Modeling Price Volatility of Nigerian Crude Oil Markets Using GARCH Model: 1987-2017

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Abstract
Volatility and the risk-return trade off of crude oil or crude oil market participation is essential to National Investment, decision making, marketing, and the determination of the financial strength of Nations among other things. Therefore, this research study was targeted at modeling price volatility and the risk-return related to crude oil export in Nigerian crude oil market using the first order asymmetric and symmetric univariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family model in three distributional assumptions namely, Normal, student's-t and generalized error distribution. To achieve this target, three objectives with three research questions and two hypotheses were raised for the study. The data for the study was extracted from the Central Bank of Nigeria online statistical database starting from January, 1987 to June, and 2017. The results from the statistical analysis reveal that the markets were optimistic of their investment and other trade related activities. Sequel to that, there were high probabilities of gains than losses. Although, the variables use in these markets were extremely volatiles and shows evidence there exists positive risk first-rated meaning that investments or investors deserved rewards for holding risky assets. In estimation, first order symmetric GARCH model (GARCH, (1,1) in student's-t error assumption gave a better fit than the first order Asymmetric GARCH model (EGARCH (1,1)) in Normal error distributional assumptions. However, the selected models were subjected to several diagnostic test such as ARCH effect test, test for serial correlation and QQ-plot in order to validate their fitness which was confirmed to be appropriate. And recommendations were made to the Government to look for new ways to diversify the economy from total dependence on oil to non-crude oil such as agriculture, manufacturing and mining sector. For investors or marketers in this markets, they were advice to be mindful in trading in a highly volatile period especially when there is evidence of high standard deviation in the descriptive statistic of the return series and in modeling volatility of price return of certain micro/ macro-economic variable the leverage effect of such variable should be properly estimated using asymmetric GARCH model.

Key Words: *Modeling, Volatility, Crude Oil Price, GARCH Models, Markets*

1.0 Introduction

Financial time series data such as stock prices, exchange rates, inflation rates, crude oil prices etc. are some of the variables that often exhibit the characteristics of clustering. A period otherwise refers to as volatility clustering whereby prices show wide swings within an extended time and it will later show relatively calmness. This is not only applicable to variables such as stock prices, exchange rate, inflations etc. but they also applicable to almost all micro economic variables. For instance, all the indicators and determinant of employment and production, consumption, investment in raising productive capacity and how much a country imports and exports (John, 2003) also suffered the same fate. They suffered sudden fluctuation and this continual fluctuation affects so many things thereby contributing to the increase in price volatility and revenue profile of these products. And these are some of the causes of economic shocks widely experience in the world. According to Agenor et al (2000) the macroeconomic effects of macro econometric variable and trade shocks arising from price volatility have a great very significant effect on developing countries.

These shocks are major sources of aggregate economic volatility and they have large impact on private and public savings because of their economic effects (Agenor et al., 2000). They are also associated with global business cycles and it manifest in the form of sharp volatility in foreign exchange earnings of primary producing economics as in the case of Nigeria. Such development usually results in macroeconomic instability, in sufficient allocation of resources, recessions and low output growth.

According to Gujarati (2009) the awareness of volatility is of crucial importance in many areas. For example, considering it sudden sharp changes in prices investors and traders alike cannot know the appropriate time to invest and when not to as a result of instability in world's prices. This does not guarantee safer investment especially now that crude oil market and other financial market like stock and foreign exchange markets are more dependent on each other than ever before. For traders in these markets or decision markers, volatility in it entirety may not be bad, but its variability may not be good enough because this makes financial planning cumbersome.

This is also applicable to the importers, exporters and traders in foreign exchange markets, this variability in the exchange rates may account for excessive losses or profits. According to Gujarati (2009) investors in the stock market are obviously interested in the volatility of stock price, for high volatility could mean huge losses or gains and hence greater uncertainty. In volatile markets such as the crude oil markets, it will be difficult for companies to raise capital in the crude oil markets.

In crude oil market, when there is a sharp fall in the international oil price and which may lead to corresponding consequent decline in financial receipts as case in the early 1980's when the economy can no longer meet it international financial commitments. These make nations to be tangle with situations that could become a big challenge. So the questions are how do we model financial time series that exhibit such characteristics behavior? For example, how we model time series of crude oil prices? A characteristic exhibited by crude oil prices such that in its level form it could be liken to random walks or called it stochastic process. That is, a situation that shows they are not stationary. Conversely, in the first difference form, they become stationary as it is in the case of other micro economic variable like GDP series. The usual traditional regression tools have proved their limitation in the modeling of high-frequency (weekly, daily of intra-daily) data (shamiri et al, 2009).

Shamiri et al., (2009), further suggested that assuming the only the mean response could be changing with covariates while the variance remain constant within time varying interval, it will often revealed to be an unrealistic assumption in practice. This fact is particularly clear in special time series data where there exist clusters of volatility such that it is visually detected.

Although, in the past view decade there have been several forms of different propositions on how to model such characteristics exhibited by price in the form of heteroscedasticity. According to Shamiri et al (2009), among the models that have be proven to be most successful are the Auto-regressive conditional heteroscedasticity (ARCH) family model originally invented by Engle (1982) and the models of stochastic variance (SV) pioneered by

Taylor. Engel (1982) argues that an adequate volatility model is the one that sufficiently model heteroscadasticity in the disturbance term and also captures the stylized fact inherent in stock return series such as volatility clustering, Autoregressive Conditional Heteroscadasticity (ARCH) effect and asymmetry.

This is one of the reason why we model variance in financial series data as well make forecast, which is very important in many areas where option price is to be examine, value at risk apply and portfolio consideration. Therefore, it becomes necessary to model out of-sample forecasting ability as a natural model selection conditions for volatility models.

Although, there are numbers of variance forecasting research carried out in this area, some researchers used squared daily returns as a substitute for ex-post variance but this has been proven by Anderson et al (1998) to be an unbiased and above all a noisy estimator. While some other literatures that review competing variance models has been neglected due to other necessary conditions needed for effective volatility model. Meanwhile, very little work has been done comparing different error distribution assumptions, with the remarkable exceptions as opined by Shamiri et al (2009).

However, none of these studies has actually focused on modeling asymmetric GARCH models forecast with respect to their error distributions. Majority of the previous research studies in this area are often done on the symmetric GARCH model, especially on stock returns, exchange rates etc while this studies focus on both symmetric and asymmetric volatility as well as their various symmetric and asymmetric error distribution assumptions on crude oil export price.

Most likely, ARCH models usually do not fully capture the thick tail characteristic as exhibited in the form of fat-tailed distribution. Of a truth, Kurtosis of most price return series is greater than three, invariably means that extreme values are observed more often for such variable than normal distribution. So long as Kurtosis of the return series is a well-established condition, the situation is peculiar to symmetry of such distribution. Many researchers seem to ignore the significant of this while other researchers, the likes of Simkowits and Beedles, (1980) and Kon (1984) have drawn our attention to the characteristics exhibited by heavy tail of a distribution (Shamiri et al, 2009), whereas Shamiri et al (2009) have shown that fat-tailed distribution is a requirement for modeling daily returns of East Asian Equity market as cited in Shamiri et al, (2009). Hence, this study will among other things add to the existing literature in several important ways. It is on this ground that the study model volatility of crude oil prices in us/per barrel from January, 1987 – June, 2017 in order proffer solutions to these problems.

2.0 Literature Review

Literature examining the GARCH modeling otherwise called the generalized autoregressive conditional heteroskedasticity model is a very complex concept that captured and measured volatility characteristics exhibited by most micro as well as macro-economic variables. These micro and macro-economic variables could be export prices, exchange rate, Gross Domestic product (GDP) etc. This model measure unequal variance and it effect on other micro or macro-economic indicator in the economy.

According to Atoi (2014), the first break-through in modeling variable that exhibit such characteristics was championed by Engle, (1982). Engle (1982) demonstrated that conditional heteroskedasticity can be modeled using conditional variance of the (Atoi, 2014).

