Modeling Returns on Prices and Sales of Crude Oil Using GARCH Model between1997-2017

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Abstract
The risks associated with the returns on prices and sales of crude oil is one of the challenging conditions that makes assessment, forecasting, planning, marketing and decision making complicated. Therefore, this research study among other things was targeted at modeling returns on prices and sales of crude and the risk-return related to prices and sales of crude oil outside the shore of Nigeria using symmetric and asymmetric univariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models in five distributional assumptions namely, Normal error distribution, student's-t error distribution , generalized error distribution, student's-t with fix degree of freedom and the generalized error distribution with fix degree of freedom. 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 July, 1997 to July, 2017. The results from the statistical analysis reveal that the returns on Prices and sales of crude oil are often volatile. Sequel to that, there were high probabilities of gains than losses on the price and sales of crude oil. Although, the prices realized were extremely volatiles and shows evidence that there exists positive risk first-rated meaning that investments or investors ought to have rewards for holding risky assets. In estimation, first order symmetric GARCH model (GARCH, (1,1) in generalized error distribution with fix degree of freedom gave a better fit while in the first order Asymmetric GARCH model, the EGARCH (1,1) in normal error distributional assumptions gave a better fit. However, comparing the two classes of the models on the bases of their fitness the EGARCH (1,1) in normal error distributional assumptions gave an overall best fitness. Also, the selected models were subjected to several diagnostic test such as ARCH effect test, test for serial correlation and QQ-plot in order to authenticate their fitness which was confirmed to be appropriate. Recommendations were made to the Government to look for new ways to expand and diversify the economy from crude oil to other areas such as agriculture, manufacturing and mining sector. For investors or marketers in this markets, they were warn to be mindful in trading when prices are highly volatile period especially when there is evidence of high standard deviation in the descriptive statistic of the returns on prices and sales of crude oil and in modeling returns on prices and sales of crude oil, the leverage effect should be properly estimated using asymmetric GARCH model

Keywords: Returns, Crude Oil, GARCH, Model

Introduction

1.1 Background to the Study

High-frequency data for example weekly, daily or into-daily of an asset return have been shown to have exhibited characteristic that have generated and as well attracted attention overtime. It is assume in most conventional financial time series that the conditional variance of an asset return

is expected to be constant; however, many researchers such as Lau et al, (1990) have found that the reverse was the case.

These development led econometrician to the invention of an adjusted method for capturing mean and variance value of a model otherwise referred to as Generalized Conditional Autoregressive Heteroskedasticity (GARCH) which was based on the assumption that the random components in the model of a variable that exhibit such characteristics which present changes in volatility. According to Dritsaki (2017) this model, called the GARCH model was developed by Engle (1982) in a simple form but were later generalized by Bollerselve (1986) as it is cited in Dritsaki (2017). Sharmiri and Isa (2009) further suggested that the method in which the mean response could be changing with covariate while the variance remains constant over time often seem to be an unrealistic assumption in practices. This fact is particularly clear in series of financial data where clusters of volatility can be seen visually.

Over the years, we have seen a number of different suggestions and approaches on how to model the second moment usually referred to as volatility of returns on prices on investment or product purchased. Although, it is now globally accepted that high frequency of financial returns are heteroskedastic but modeling this condition otherwise referred to as heteroskedasticity remain a big challenge. No wonder, Dritsaki (2017) once opined that generalized Autoregressive Conditional Heteroscedatility (GARCH) have a long and outstanding history but they are not free from limitations. Example, Black (1976) in his study claims that stock market returns are negatively correlated with likely changes in volatility returns implying that volatility tends to rise in to bad news and fall in response to good news. Conversely on GARCH models it is assume that only the size of return of the conditional variance should be defined and not the positively or negatively or volatility's return, which are unpredicted.

Also, crude oil is one of those commodity characterized with a lot of challenges. Its markets react "nervously" in the presence of oligopoly, political disorder, worried, economic crisis or possible fear of war of man-made disaster like the case of the Niger Delta struggle and other major natural catastrophe that tends to threaten peaceful co-existence. During such a distress periods,prices of financial assets are mostly volatile.

It is against this background that this study is targeted at modeling returns on prices and sales of crude oil using GARCH model between July, 1997 to July, 2017 with a view of providing a volatility measure like a standard deviation that can be used in making decision concerning risks associated with prices, to portfolio selection and derivative pricing.

