003 when the variance increased a bit and this continued at this degree till around 2007 when the variance rose and this remained at that rate until around 2010 when the variance reduced to a lower level, then this level of variance too lasted till 2014 showing apparently that there is volatility in the series. The reasons for this could be traced to occurrences in the market such as liberalization of the economy, financial crisis, alarming decline in economic activities. This gives the basis to estimate the forecasting performance of the time series.

4.2 Hypothesis Statement for Diagnostic Tests

i. Test for ARCH effect;
   H_0: The series is homoskedastic
   H_1: The series is conditionally heteroskedastic

ii. Test for Autocorrelation;
   H_0: There is no serial correlation in the series
   H_1: There is serial correlation in the time series

iii. Test for Normality;
   H_0: The series are normally distributed
   H_1: The series are not normally distributed

Using 5% level of significance, the null hypothesis (H_0) is significant if the statistic value is greater than 5 percent while the alternative hypothesis (H_1) is significant if the probability value is less than 5 percent.

4.3 Summary Statistics for the Estimated ARIMA Models

Starting with the ARIMA (p, d, q) models. The diagnostic results for the several ARIMA models estimated are presented in table 1;

Table 1: Diagnostic results of estimated ARIMA models

	PROBABILITY VALUES				
ARIMA models	Autocorrelation LM Test	Heteroskedasticity	Normality Test	AIC	SIC
(3, 1, 3)	0.0017	0.0000	0.0000	22.5473	22.5847
(2, 1, 2)	0.1484	0.0000	0.0000	22.2474	22.2665
(2, 1, 3)	0.3512	0.0000	0.0000	21.178	21.1965
(3, 1, 2)	0.2652	0.0000	0.0000	21.3856	21.3918
(1, 1, 3)	0.0152	0.0000	0.0000	21.5614	21.5929
(3, 1, 1)	0.0095	0.0000	0.0000	23.1852	23.1945

The estimated ARIMA models; (3, 1, 3), (1, 1, 3) and (3, 1, 1) suffer from autocorrelation and heteroskedasticity, and also appear to be not normally distributed because their p-values are less than 5 percent. Models (2,1,2), (2,1,3) and (3,1,2) are free from serial correlation because their p-values are greater than 5 percent, but they appear to be suffering from heteroskedasticity and are not normally distributed because their p-values are less than 5 percent. However, autocorrelation and heteroskedasticity are serious problems in time series analysis; thus, all the ARIMA models estimated are inefficient judging by the hypothesis stated in section 4.2, rendering all the ARIMA models unreliable. In other words, none of the ARIMA models is efficient to estimate the forecast of the NSE All Share Index. The estimated ARIMA models are presented as follows:

$\theta_t = 85.81321 + 0.573560\mu_{t-3} + (-)0.301008\mu_{t-3}$ (10)
$P-value$: 0.3426 0.0119 0.0456
std: 0.110495 0.7401446 0.696857

$\theta_t = 96.32825 + (-)\, 0.499141\mu_{t-2} + 0.677742\mu_{t-2}$ (11)
$P-value$: 0.0057 0.0019 0.0057
std: 0.374774 0.417456 0.418256

$\theta_t = 90.59991 + 0.151990\mu_{t-2} + 0.269321\mu_{t-3}$ (12)
$P-value$: 0.0757 0.0494 0.0046
std: 0.214480 0.360536 0.214480

$\theta_t = 88.52917 + 0.295823\mu_{t-3} + 0.152247\mu_{t-2}$ (13)
$P-value$: 0.1012 0.9480 0.4360
std: 0.088345 .660125 0.795782

$\theta_t = 76.55422 + 0.564437\, \mu_{t-1} + 0.244682\, \mu_{t-3}$ (14)
$P-value$: 0.0174 0.6487 0.0090
Std 0.208547 0.462906 0.232259

$\theta t = 67.88426 + 0.428641\, \mu_{t-3} + 0.374822\, \mu_{t-1}$ (15)
$P-value$: 0.8991 0.7374 0.5867
Std : 0.320372 0.705945 0.604014

The equations 10 to 15 are the estimated ARIMA models on the study.

4.4 Summary Statistics for the Estimated Series of ARCH Models

Following the ascertainment of the presence of volatility clustering and ARCH effect in the NSE All Share Index, the ARCH family series;

ARCH (1), GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and PGARCH (1,1) were estimated, and their diagnostic results are presented respectively in Table 2, purposely to determine the most efficient model by comparison of all the ARCH family series estimated.