Engle (1982) demonstrated that conditional heteroskedasticity can be modeled using an auto-regressive conditional variance of the disturbance term with the linear (combination of the square disturbance in the recent past second past see Atoi (2014) Having realized the potentials of an Autoregressive conditional heteroskedasticity (ARCH) model several studies have using it in modeling model financial series.

However, when using the ARCH model in determining the optimal lag length of variables are very cumbersome. Therefore, often time users encounter problems of over parameterization. Thus, Rydberg (2000) argued that since large lag values are required in ARCH model therefore there is the need for additional parameters.

Sequel to that, and many other Lapses and little minor challenges encountered in the ARCH model, (Bollerslve et al, 1986) independently proposed an extension to ARCH model which was refers to as Autoregressive Moving Average (ARMA). This was done with view to achieving parsimony. And this eventually lead to the development of the model called the generalized Autoregressive conditional heteroskedacity (GARCH), which model conditional variance as a function of its lagged value of the disturbance term of linear regression model.

Although, GARCH model have been proven to be useful in capturing symmetric effect of volatility but the model is bedeviled with some limitations such as relatively non-negative constraints imposed on the parameters to be estimated. Therefore, this study among other things investigates as well test GARCH family model performance in modeling price volatility.

Sequel to the above , there is the need to review other numerous studies carried out in this area, the method they employed, the countries and the result obtained. There are several studies carried out in this area but the general observation from these studies is that the results have been characterized with mixed feeling, depending on several factors including sample period, methodology adopted, estimation technique, measure of volatility adopted and the countries under consideration (either developed or developing).
For example, Tatyana (2010) studied the dynamics of oil prices (Brent and WTI crude oil markets) and their volatilities by Linking four GARCH related models namely; GARCH (1,1), GJR – GARCH (1,1), EGARCH (1,1) and APARACH (1,1). The findings of this study showed that oil shocks have permanent impact and there exist asymmetric consequence on the volatility of the markets under consideration.

Also, Abduchakeem et al (2016) in analyzing oil price – macroeconomic volatility in Nigeria using GARCH model and its variants (GARCH-M, EGARCH and TGARCH) using daily, monthly and quarterly data. From the findings the result reveal that: all the macroeconomic variables considered (real gross domestic product, interest rate, exchange rate and oil price) are highly volatile; the asymmetric models (TGARCH-M) suggested that oil price is a major source of economic volatility in Nigeria.

In like manner, Narayan et al (2007) modeled the volatility of daily oil prices using exponential generalized Autoregressive conditional heteroskedasticity (EGARCH) model. The results also reveal that asymmetric effects exist, persistent, and is permanent in the oil prices series. Also, Olowe (2009) investigated weekly oil price volatility of all countries average spot price using EGARCH (1,1) within January 3, 1997 – March 6, 2009. The result shows that the oil price return series has high persistence of volatility, volatility clustering and asymmetric characteristics.

Olugbenga et al (2017) study the impact of oil price volatility on investment decision making in marginal fields development in Nigeria. The study also investigated the relationship between oil price volatility and marginal field investment analysis in Nigeria. The marginal field's crude oil production was used as a replacement of investment analyze. A monthly data from October, 2015 – April 2016 was considered. The GARCH model, Johansen co-integration and Granger causality tests were used in estimating the results. However, the result showed a significant positive relationship between oil price volatility and crude oil production ($P < 0.05$).

Omisakin (2008) no an analysis of oil prices stocks on the Nigeria economy using an annual data on seven key macro-economic variables, from 1979-2005, vector Autoregressive model was used in estimating variables and it was pointed out that oil price shocks contribute to variability in the economic price.

The concept and overview of price volatility according to olugbenga et al (2017), suggested that the econometric terms, volatility is defined as the rate at which the price of a security increases or decreases in a given set of returns. Volatility is measured by returns. It is measured by calculating the standard of deviation of either daily or monthly or the yearly returns of stocks price over a given period of time. It shows the extent to which the price of a certain products may increase or decrease. If the prices of a certain products fluctuate rapidly in a short time period, it indicates volatility is on the increase. If the prices of a certain products fluctuate slowly in a longer interval of time, it clearly shows that volatility is low. Although, Atoi (2014) suggested that an increase or decrease in the value of stock return tends to have a corresponding effect on the economy, mostly through the money market; an increase in product prices can motivate investment and increases the demand for credit, which eventually leads to increase interest rates in the overall economy as supported by (Spiro, 1990).

Hence, there is the need to develop an appropriate volatility model to captured variations in product price returns which is of significant policy importance to econometricians and economic managers alike. Most especially, reliable volatility model for crude oil export prices returns that will guide traders, investor, Government agencies etc in their risk control management decisions and portfolio selection.

Modeling can be seen as a process of simplifying system used to simulate some aspects of the real economy (see John, 2002). In this context, the real economy could be refers to as price volatility. The characteristics behavior of price to violate the normality assumption (Homoskedasticity) other wises refers to as heteroskedasticity that lead to the introduction of the concept of modeling volatility. Heteroskedasticity, according to Olugbenga et al, (2017) is one of the key problems that require attention when performing time series analysis on crude oil price due to uncertainty in the movement of oil prices. The sudden up and down in the movement of crude oil export price is referred to as price volatility. And this can be model econometrically using the residual conditional variance of the regression equation involving crude oil export price as the dependent variable.

Although, according to Ederington et al (2011) Models for oil prices can be classify into three main categories: Structural models, reduced form or hybrid and econometric model. The structural models are basically used in capturing the interaction between primary or supply and demand conditions and factors influencing supply. It tends to focus on longer time-horizons which may include macro-type models used for forecasting. The Reduced form or hybrid models on the other hand leverage on the hypotheses about the reduced form to examine the stochastic behavior of oil prices, whereas the Econometric models hypothesize specific types of time series behavior in the conditional first and second moments of crude oil price series. Reduced form or hybrid and econometric has the tendency to focus on short-term dynamic behavior of crude oil prices.

The significant measurement typically missing from present models of crude oil prices but which has become an issue of great importance to oil market observers and participants is the role that speculators play in the market and the implications of such role on crude oil sale. However, this study will be constrain to used econometric models form as it has the tendency to model residual of both mean and conditional variance of the dependent variable (Crude oil export price). In order to achieve that, Engle (1982) suggested that Autoregressive conditional heteroskedasticity (ARCH) model is the alternative model to the standard deviation, method. The ARCH model is the only time series model that can best and sufficiently model heteroscadasticity in the disturbance term of a linear regression equation involving crude oil price as the dependent variable and also captures the stylized fact incorporated in the crude oil export price return series such as volatility cluster, autoregressive conditional variance and in modeling Heteroskedasticity (ARCH) effect of both symmetric and asymmetric terms. This also take into consideration high persistence of volatility which is one of the crux for models that have the most powerful ability for charactering change in volatility. According to Olugbenga et al (2017), the ARCH model is basically rooted in monthly return (usually squared returns) of stock prices.

Olugbenga et al, (2017) further opined that an ARCH model is a stochastic process with autoregressive conditional heteroskedasticity. It is a simple model that can capture or described a stochastic process which could either be non-stationary but asymptotically stationary. If the stochastic process shows clustering volatility, then the ARCH models can be applied.

Although, due to the shortcoming as a result of weak signals about the level of volatility led Belleslev to develop an extended version of the ARCH model refers to as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Olugbenga et al, 2017). The most interesting aspect of this model (GARCH) is that even with a small number of terms it appears to perform better than an ARCH model with many terms. The general belief about the model is that during a period of decline in growth, volatility is likely to increase and during a period of increasing growth, it is likely to decline as used in most studies.

Autoregressive conditional heteroscadasticity and its variances extensions are Generalized ARCH, GJR-GARCH (TGARCH), Exponential GARCH, component – GARCH, and GARCH-M. In some cases, the first-order GARCH family models have been extensively proven to be appropriate for modeling and forecasting financial time series as observed by Hsieh (1991), Bera et al (1993), Hansen et al (2004), Eric (2008), Olowe (2011), Hojatallah et al (2011). But in these studies little or no attention has been given to their suitable error distribution assumptions for modeling especially the normality, student's-t and generalized error distribution assumption.