Methodology
Model Specification with their Distribution Assumptions
Black (2002) defined model specification as a simplified system used to simulate some aspect of the real or actual world economy. It states the reality in the form of design to enable the research described the essence or inter-relationship within the variables or condition under the present studied. However, in line with the objective of this study, the model emphases in the study can be classified into two categories: the symmetric GRACH models and asymmetric GARCH models.

Symmetric GARCH Models
According to Dritsaki (2017), the traditional methods of volatility modeling measure variable or standard deviation with no consideration to other characteristics of time series (financial data) such as leverage effect, volatility clustering, long memory, good and bad news. Example of such

model to be considered here is the Autoregressive conditional Heteroscedasticity (ARCH) model as proposed by Engle (1982) and it will be derived thus: given that the residual obtained from a linear equation is as follows:

$$\varepsilon_t = Z_t \sigma_t \qquad (31)$$

Where Z_t is independently identically distributed (i.id) with mean = 0, and variance = 1, i.e. N(0,1). σ_t is the variance otherwise referred to as volatility that evolves within a certain time interval. However, the variance (volatility) σ_t^2 in the elementary ARCH (q) model is defined as;

$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-1}^2 \qquad (3.2)$$

Where σ_t^2 is defined as the conditional variance or standard deviation, w is a constant and σ_I is the ARCH coefficient. Note: w > 0 and σ_I >0 for σ_t^2 to be positive. By interpretation, the model in equation (3.2) shows that after a large shock, it is likely that a large shock will follow. Similarly, after a small shock, it is likely that a small shock will also follow. Conversely, a large previous ARCH $\left(\varepsilon_{t-1}^2\right)$ implies a large ARCH $\left(\varepsilon_{t-1}^2\right)$ current period effect of volatility. Similarly a small previous ARCH $\left(\varepsilon_{t-1}^2\right)$ effect of volatility implies a small ARCH $\left(\varepsilon_{t-1}^2\right)$ current period effect of volatility (variance). Although, there are allot of shortcoming about this model itself inreality. The shortcoming is that, it may not occur in reality as presumed by model. However, to overcome this short coming as stated above, Kroner and Lastrapis (1991) proposed a new model where conditional variance does not depend mainly on lagged square error values but also on previous values of the same variance. The model was known as generalized Autoregressive conditional Hetereskedasticity (GARCH) model.

The Generalized form of GARCH is written as GARCH (p,q), where value P is the order of the GRCH of the model and q is the order of the ARCH component of the model. It is derived thus: Supposing the return of time series data on crude oil at time σ is given as

$$COPR_t = \mu_t + \varepsilon_t \qquad (3.3)$$

$$COP \; \sigma_t^2 = w + \sum_{t=1}^{q} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} Bj\sigma_{t-j}^2 \qquad (3.4)$$

Where μ_t is the mean value of the returns on pricesof crude oil in the time series data on,ε_t is the error term as at time t. The error term (ε_t) is assumed to be normally distributed with zero mean and conditional variance $\left(\sigma_t^2\right)$. P order of the GARCH and q order of ARCH model as earlier stated where as the parameters to be estimated are μ, w, α_I and Bj which all must be positive (μ> 0, w > 0, $\alpha_i \geq$ 0 and B$_j \geq$ 0) for the conditional variance (σ_t^2) to be positive.

According to Dritsaki (2017), it is expected that the value of the parameter "w" to be small while σ_t^2 in the model measured responses of volatility in the returns on prices of crude oil as variance and Bj expresses the differences in the returns on prices/sales of crude oil as a result of outliers on conditional variance. It is expected that the sum σ_i + Bj<1,

In summary, the model GARCH (1, 1) for the returns on prices of crude oil appears in the following form:

      Mean Equation: RCOP$_t$= μ + W   (3.4)

      Variance Equation: Cop σ_t^2 = W + $\alpha_1 \varepsilon_{t-1}^2$ B$_j \sigma_{t-1}^2$ (3.5)

For the variance to be positive the regression co-efficient must always be as thus: w$\geq$ 0 $\sigma_1 \geq$ 0 and B$_j \geq$ 0.Also, another example of symmetric GARCH model is the Generalized Autoregressive

conditional Heteroskedasticlity in means (GARCH-M).This model was proposed by Engle *et al* (1987) which mostly estimates the return of financial data series as dependent of the conditional variance or a standard deviation as cited in Deebom and Essi (2017). This model capturesmostly high risk associated with high return in the series.