Table 2: Diagnostic Results of the Estimated Models for the ARCH Family Series

ARCH Models	Correlogram of Standardized Residuals Squared Status	ARCH LM Status (p-values)	Jarque Bera Test (p-values)	AIC	SIC
ARCH (1)	P-values > 5%	0.7167	0.0000	14.52775	14.60347
GARCH (1, 1)	P-values > 5%	0.6771	0.0000	14.2573	14.30057
TARCH (1, 1)	P-values > 5%	0.1055	0.0000	14.17689	14.23098
EGARCH (1, 1)	P-values > 5%	0.3344	0.0000	14.16665*	14.22074*
PGARCH (1, 1)	P-values > 5%	0.9544	0.0000	28.31977	28.37385

All the series of ARCH family models, that is, ARCH (1), GARCH (1, 1), TARCH (1, 1), EGARCH (1, 1) and PGARCH (1, 1) passed the diagnostic tests on autocorrelation and heteroskedasticity. The reason is because all their p-values in the autocorrelation test using correlogram, and heteroskedasticity test using ARCH-LM are greater than 5 percent, it implies they are free from Serial Correlation and do not have ARCH effect. However, none of them passed the normality test since their p-values are less than 5 percent. It means their residuals are not normally distributed. But the normality case is a slight problem, thus all the models can be regarded as good ones. Now, one of the tasks in this analysis is to determine the best out of these models. Therefore, this leads to comparing their AIC and SIC in order to determine the best model out of them. The parameter estimates denoted from equation 4 to 9 are presented;

$$\sigma_t^2 = \quad 162.3560 + 0.550960\,\sigma_{t-1}^2 \tag{16}$$

$P - value$: 0.0001 0.0405

Std: 0.228983 0.299034

$$\sigma_t^2 = \quad 2.161912 + 0.871594\,\mu_{t-1}^2 + 0.232096\,\sigma_{t-1}^2 \tag{17}$$

$P - value$: 0.2914 0.1665 0.0468

Std: 0.272053 0.294407 0.146148

$$\sigma_t^2 = 4.781580 + 0.945534\,\mu_{t-1}^2 + 0.153031\,\sigma_{t-1}^2 + (-)0.190468\,\mu_{t-1}^2\,\bar{I}t - 1 \tag{18}$$

$P - value$: 0.6805 0.0012 0.004 0.0887

Std: 0.316574 0.003399 0.017266 0.306420

$$\mathrm{Log}(\sigma_t^2) = -0.047443 + 0.309627 \left|\frac{\mu_{t-1}}{\sigma_{t-1}}\right| + 0.025356 \frac{v_{t-1}}{\sigma_{t-1}} + 0.988812\,\mathrm{Log}(\sigma_{t-1}^2) \quad (19)$$

$P - value$: 1.568876 0.0000 0.0000 0.0338

Std: 1.568876 0.290456 0.20442 0.344949

$$\sigma_t^{\delta} = 1601113 + \sum_{j=1}^{q}(-)1.536629\,\sigma_{t-1}^{\delta} + \sum_{t=1}^{p}(-)0.937765\,\mu t - 1\delta - \sum_{t=1}^{p} 0.456095\,\mu t - \delta \quad (20)$$

$P - value$: 0.3191 0.0888 0.5604 0.0142

Std: 0.269822 0.2911992 0.320205 0.243342

Based on the AIC and SIC criterions, EGARCH is considered to be the most efficient model out of all the estimated ARCH family models, and this is depicted by equation (19). The first coefficient is the usual constant in models. The second coefficient measures the effect of previous year residual of variance on current variance. It shows positive correlation between past residuals and current variance in the stock market price. The third coefficient measures the asymmetric effect or the leverage effect. Theoretically, the conditions for the presence of asymmetries are the sign and the significance of the coefficient. If the coefficient is significant and negative, asymmetric effect is present which implies that positive and negative shocks of equal magnitude have a differential or non-proportionate effect on current volatility. However, equation (19) shows that asymmetry does not exist because the third coefficient is positive. The fourth coefficient measures the correlation between past variance and current variance which is found to be positive. Table 3 is a derivative of Tables 1 and 2, showing the summary statistics of the overall estimated models. It shows the comparison of ARCH models and ARIMA models, and proves that ARCH model is more efficient than ARIMA model, and thereby fills the knowledge gap identified under literature review. The most efficient model to forecast the volatility of the Nigeria stock market prices is EGARCH (1, 1) model, which belongs to the family of ARCH family models. This is because the model has the least AIC and SIC, and most importantly, it is homoskedastic and free from serial correlation.

The essence of building volatility model for risk forecasting on the NSE All Share Index is to provide investors and policy makers information regarding the future performance of the Nigeria Stock Exchange (NSE).