This is considered because review of relevant literature shows that several researchers have neglected the contribution of the error distribution assumptions while modeling market price volatility. The wrong use of an appropriate error distribution in volatility model for financial time series may cause misspecification in volatility model, leptokurtic and autocorrelation behavior of such series. Whereas Klar et al., (2012) posited that in appropriate specification of the concept distribution may lead to a sizeable loss of correctness of the corresponding estimators, wrong risk determination, inaccurately priced options and inadequate assessment of value-at-risk (VAR). In modeling volatility these is need to specify the form of the error distribution to be used in the estimation. Hence, this study seeks to investigate and as well as close gap the vacuum in several literatures by using the three commonly used first order symmetric GARCH family models on the form students-t, normal (Gaussian) and generalized error distribution (GED) with a view to compare them to when it is used in asymmetric GARCH family models, while considering the best fitted model for forecasting volatility with the best error distribution for crude oil export price within the years under consideration.

3.0 Methodology

This Paper uses two steps estimation Procedure for Modeling Volatility.

a. The Time series/ Statistical Approach and
b. The Statistical / Econometrics Approach

3.1. The Time series/ Statistical Approach: This involves the time plot and Normality test. According to Etuk (2017) time series is a set of data collected sequentially in time and therefore such data have the characteristics of being correlated rather than being independent like other data are assumed to be. Therefore, it is particularly important to draw a time plot to examine the trend in their relationship graphically within the years under the study. Normality Test is conducted on the transformation of return of crude oil price using the Jarque-Bera test statistics. According to (Chinyere, Dickko and Isah, 2015) Jargue-Bera is defined as joints test of skewness and kurtosis that examine whether data series exhibit normal distribution or not; and this test statistic was developed by Jargue and Bera (1980). It is defined as;

$$X^2_{\sim} \; \frac{N}{6}\left[S^2 + \frac{(K-3)^2}{4}\right] \qquad (3.23)$$

Where S represents Skewness, K represents Kurtosis; N represents the size of the macroeconomic variables used. The test statistic under the Null hypothesis of a normal distribution has a degree of freedom 2.When a distribution does not obey the normality test Abdulkarem et al (2017) suggests that the alternative inferential statistic for such especially the case of error distribution assumptions with fixed degree of freedom are fussed into the ARCH and GARCH models.

3.2 Statistical/ Econometric Approach: This shall be done under the following procedure: Testing for ARCH (1) affects, Model Estimation with Symmetric and Asymmetric GARCH Model, Model Diagnostic.

3.2.1 Testing for ARCH (1) effects

This test is carry out to examine the presence of heteroscedascity in the residuals of crude oil export prices, and this is done using LaGrange multiplier (ML) as proposed by Engle (1982). This is done by obtaining the residuals first from the ordinary least squares regression of the conditional mean equation which might be represented in (ARMA) process. Supposing an ARM (1,1) process is considered for example, if the conditional mean equation is

$$X_t = \theta_1 X_t + \varepsilon_t + \theta_1 \varepsilon_{t-1} \qquad (3.24)$$

Once the residuals ε_t is obtained, then the squared residual on a constant and its q lags as in the following equation:

$$\varepsilon_t^2 = \alpha_0 + \alpha_i\ \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 = \alpha_0 + \sum_{1=1}^{q} \alpha_i \sum_{t-1}^2 \qquad (3.25)$$

The ARCH model (q) is

$$\sigma_t = \alpha_0 + \alpha_i\ \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q} + \varepsilon_t\ \alpha_0 + \sum_{1=1}^{q} \alpha_i \sum_{t-1} + \varepsilon_t \qquad (3.26)$$

Where;

σ_t is the unconditional variance
α_0 is the constant term
α_i is the co-efficient of the ARCH term
ε_{t-i} is the corresponding lags of the errors at time t-1
q is the length of ARCH lags and
ε_t is the error term

The Test Hypothesis**:**
H_o: $\alpha_1 = ... = \alpha_q = 0$ (Absence of ARCH effect up to order q) Against H_1: $\alpha \neq 0$ for some i $\sum$ {1,….q} at least one variable has presence of ARCH effect. The number of observations times the R-squared (nR^2) gives the test statistics for the joint significance of the q – lagged squared residuals with q degrees of freedom. Hence, nR^2 is tested against $X^2(q)$ distribution. If $nR^2 > X^2(q)$ table result, then the Null Hypothesis will be rejected and conclude that there is an ARCH effect in ARMA model.

3.2.2 Model Estimation Using Symmetric and Asymmetric GARCH Models:

In line with the objective of the study, the model adopted for the study was derived as thus: Supposing we have a regression model given as;

$$Yt = K_1 X_{1t} + \varepsilon_t \qquad (3.1)$$

Where ε_t is the residuals, then

$$\varepsilon_t = \sqrt{h_t \times Z_t} \qquad (3.2)$$

$$h_t = \alpha_0 + \sum_{i-1}^{\rho} \lambda i + \sigma_{t-1}^2 + \sum_{j-1}^{9} B_j\ \mu_{t-j} \qquad (3.3)$$

While α_o is a constant term, λ_i is the co-efficient of β_1 is the elasticity coefficient and ε_t is the stochastic disturbance term. It is important to note that, for equation (3.1) and (3.3) to exist, them; $\alpha_o, \lambda_i, \sigma_{i\text{-}t,}\beta_j > 0$
However, GARCH (p,q) is model as thus: The mean is written as

$$X_t = \mu + \lambda x_{t-i} + \varepsilon_t,\ \varepsilon_t^{\upsilon}\ N(0,\sigma_t) \qquad (3.4)$$

Where; the variance component is written as thus

$$\sigma_t^2 = \alpha_0 + \sum_{i-1}^{\rho} \lambda i \sigma_{t-1} + \sum_{j-1}^{q} y_j \mu_{t-j} \qquad (3.5)$$

The mean equation (3.4) become a standard, for other models alongside with conditional variance components, when p=1 and q=1 then it is consider as a case of GARCH (1,1). Where all the parameters $\alpha_o, \lambda_i, y_j, \geq 0$; σ_t^2 is the conditional variance, α_o, λ_j constant term,

λ_j and y_j are coefficients of the ARCH and GARCH term respectively, σ^2_{t-i} and μ^2_{t-j} are the squared errors at lag_{t-i} and t-j respectively.

Equation (3.1), (3.2), (3.3) (3.4) and (3.5) provide a priori expectation expected signs and the significant of the value of the co-efficient of the model parameters to be estimated in light of economic theories and empirical evidence. Equation (3.5) is defined as GARCH (p,q) model an extended framework of ARCH(q) model as proposed by Bolleslev (1986) in which it is refers to as the P lags of past conditional variance. The GARCH (p,q) with $Ƶ_t$ as a discrete time stochastic process is defined as:-

$\Sigma_t = Z_t\sigma_t$ and is weakly stationary with

$E(\varepsilon_t) = 0$ and

$$\text{Var}(\varepsilon_t) = \alpha_0\left[1-\left(\sum_{l=1}^{\rho} X_i + \sum_{j=1}^{q} y_j\right)\right]^{-1} \qquad (3.6)$$

$\text{Cov}(\varepsilon_t, \varepsilon_t) = 0$ for $t \neq s$ if and only if

$\sum_{i=1}^{\rho} \lambda_i + \sum_{j=1}^{q} y_j < 1$, $(\alpha_o > 0)$, for the system be stationary

Also, GARCH in MEAN (GARCH – M) Model as propose by Engle et al (1987) mostly estimate return of financial data series as dependent of the conditional variance of a standard deviation. It model high risk that often accompany high expected return. The simplest form of GARCH-M model is the GARCH-M model is the GARCH-M (1, 1) written as:

Mean equation: $X_t = \mu + \lambda\sigma^2_t + \varepsilon_t$, $\varepsilon_t \sim N(0,\sigma_t^2)$ (3.7)

Variance equation;

$$\sigma^2 = \alpha_0 + \alpha_1, \Sigma^2_{t-1} + \beta_1\sigma^2_{t-1} \qquad (3.8)$$

Similarly, the Threshold Generalized Autoregressive Conditional Heteroskedasticity Model is generally specified in its conditional variance using the acronym TGARCH (p,q) and it is written as thus;-

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i\ \varepsilon^2_{t-1} + \sum_{i=1}^{q} y_i I_{t-i}\ \Sigma^2_{t-1} + \sum_{j=1}^{\rho} \beta_j \sigma^e_{t-j} \qquad (3.9)$$

Where $I_{t-i} = 1$ if $\varepsilon_t^2 < 0$ and zero. In equation (3.7), Goods news implies that $\varepsilon_t^2 > 0$ whereas bad news implies that $\varepsilon_t^2 < 0$ under these conditions, (shocks) of equal magnitude have differential effects on the conditional variance. However, good news has an impact of α_i white bad news has an impact of $\alpha_i + y_i$. Bad news increases volatility if $y_i > 0$ which invariably means that there is existence of leverage effect in the *i*th order when $y_i \neq 0$ them the news impact is asymmetric. But, the first order representation of the equation is given as TGARCH (p,q) is;

$$\sigma_t^2 = \beta_0 + \alpha_1 \sum_{i=1}^{q} \alpha_i\ \varepsilon^2_{t-1} + y_1\ I_{t-i}\ \Sigma^2_{t-1} + \beta_j \sigma^e_{t-j} \qquad (3.10)$$

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model as proposed by Nelson (1991). The conditional variance of EGARCH (p,q) model is specified generally as;

$$\text{Log } \left(\sigma_t^2\right) = \beta_0 + \sum_{i=1}^{q} \left\{ \alpha_i \left| \frac{\alpha_{t-i}}{\sigma_{t-1}} \right| + y_i \left(\frac{\alpha_{t-i}}{\sigma_{t-1}} \right) \right\} + \sum_{j=1}^{\rho} B_j \; Log\left(\sigma_{t-j}^2\right) \tag{3.11}$$

$\varepsilon_{t-i} > 0$ and $\varepsilon_{t-j} < 0$ depicts good news and bad news respectively, whereas their total effects are given as $(1+y_i)|\varepsilon_{t-i}|$, and $(1+y_i)|\varepsilon_{t-i}|$. When $y_i < 0$, the expectation is that bad news enhances volatility persistence to be high. The EGARCH model achieves covariance stationarity when $\sum_{j=1}^{\rho} B_j < 1$

However, the target of this study is to model the conditional variance using EGARCH (1,1) model which would be refine as

$$\text{Log } \left(\sigma_t^2\right) = \beta_0 + \alpha_1 \left| \frac{\varepsilon + 1}{\sigma_{t-1}} \right| + y_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log\left(\sigma_{t-1}^2\right) \tag{3.12}$$

The total effects of good and bad news for EGARCH (1,1) are $(1+y_i)|\varepsilon_{t-i}|$ and $(1+y_i)|\varepsilon_{t-i}|$ respectively. We accept the Null Hypothesis that $y_i = 0$ shows the presence of leverage effect, i.e. bad news have stronger effect than good news on the volatility of the return series.

And the power Generalized Autoregressive Conditional Heteroskedasticity (P GARCH) model as proposed by Ding et al (1993) expressed conditional variance using P GARCH (p,d,q) as;

$$\sigma_t^d = \beta_0 + \sum_{1=1}^{q} \alpha_i \left(\left|\Sigma_{t-i}\right| + Y_i \; \Sigma_{t-i} \right)^d + \sum_{J=1}^{q} B_j \; \sigma_{t-j}^d \tag{3.13}$$

The failure to accept the null Hypothesis $Y_1, \neq 0$ shows the presence of leverage effect. In order to ensure that the all the model used here efficiently capture the characteristic of Gaussian and non-Gaussian process for high volatility in financial time series equation (3.5), (3.7), (3.8, (3.9),(3.10) and (3.11) above were subjected to error distributional assumption as specified .

Firstly, the normal distributional assumption; this assumed that the variance in the entire GARCH model given above utilizes the likelihood function of their residuals and variance.

$$L(\theta_t) = \frac{1}{2} \sum_{t-1}^{T} \left(In 2\pi + In\sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2} \right) \tag{3.14}$$

σ_t^2 is Specify field in each of the GARCH models.

Similarly, following the assumption that GARCH models follow generalized Error distribution tends to account for the Kurtosis in series returns, which are not properly captured using the normality assumption as shown in equation (3.12) above, the volatility models are estimated with generalizes error distribution by maximizing the Likelihood function below;

$$\mathrm{L}(\theta_t) = \frac{1}{2}\log\left(\frac{\sqrt{\frac{1}{v}}}{\sqrt{\left(\frac{3}{v}\right)\left(\frac{v}{v}\right)^2}}\right) - \frac{1}{2}\log\sigma_t^2 - \left(\frac{\sqrt{3/v}\left(yt - X_t^1\theta\right)^2}{\sigma_t^2\sqrt{\left(1/v\right)}}\right)v/2 \tag{3.15}$$

Where V represents the shape of the parameter use in the estimation and this shows the Skewness of the return series used in the estimation and V > 0. The higher the value of V, the greater the corresponding associated with the weight of the tail. Generalized Error distribution (GED) reverts to normal distribution if V = 0. And finally in the case of the student's distribution the volatility models here are estimated to maximize the likelihood function of a student's t distribution;

$$L(\theta)_t = \frac{-1}{2}\log\left(\frac{\pi(\gamma)\sqrt{r/2}^{\,2}}{\sqrt{\frac{(\gamma H)^2}{2}}}\right) - \frac{1}{2}\log\sigma_t^2 - \frac{(\gamma H)}{2}\log\left(1 + \frac{\left(Y_t - X_t^1\theta\right)^2}{\sigma_t^2(\gamma - 2)}\right) \tag{3.16}$$

Where γ is the degree of freedom that controls the behaviour of the tail.$\gamma > 2$.

3.3 Nature and Sources of Data

Data used for this study was sourced for from the central Bank of Nigeria (CBN) statistical database website (www.cbn.gov. ng). The variables comprised of monthly crude oil export prices (COP), extracted from the month of January, 1987 – June, 2017. These make a total of 366 data points. Crude oil export prices conditional variance models are fitted to conditionally compound monthly return computed as,

$$\mathrm{COPRt} = \log\left(\frac{COPt}{COP_{t-1}}\right)*100 \tag{3.17}$$

For t = 1, 2, ….t-j where $COPR_t$ is the crude oil export price return at time t, COPt is crude oil export price at time t and COP_{t-1} is crude oil export price at time "$_{t-1}$".

The variable was well differenced (D) to get rid of outlier and as well obtain stationarity within them. The data was analysis using Eviews Software version 9.