Table 3: Summary of the overall diagnostic results

S/No.	Estimated Models	SC Status	HTD Status	Normality	AIC	SIC
1	ARIMA (3,1,3)	*****	*****	*****	22.54732	22.58473
2	ARIMA (2,1,2)	+++++	*****	*****	22.24738	22.26648
3	ARIMA (2,1,3)	+++++	*****	*****	21.17798	21.19645
4	ARIMA (3,1,2)	+++++	*****	*****	21.38563	21.39176
5	ARIMA (1,1,3)	*****	*****	*****	21.56143	21.59286
6	ARIMA (3,1,1)	*****	*****	*****	23.18515	23.19453
7	ARCH (1)	+++++	+++++	*****	14.52775	14.60347
8	GARCH (1,1)	+++++	+++++	*****	14.2573	14.30057
9	TARCH (1,1)	+++++	+++++	*****	14.17689	14.23098
10	EGARCH (1,1)	+++++	+++++	*****	14.16665	14.22074
11	PGARCH (1,1)	+++++	+++++	*****	28.31977	28.37385

***** denotes Fail, +++++ denotes Pass, HTD denotes Heteroskedasticity, SC denotes Serial Correlation, AIC denotes Akaike Criteria, SIC denotes Schwarz criteria.

The implication of the statistical findings shows that risk in the Nigeria Stock Exchange (NSE) at the current period is explained by previous information regarding investments and previous investment risk in the stock market. The third coefficient which was found with absence of leverage effect in the respective regressor simply implies that there is insufficient information about the investment risk in the NSE. Normally, all the available information should entail both the positive and negative news. Though, this does not invalidate the forecasting power of the selected model (EGARCH).

4.5 Forecasting Performance

Based on the objectives of this study, in which forecasting is one of them, it is therefore necessary to proceed with estimating the forecast of the time series applying the EGARCH model estimated, which was found the most efficient out of all the estimated models. Based on the adopted 1985-2014 sample of the NSE All Share Index, a four years forecast of the variable is estimated, and the result is presented in Figure 3.

Figure 3 gives an empirical performance of the volatility forecast estimation on the Nigerian stock market prices. The upper graph measures the forecasting evaluation. The middle line is the forecasted values of the variance. The gap between the other two lines represents the 95% confidence interval, in which the line of the forecasted values falls within. This implies the forecasting performance is significant at 95 percent level.

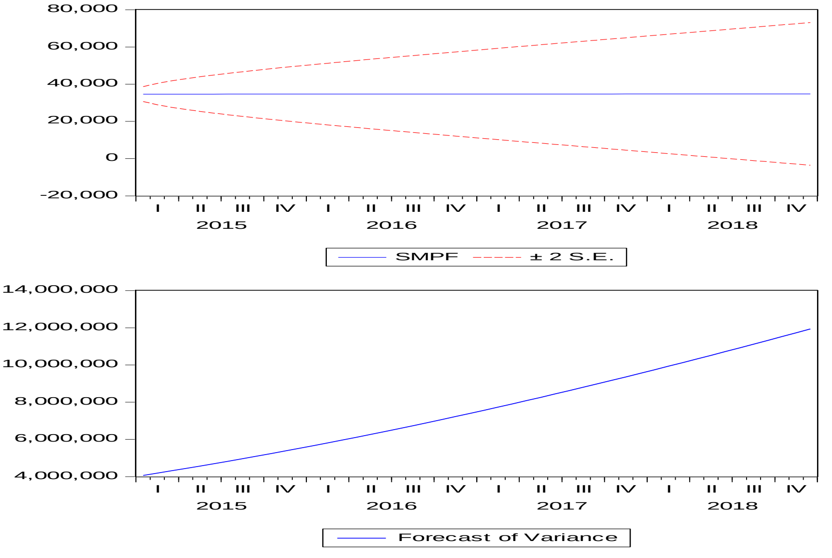

Figure 3: Volatility Forecast of the NSE All Share Index: 2015-2018

The lower diagram shows the four years forecast of the Nigeria stock market variance. Variance in the stock market prices will continue to be on an increase for the next four years. It means investment risk in the stock market will continue to increase overtime. As found from estimation; the NSE lacks adequate information regarding determinants of risk, this can be said to be one of the causes of increasing volatility rate in the Nigeria Stock Market.

Forecasting performance of the volatility in the Nigeria Stock Market shows how risk grows in the future. This will serve as an imperative guide to investors regarding their future investments, that is, it will guide them to determine how they manage their portfolio based on the future prediction. If volatility in the stock prices is on an explosive increase, it may diminish corporate wealth leading to the reduction in the country’s wealth. This may lead to fall in demand for money consequently this prompts monetary authorities being the policy maker to adopt expansionary monetary policy by reducing interest rate to alleviate the situation.