Results and Discussions

4.1 Time plot / Test for Volatility clustering

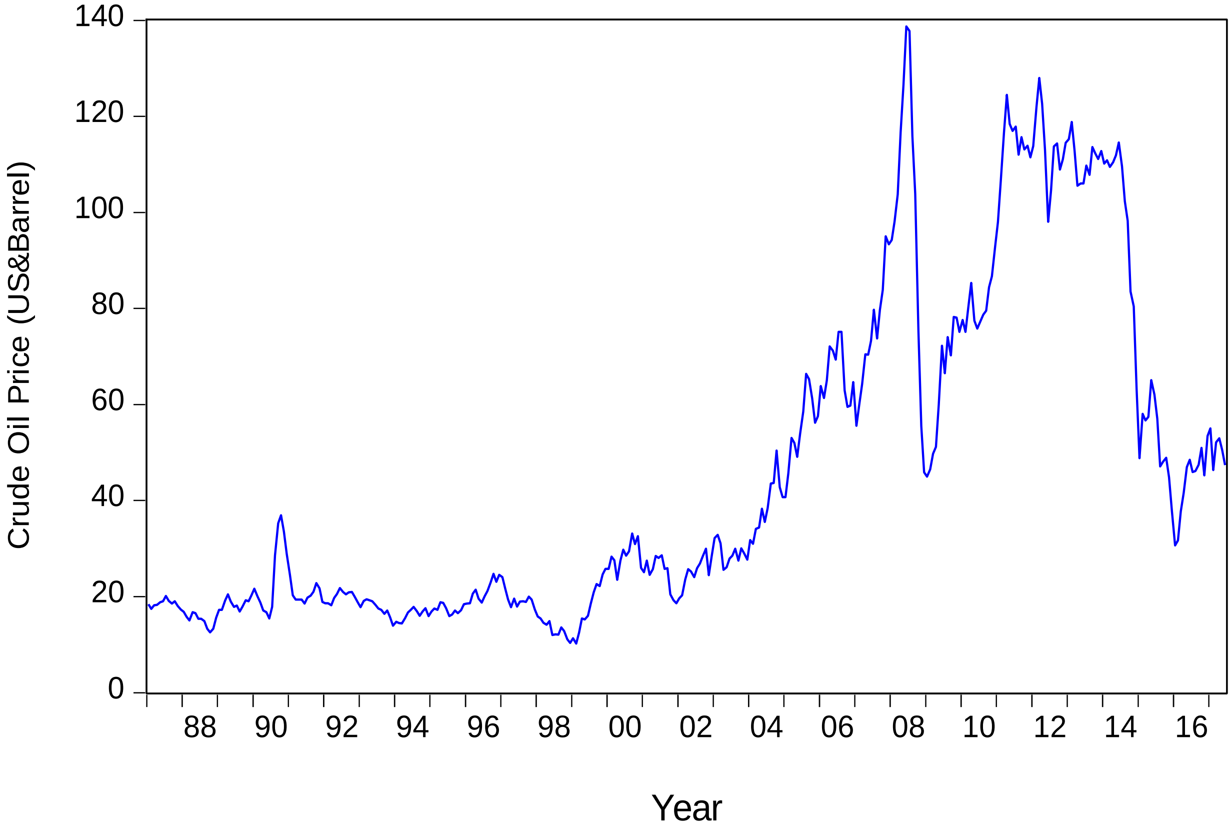

Figure 4.1: Monthly Price of Nigeria Crude Oil Export Market (US Dollar/Barrel) – From January, 1987 to June, 2017.

Figure (4.1) illustrates the dynamics of crude oil prices series. The behavior of crude oil prices from January, 1987 to June, 2017 and this reveal an upward trend which later falls within the year 2014-2016.

Test for Volatility clustering

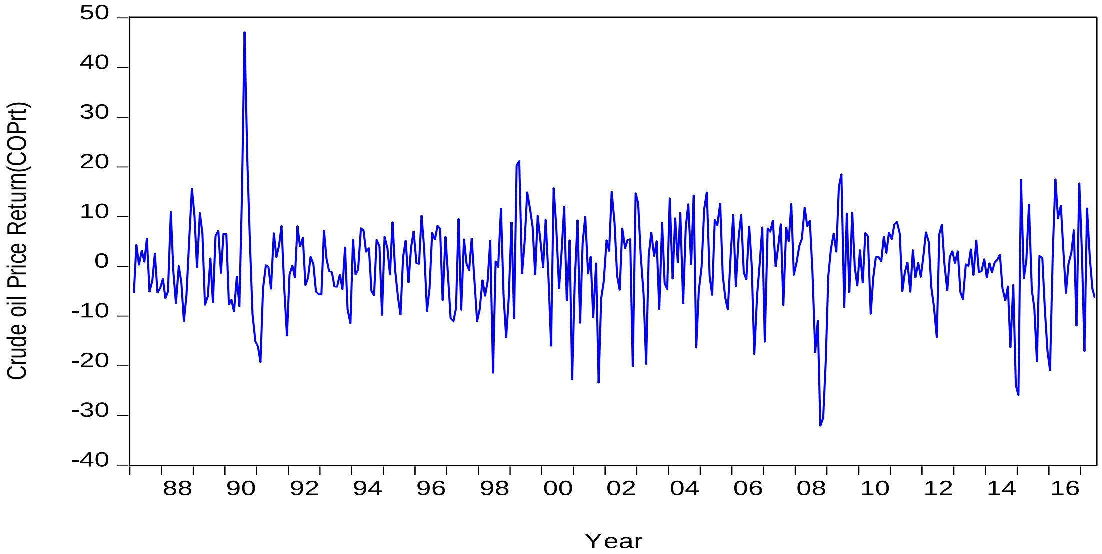

Figure 4.2: Monthly Price Return of Nigeria Crude Oil Export (US Dollar/Barrel) – From January, 1987 - June, 2017.

Figure 4.2 above, clearly show evidence of volatility clustering in the returns series of crude oil export price US dollar/Barrel and the crude oil export price exhibit sharp increase with a corresponding sharp decrease.

4.2 Descriptive Statistics of Crude oil price Return Series.

This is done to tested normality and to examine whether the variable under the study is useful for analysis

Table 4.1: Summary Statistic of Crude oil Export Price Return

Mean	Median	Min	Maxi	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Prob. Value
0.002594	0.005365	-0.321046	0.470843	0.089797	-0.131519	5.343272	84.56002	0.000000

Source: ***Researcher's Computation, 2017. It is all tested Significant at 1 and 5% respectively***

Table 4.1 shows the descriptive statistic for the data variable and its return series covering the period of January, 1987 –June, 2017. The Margins between the minimum and maximum values of the series indicate evidence of variability of the trend of the series within the period under coverage.

4.3 Test for ARCH effect

Table 4.2: Estimation Results for Test for ARCH Effect

Heteroskedasticity Test: ARCH	**Lag 1**
F-statistic	13.39122
Prob. F(1, 361,5, 353,)	0.0003
$n*R^2$	12.98377
X^2 (1,5,)	0.0003

Source: ***Researcher's Computation, 2017. It is all tested Significant at 1 and 5% respectively***

Both the F-statistic and $n*R^2$ test in table 4.2 indicate the existence of ARCH effect on an increase in the variable even at 1% level of Significance for the first order autoregressive process. The test for higher order lags is neglected reasoning been that Lag one test is adequately enough for the modeling of volatility models considered in the study. The First Order Symmetric GARCH Family Models In Error Distribution Assumption is estimated as specified in equation (3.4), (3.5), (3.7), (3.8) and (3.9) in their specific error distribution assumption as in equation (3.12), (3.13) & (3.14).

Table 4.3: Estimation Results of the First Order Symmetric GARCH Models in Error Assumption Distribution.

Models	Equations	Model Parameter	Normal Error Distribution		Student's –t Error Distribution		Generalized Error Distribution		Model with Minimum AIC &SICAcrossError Distr
			Coefficients	P-Value	Coefficients	P-Value	Coefficients	P-Value	
GARCH (1, 1)	Mean	Intercept	0.001443	0.7188	0.003040	0.4384	0.002404	0.5518	
		GCOP(-1)	0.174167	0.0031	0.168070	0.0030	0.169706	0.0035	
	Variance	Intercept	0.000701	0.0383	0.000542	0.0883	0.000630	0.0777	
		ARCH	0.259159	0.0000	0.191681	0.0031	0.229175	0.0003	
		GARCH	0.680844	0.0000	0.755009	0.0000	0.713596	0.0000	
		AIC	-2.107316		-2.121125		-2.108618		-2.121125
		SIC	-2.053784		-2.056886		-2.044380		-2.056886
		ARCH+GARCH	0.940003		0.94669			0.942771	
GARCH (1, 1)-M	Mean	**SQRT(GARCH)**	0.183998	0.4079	0.179470	0.3952	0.171953	0.4257	
		Intercept	-0.012147	0.4708	-0.010320	0.5261	-0.010405	0.5299	
		GCOP(-1)	0.176889	0.0028	0.168910	0.0029	0.172616	0.0030	
	Variance	Intercept	0.000745	0.0328	0.000531	0.0894	0.000635	0.0736	
		ARCH	0.265656	0.0000	0.194859	0.0029	0.232898	0.0003	
		GARCH	0.668938	0.0000	0.754003	0.0000	0.709608	0.0000	
		AIC	-2.104650		-2.118279		-2.105658		-2.118279
		SIC	-2.040411		-2.043334		-2.030713		-2.043334
		ARCH+GARCH	0.934594		0.948862		0.942506		

Source: ***Researcher's computation, 2017. It is all tested Significant at 1 and 5% respectively***

The First Order ASymmetric GARCH Family Models In Error Distribution Assumption is estimated as specified in equation(3.9),(3.10) and (3.11) in their specific error distribution assumption as in equation (3.12), (3.13) & (3.14).

Table 4:4: Estimation Results for Asymmetric First Order GARCH Family Models in Error Distributional Assumptions.

Model(s)	Equation(s	Model Parameter(s)	Normal Error Distribution		Student's –t Error Distribution		Generalized Error Distribution		Model with Minimum AIC & SIC Across Error Distr
			Coefficients	P-Value	Coefficients	P-Value	Coefficients	P-Value	
TGARCH (1, 1)	Mean	Intercept	0.000667	0.8751	0.001938	0.6276	0.001611	0.6959	
		GCOP(-1)	0.178949	0.0032	0.179008	0.0016	0.175576	0.0030	
	Variance	Intercept	0.000650	0.0490	0.000496	0.1053	0.000580	0.0909	
		ARCH	0.210151	0.0002	0.123663	0.1139	0.177659	0.0150	
		Asymmetric	0.067327	0.4524	0.091472	0.3337	0.068794	0.4772	
		GARCH	0.700169	0.0000	0.778623	0.0000	0.733782	0.0000	
		AIC	-2.102914		-2.118247		-2.104302		-2.118247
		SIC	-2.038675		-2.043301		-2.029357		-2.043301
		ARCH+GARCH	0.91032		0.902286		0.911441		
EGARCH (1, 1)	Mean	Intercept	0.000996	0.8050	0.001330	0.7361	0.001499	0.7069	
		GCOP(-1)	0.165820	0.0038	0.170435	0.0024	0.164921	0.0040	
	Variance	Intercept (C(3))	-0.917644	0.0022	-0.727631	0.0162	-0.842727	0.0088	
		ARCH(C(4))	0.437900	0.0000	0.349107	0.0015	0.400559	0.0001	
		Asymmetric(C(5))	-0.068282	0.1625	-0.080388	0.1671	-0.070817	0.2056	
		GARCH (C(6))	0.884734	0.0000	0.908970	0.0000	0.893938	0.0000	
		AIC	-2.118714		-2.128986		-2.117669		-2.128986
		SIC	-2.054475		-2.054041		-2.042723		-2.054475
		ARCH+GARCH	1.322634		1.258077		1.294497		
PARCH (1,1, 1)	Mean	Intercept	0.000950	0.8113	0.001427	0.7191	0.001541	0.6990	
		GCOP(-1)	0.154498	0.0054	0.170937	0.0018	0.163322	0.0034	
	Variance	Intercept(C(3))	0.006899	0.0681	0.006033	0.1102	0.006677	0.0992	
		ARCH(C(4))	0.210965	0.0000	0.173097	0.0029	0.194785	0.0005	
		Asymmetric(C(5))	0.227742	0.1000	0.264919	0.2065	0.234415	0.1826	
		GARCH(C(6))	0.758050	0.0000	0.795798	0.0000	0.772165	0.0000	
		AIC	-2.113325		-2.124958		-2.113101		-2.113325
		SIC	-2.049086		-2.050013		-2.038156		-2.050013
		ARCH+GARCH	0.969015		0.968895		1.00658		

Source: ***Researcher's Computations, 2017. It is all Tested Significant at 1 and 5% respectively***

Model Fitness & Selection

From the fifteen models (symmetric and Asymmetric) estimated above, models were selected on the basis of Schwarz information criterion (SIC) as supported by Alhassan et al (2016) in order to select the best model for forecasting. The results are presented in the table below:

Table 4.5: Model Fitness and Selection

First Order GARCH Family Model.	Error Distributional Assumptions			Minimum SIC
	Normal Error Distr.	Student's-t Error Distr.	Generalized Error Distr.	
GARCH(1,1)	-2.053784	-2.056886	-2.044380	**-2.056886**
GARCH-M(1,1)	-2.040411	-2.043334	-2.030713	-2.040411
TGARCH(1,1)	-2.038675	-2.043301	-2.029357	-2.043301
EGARCH(1,1)	-2.054475	-2.054041	-2.042723	**-2.054475**
PARCH(1,1,1)	-2.049086	-2.050013	-2.038156	-2.050013

Source: ***Researcher's Computation, 2017***

Conclusively, the best fitted selected model are written as shown below: For the first order Symmetric GARCH Model in student's-t error distribution

Mean Equation:

COPRT = 0.00304 + 0.16807*COPRT (-1)

Variance Equation:

GARCH = 0.00054 + 0.19168*RESID (-1)^2 + 0.75501*GARCH(-1)

Similarly, for the first order Asymmetric GARCH Model we have EGARCH in normal as given below:

Mean Equation:

COPRT = 0.00010 + 0.16582*COPRT (-1)

Variance Equation:

LOG(GARCH) = -0.91764 + 0.43790*ABS(RESID(-1)/@SQRT(GARCH(-1))) - 0.06828*RESID(-1)/@SQRT(GARCH(-1)) + 0.88473LOG(GARCH(-1))

Parameter Estimation of the Selected GARCH Family Models

Table 4.6 presents the impact of news on volatility of crude oil export price in the best fitted asymmetric volatility models, and their volatility persistence arising from the parameter estimates of the five best models.

Table 4.6: News Impact Assessment and Test Volatility for Persistence

Parameter Estimates of GARCH	Asymmetric GARCH Family Models			Symmetric GARCH Models	
	TGARCH	**EGARCH**	**PGARCH**	**GARCH**	**GARCH-M**
Distributional Assumptions	Student's-t	Normal	GED		
Good News	0.123663	0.437900	0.173097	-	-
Bad News	0.215135	0.369618	0.438016	-	-
Volatility Persistence	0.902286	1.322634	0.968895	0.94667	0.948862

Source: ***Researcher's Computation, 2017***

Model Diagnostics

In order to ascertain the fact the selected models are good enough for forecasting, there is the need for further confirmatory test and this shall test for the presence of ARCH effect, serial correlation and Q-Q plots for the residuals using the selected models,

Test for ARCH Effect: This is done in conformity with the residuals of the models as review in the concept of homoscedasticity as account for, in Arch effect model. This was estimated using the ARCH –LM model and the results are shown below:

Table 4.7: Heteroskedasticity Test for the Five Best Fitted GARCH Family Model

Models	Heteroskedasticity Test: ARCH	Lag 1	Lag 5	Lag 10
GARCH(1,1) in Student's-t Error Distribution	F-statistic	0.683883	0.498243	0.453985
	Prob. F(1,1234)	0.686371	2.515806	4.624236
GARCH-M(1,1) in Student's-t Error Distribution	F-statistic	0.652177	0.490809	0.476347
	Prob. F(1,1234)	0.654607	2.478527	4.848895
TGARCH (1,1) in student's –t Error Distribution	F-statistic	0.257402	0.403268	0.409138
	Prob. F(1,1234)	0.258644	2.038968	4.172819
EGARCH(1,1) in Generalized Error Distribution	F-statistic	0.090917	0.341227	0.381143
	Prob. F(1,1234)	0.091398	1.726787	3.890427
PARCH(1,1) in Student's-t Error Distribution	F-statistic	0.720752	0.414262	0.413184
	Prob. F(1,1234)	0.723301	2.094228	4.213588

Source: ***Researcher's Computations, 2017***

5.1 Discussion of Results

The monthly crude oil price data for this study spans from January, 1987 – June, 2017 with the total data points of 366, conditional variance models were fitted to continually, compound monthly exchange rate. Fifteen models (15) were estimated using the first order GARCH family model in its three error distribution assumptions. In the estimation of the models, certain conditions were taken into considerations and this incorporate the pattern as shown by the variable. These include the following: Time series plot, Descriptive statistic, Test for ARCH effect test, GARCH family model Estimation and Model diagnosis test.