Obtaining an accurate and reliable volatility forecast performance of stock market price is crucial for monetary authorities, since higher uncertainty requires more active policies. Furthermore, the forecast may be useful to the monetary authority as a tool employed to control disequilibrium of money supply and demand. Following the forecast estimate, which shows volatility to be on increase for the next four years, if by assumption, the percentage of the investors in the risk-averse category is more than the other categories of investor, the monetary authority may conclude that people are more likely to hoard cash in the next four years because of risky situation projected. In order for them to control this problem of idle cash that may prevail, they plan to contract the volume of money supply.

All Share Index (ASI) is a stock index adopted for value measurement of the Nigeria Stock Exchange. It is a tool used by investors and financial managers to describe the market and to capture the return on their investments. They also use the stock index to determine the overall direction of the market and the paradigm of its movement, in order to make investment decisions such as when to sell-off their holdings of shares and when to buy companies' shares.

Volatility index can be a useful financial tool in making investment decision. Forecasting volatility in the stock market may be helpful to investors in making prediction on returns from investing in the market, and also to project an estimate of loss that a portfolio is likely to suffer in a period.

The limitation of this study is that the forecasting performance may not be 100 percent feasible. The finding of the forecasting estimation is just a scientific projection, that is, projection based on theoretical technique. Notwithstanding, the finding is justifiable, based on the logical approach (econometric technique) adopted for estimation, as compared with making projection based on merely a priori expectation.

Stock market contributes to economic growth through the specific services it performs either directly or indirectly. The major functions of the stock market are mobilization of savings, creation of liquidity, risk diversification, improved dissemination and acquisition of information, and enhanced incentive for corporate control. Improving the efficiency and effectiveness of these functions, through prompt delivery of their services can augment the rate of economic growth (*Sylvester and Enabulu, 2011).* The economic implication of the statistical findings shows that rising volatility may imply a long run decline in economic activities, and thus, disequilibrium of money supply and money demand.

5.0 Conclusion and Policy Implications

Assessment of volatility in the NSE All Share Index was conducted, and the presence of volatility was evident, therefore, this presented justification to proceed to forecasting of the volatility in the NSE All Share Index. Several Autoregressive Integrated Moving Average models (ARIMA) and series of Autoregressive Conditional Heteroskedasticity models (ARCH) such as GARCH, TARCH, EGARCH and PGARCH were estimated for comparison, objectively to develop an efficient model to forecast volatility in the NSE. Therefore, the results obtained from the statistical estimation exposed the ARIMA models to be inefficient in developing a volatility model to forecast the Nigerian stock market prices, while the series of ARCH models were all found to be efficient. Furthermore, the most efficient model out of the ARCH series is the EGARCH model, as determined by the adopted model selection criteria (AIC and SIC). The EGARCH model was used to estimate a four years out of sample volatility forecast, and thereby concludes that the conditional variance in the Nigeria stock market prices to be increasing overtime.

The policy implication of the findings showing the volatility in the Nigerian stock market prices to be on an increase simply means there is tendency for trading in the Nigeria stock market to be riskier overtime. This is a useful tool in predicting returns from investing in the Nigerian stock market prices. In other words, both the indigenous and foreign investors can thereby make their own investment policy based on this, which will guide them in trading in the Nigerian stock market.

The out of sample forecast result which shows volatility in the Nigeria stock market prices to be on an increase implies investing in the stock market will be riskier for the next four years. Tobin (1956) categorized investors into three categories; the risk-lover, risk-averse and risk-diversifier. Investors that belong in the first category will find it rational to invest more in the next four years because they believe in higher the risk the bigger the return concept. While the investors in the risk-averse category believe it is only rational to invest when the risk is absent. The investors in the third category normally have a way of adjusting their portfolio with respect to the rate of interest. They invest more of their portfolio in stock when the risk is very minimal and keep less of their portfolio in cash holding. While they invest less when the risk is high and holds more of their portfolio in cash. Therefore, volatility forecast provides a measure of risk which is crucial for risk management in investments.

ARIMA, ARCH, GARCH, EGARCH, TGARCH AND PGARCH have been applied in this study to forecast stock market prices in Nigeria. For further studies on volatility forecasting, a series of new methodology should be considered such as; Beta-T-GARCH and dynamic conditional stochastic volatility (DCS) models. As summarized in Engle (2002), Dynamic Conditional Correlation is a class of stochastic volatility model that has flexibility of univariate GARCH, and possessing a computational advantage over GARCH.

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