In the estimation as shown in Figure (4.1) illustrates the dynamics of crude oil prices and its return series. The behavior of crude oil prices from January, 1987 to June, 2017 and this reveal an upward trend which later falls within the year 2014-2016. Also, Figure 4.2 above, clearly show evidence of volatility clustering in the returns series of crude oil export price US dollar/Barrel and the crude oil export price exhibit sharp increase with a corresponding sharp decrease. This also shows that crude oil export return price US dollar per Barrel has not been actually stable within the sample period under this study. The return series follow an unsteady pattern and the returns series confirmed that there is an evidence of volatility clustering. This is also supported by Abdulkareem et al (2016) findings. The period of high volatility, accompany with period of relative calmness the preliminary investigations show that the variable exhibit unusual fluctuation using time series plot then after transformation the trend in the graph became stationary with an increasing volatility clustering.

In another development, the variable was subjected to descriptive test for normality and the result shows that the variable violates all the characteristics of variables that are normally distributed. Table 4.1 shows the descriptive statistics for all the variables and their return series covering from January, 1987 – June, 2017.The mean (0.002594) have positive signs, meaning it is mean reverting. The standard deviation (0.089797) measure the riskiness of the series under the study. The Higher the standard deviation, the increase in volatility of the crude oil prices return and the risky the investment in this trade. The 8.09797% difference between minimum and maximum return series is a clear evidence of the level of price variability in fairness to trading in crude oil market within the sample period. Again, the co-efficient of skewness -0.131519 is less than zero indicated that the distribution is negatively skewed which one of the common characteristics of fairness in crude oil price return series while the Kurtosis (5.343272) is greater than three (3). However, the Kurtosis of a normal distribution is 3 which mean the distribution not normal. And the Jarque-Bera (84.56002) accomplish with a very small corresponding probability value (0.000000), the Null Hypothesis of Normality is rejected and the alternative inferential statistic as suggested by Abdulkarem et al (2017) become necessary with their corresponding error distribution assumptions and fixed degree of freedom fussed into the ARCH and GARCH models .

A look at the table (4.3) reveals the values of F-statistics (13.39122) to be higher with its corresponding chi-squares statistics less than the Obs. R-squared (nR^2) (12.98377) i.e. the Obs. R-squared is greater than prob. Chi-square. Hence, the Null hypothesis is rejected therefore it can be concluded that there exist ARCH effect in crude oil export price return series, even when it was tested at 1% significance level. See complete estimation results for the test for ARCH effect in appendix. This confirmed Abdulkarem et al (2017) assertion about variables that can be estimated using GARCH family model

Table 4.4 and table 4.5 presents comprehensive analysis on crude oil export price in dollars per Barrel while selection were done only with the model with the least Schwartz information criterion. The symmetric models in the table4.4 above reveal that all the ARCH Coefficients in the three error distribution assumption are statistically significant at the 5%levelof significance. This evidently confirmed the presence of ARCH effects and this support the fact that the previous month's crude oil export price information can actually influence the present month crude oil export price return. That is crude oil export price volatility is influence by its own ARCH and GARCH.

Similarly, it is clear that @ SQRT (GARCH) coefficients are not significant and it does not provide much needed information on the volatility of return series. However, the results in

GARCH (1,1) and GARCH-M (1,1) shows that the sum of the ARCH and GARCH coefficients are less than one. This indicates that using GARCH (1,1) and GARCH-M(1,1) in modeling characteristics exhibited by volatility of crude oil export price within the sample period reveal a mean reverting condition.

Also, considering the degree of effect or persistence in GARCH (1,1) according to the order their of error distribution assumptions such Normality, student's-t and the generalized error assumptions. The GARCH (1,1) in Normal error distribution have (94.003%), GARCH(1,1) in Student's-t gives have (94.669%) and GARCH(1,1) in Generalized error distribution have (94.2771%). This follows that GARCH (1,1) in Normal error distribution have the highest volatility persistence, follow by GARCH (1,1) in student's-t and GARCH (1,1)in generalized error distribution. Meanwhile ,the degree of effect or persistence in GARCH-M(1,1) are as follows: GARCH-M(1,1)in Normal error distribution is (93.4594%), GARCH –M (1,1) in student's-t (94.8862%) and GARCH-M(1,1) in Generalized error distribution is (94.2506%). This shows that using GARCH-M(1,1) in modeling volatility, GARCH-M(1,1) in normal error distribution have the highest level of volatility persistence or effect, follow by the GARCH-M(1,1) in Generalized error distribution and the GARCH-M (1,1) in student's-t distribution. Using the GARCH-M (1,1), it shows that increased risk leads to a higher return.

Finally, comparing the two models on the basis of fitness and performance using the Schwartz information criteria, GARCH(1,1) in student's error distribution assumption has the value (-2.056886) with the Akaike information criteria(AIC) of -2.121125 and GARCH-M(1,1) in student's-t error distribution (-2.043334) with the Akaike information criteria(AIC) (-2.121125) were chosen as the best fitted symmetric models for estimating crude oil export prices within the sample period.

Based on the results of the findings the symmetric GARCH models in student's-t error distribution clearly perform than the asymmetric GARCH models. This is also confirmed in Shamiri and Isa (2009) findings while modeling and forecasting volatility of the Malaysean stock markets. According to the Schwartz information criterion, GARCH (1,1) in student's-t error distributional Assumption in symmetric GARCH and EGARCH (1,1) in normal error distributional assumptions in Asymmetric GARCH outperform other models irrespective of their class. Although, one unique behavior about GARCH-M (1,1) model is that it allow conditional mean of a financial data return sequence to depend on its conditional standard deviation or variance.

Similarly, in evaluating GARCH family models performance in Nigerian crude oil markets there is the need to do a comparative volatility modeling of Nigeria crude oil using symmetric and Asymmetric GARCH models. This will help us in drawing conclusion about the best fitted model. The asymmetric first order GARCH family models in error distributional assumptions in the equation (3.10),(3.11) and (3.12) were also estimated using the residual from equation (3.23) for each of the model in their error distribution assumptions. Also, the value of the Power GARCH otherwise refers to as the PGARCH (1,1,1) inputted according their order of degrees. This evaluated alongside with other two models generated nine volatility models as shown in the table 4.4 above.

In the table 4.4 above, the entire ARCH (α) coefficient in all the models shows positive sign and they are statistically significant at the 5% level of significance except the case of TGARCH in student's–t whose probability value (p-value) is 0.1139. These confirmed the presence of ARCH effect. It also imply that the previous month's crude oil export price return series information influence this presence month's crude oil export price return series. However, in spite of such deduction one can equally say that there exist a leverage effect and this means bad news can have impact on conditional volatility than good news. But for TGARCH in student's–t error distribution models, the above implications is a contradiction simply because the non-significance of the p-value, mean that the previous month's volatility can't influenced this present month's volatility. Also the asymmetric term has positive co-efficient but not statistically significant at the 5% level of significance. This is also a confirmation to (Abdulhakeen et al, 2016) findings.

But the asymmetric terms in the other models have negative signs in their co-efficient but they are not statistically significant at 5% level of significance. This means that there exist negative correlation between the past crude oil export price return series and future volatility of the return series. And that the higher leverage effect that occurs due to negative crude oil export prices return will likely translate to low equity price otherwise result in sky rocking of debt to equity ratio. Also, it can be deduced that negative shocks reduces the volatility of crude oil export price returns and that negative return of crude oil has more impact on the volatility of crude oil export price s than the positive return series.

Also, the addition of the ARCH and GARCH coefficients are very closed to unity i.e. TGARCH(1,1) in normal error distribution (0.91032), TGARCH in student's-t error distribution (0.902286) and TGARCH(1,1) in Generalized error distribution (0.911441), then this invariably means they are all mean reverting in nature.

And the degrees of shocks are permanent at 91.032%, 90.2286% and 91.1441% of persistence respectively. This implies that using TGARCH(1,1) in modeling volatility within the present sample period TGARCH(1,1) model in Generalized error distributions have the highest volatility persistence(91.1441%) follow by TGARCH(1,1) in normal error distribution(91.032%) and the TGARCH in student's-t error distribution(90.2286%) . Whereas comparing the models on the basis of the Schwarz information criterion (SIC) and Akaika information criteria (AIC),TGARCH(1,1) model in student's-t error distribution have the least value (-2.043301) with (AIC) (-2.118247) this was considered the best fit.

Similarly, The EGARCH (1,1) model estimation was also considered in the modeling and all the co-efficient of the ARCH(α) terms show negative signs and significant at the 5% level of significance. This simply means that there exists the presence of ARCH and leverage effect. It is clear that the result reveal negative correlation between the past return of crude oil price and future volatility. It also shows that bad news has more impact on the volatility of the returns series (crude oil export price) than the positive news. Also, all the asymmetric terms such as (-0.068282 in normal error distribution, -0.080388 in student's –t, -0.070817 in Generalized) has negative signs but they are not statistically significant at 5% level of significance. This reveals that negative shocks reduce the volatility of the variable than the positive shocks of the same magnitude whereas leverage effects are considered necessary on the basis of EGARCH (see Abdulhakeem et al, 2016).

The sum of the ARCH and GARCH has the following values; EGARCH (1,1) in normal error distribution assumption (1.322634), EGARCH(1,1) in student's–t error distribution assumption(1.258077) and EGARCH in Generalized error assumption distribution is (1.294497). These simply mean that all the EGARCH models are mean reverting and their volatility persistence are only temporary. Although, the degree of their persistence are high, ranging from 132.2634% to 125.8077% and 129.4497% respectively.

Similarly, the Schwarz information criterion and Akaike information criteria is given that EGARCH(1,1) in normal error distribution (-2.054497) while (AIC) -2.128986 in EGARCH(1,1) in student's-t .However, EGARCH(1,1) in Normal Error distribution was considered the best fitted since the model have the least Schwartz information criterion and according to Alhassan et al(2016) SIC is use as the best choose for selection of model fitness since it levies heavy penalties for loss of degree of freedom.

Finally, the PGARCH(1,1) was also considered for the study and the results from the estimation as shown in table (4.4)above indicate that all the ARCH(α) co-efficient in the models has positive signs (0.210965, 0.173097,and 0.194785) and they are statistically significant at the 5% level of significance. This reveals that the models have ARCH and leverage effects. Hence, we can say that there exist negative correlation between the first return of the series and future volatility. Also, this shows that negative news have more impact on the volatility of return than the positive news. Furthermore, all the asymmetric terms have positive signs (0.227742, 0.264919, and 0.234415) but they are not statistically significant at the 5% level of significance and this confirmed the fact that there exists leverage effect. Although, the leverage effect is not necessary considered on the basis of PARCH modeling. Also, the sum of the ARCH and GARCH terms estimated at 0.969015, 0.968895 and 1.00658. These reveal that the models are mean reverting with persistence shocks. The degrees of volatility persistence are in the following order PGARCH in Generalized (100.658%), normal (96.9015%) and student's-t error distribution (96.8895%).
In the results, the TGARCH(1,1),EGARCH (1,1)and PARCH(1,1,1) indicated the existence of leverage effect in the market. This invariably means that bad news have much effect on subsequent period volatility than good news of the same magnitude. The GARCH(1,1) in Student's–t error distributional assumption for symmetric first order GARCH family model and EGARCH (1,1) in normal error distributional assumption were considered the appropriate model since they were able to meet the model selection criterion. GARCH(1,1) having the ARCH and GARCH summations mostly less than one whereas the later having greater than one i.e. making ensure that stationarity of the model, been able to capture leverage effect and its ability in eliminating ARCH effects.

Model fitness and selection are done as reveal in table 4.5. In table 4.5, GARCH and GARCH-M in student's-t error distribution were considered best fitted symmetric models since they have the least Schwarz information criterion across the models while in the asymmetric GARCH models, TGARCH in student's–t, EGARCH in normal and PGARCH in student's-t error distribution assumption were considered the best fitted. However, GARCH (1,1) in student's-t error distribution assumption with SIC (-2.056886) was considered the overall best fitted. In view of the above, the overall best fitted model is GARCH (1,1) model in student's-t error distribution for symmetric follow by EGARCH in normal distribution for Asymmetric GARCH family model.

Our overall selected EGARCH model in normal error distributional assumption result suggested that there exist a comparatively petite volatility in the crude oil market, although on a diminutive level with a price fluctuation approximately at the level of 0.002594 USD/barrel for Nigerian crude oil which is also in conformity with Morardand Balu (2014) findings.

Table 4.6 talks about new impact assessment and test for volatility persistence. Although, these are carried out using the parameters estimated with respect to the selected GARCH family model. The results of the parameter estimate of the selected first order asymmetric

GARCH family model in table 4.6 vividly show that bad news actually have more impact on volatility than good news. Also, it is revealing that EGARCH in normal error distribution has the highest overall volatility persistence. These models were diagnosed to ascertain whether the ARCH effect (Heteroscedacity) have been actually eliminated using serial correlation test and QQ–plot of the residuals of the models. From the results in table 4.7 the hypothesis that there is no Arch effect (Null Hypothesis) is confirmed at the 5% significant level.
This was carried out to confirm whether the models have serial correlation which is not good enough for models that can be used in making forecast**.**

Conclusion

The results from the study have been amazing as marketers, and investors alike have clearer views on how to go about their transaction. Also, the leverage crude oil market shown by EGARCH model is statistically significant at 1% level with a negative sign, which reveal that negative shocks meaning a higher next period conditional variance than positive shocks with the same sign, showing that the existence of leverage effect is observed in returns of the crude oil market index. Contrarily to the EGARCH model, the leverage crude oil market shown by TGARCH is statistically significant with a positive signs, this reveal that at some point in the market positive shocks meaning a higher next period conditional variance than negative shocks with the same sign, showing that the existence of leverage effect is observed in returns of the crude oil market index. In conclusion the economic slowdown in a promising market like this is challenging. However, the new convention in the market represents new challenges for economist, econometricians and researchers a like to urgently do structural reform in adjusting to news in the context of modeling price Volatility in any markets.

Recommendations

In the words of Jin (2008), opined that volatility increases the risk and uncertainty of external transactions and predisposes a country to volatility related risks.
Considering the level of risk that accompany external trade and investment in stocks and price of commodities with its corresponding return series, investors, financial analyst and Government are advice to be careful and such the following recommendations were suggested as thus :

- When modeling price volatility different error distributional assumptions should be specifically incorporated into the system as incorrect error specification may lead to incorrect estimation, which could cause loss of efficiency in the model.
- Also, investors should not close their eyes to the impact of news while forming prospect on investment as the higher the standard deviation in the descriptive statistic of the return series maybe vulnerable risks.
- Government should look for new ways to diversify the economy from total dependence on oil and non-crude oil such as agriculture to explore other sectors like the manufacturing sector to reduce price volatility in the economy and its overall effect on other macroeconomic indicators.
- Exchange rate between Nigeria and her foreign trading partners should be regulated to currency variability which may in turn affect other Macroeconomic indicator

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