The GARCH – M is specify as thus:

Mean equation $CORR_t = \mu + \lambda\sigma_t^2 + \varepsilon_t$ (3.6)

Variance Equation: $COPR\ \sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + B_1\sigma_{t-1}^2$ (3.7)

Similarly, $\alpha_0 \geq 0$, $\alpha_0 \geq 0$ and $B_1 \geq 0$ for $COP\ \sigma_t^2$ to be positive and all these parameters are to be estimated.

Asymmetric GARCH Model

According Drisaki (2017), asymmetric GARCH model captured the inadequacy in symmetric GARCH model and this inadequacy includes: inability of the symmetric GARCH to model leverage effect, long memory, the impact of good and bad news. Examples of this type of model are the exponential generalized autoregressive conditional Heteroskedasticlity (EGARCH), Thresh hold GARCH (TGARCH), Asymmeteric power (APGARCH) etc for the purpose of this study, we shall constrained the research to EGARCH and TGARCH.

Therefore, the exponential generalized auto regressive conditional Heteroskedasticlity EGARCH as proposed by Nelson (1991) are specified thus:

$$\text{Log}\ \sigma_t^2 = w + \sum_{0=1}^{\rho}\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-1}}\right| + \sum_{j=1}^{q}BjLog\ \sigma_{t-j}^2 + \sum_{k=1}^{r}Y_k\frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad (3.8)$$

Where w, α_i, B_j and Y_k are all parameters to be estimated using the maximum likelihood method. $\varepsilon_{t-1} > 0$ and $\varepsilon_{1-j} < 0$ represents good 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 volatility persistence would be high, Also, $/B_j/<1$ and Y_k parameters captured leverage effect.Dritsaki (2017) opined that the condition variance of the model in equation (3.8) expresses in logarithmic form ensures the non-negativity are captured without imposing any constraints of negativity on the estimation. In general, the model in equation (3.8) can be expressed in the order $\rho = 1$ and q =1 i.e. EGARCH (1,1) is given as

$$\text{Log}\ \sigma_t^2 = w + \alpha_1\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + B_1\log\sigma_{t-1}^2 + Y_1\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (3.9)$$

Where there exist a positive shock if $\frac{\varepsilon_{t-1}}{\sigma_{t-1}} > 0$, the model in equation (3.9) becomes

$$\text{Log}\ \sigma_t^2 = w + \beta_1\log\sigma_{t-1}^2 + (\alpha_1 + Y_1)\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (3.10)$$

Similarly, where there is a negative shock if $\frac{\sum_{t-1}}{\sigma_{t-1}} < 0$, the model in equation (3.9) becomes.

$$Log\ \sigma_t^2 = w + \beta_1\log\sigma_{t-1}^2 + (\alpha_1 - y_1)\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (3.11)$$

Another example of an asymmetric GARCH family model is the Glosten*et al*(1993) Generalized Autoregressive Conditional Heteroskedastility GJR – GARCH (P,q) model. It is otherwise referred to as the threshold GRACH (p,q) model and it is written as;

$$\sigma_t^\delta = w + \sum_{1=1}^{p} \alpha_1 \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta j \sigma_{t-1}^2 + Y_t I_{t-1} \varepsilon_{t-1}^2 \qquad (3.12)$$

$$I_{t-1} = \begin{cases} 1 \text{ when } \varepsilon_{t-1} < 0, \text{ positive} \\ 0 \text{ when } \varepsilon_{t-1} \geq 0, \text{ Negative} \end{cases}$$

Where w, α_i, B_j and Y_i are parameters to be estimated. The I_{t-i} is a dummy variable, which implies that I_{t-i} is a functional index which lies between one and zero, when $\varepsilon_{t-1} = 0$, is positive and when $\varepsilon_{t-1} = 1$ is negative. Deebom and Essi (2017) suggested that if parameter $Y_i > 0$ then negative error or leveraged effect. This implies that negative development of bad news have larger impact than good news. Conclusively, it is assume that the GJR – GARCH model parameters are positive and the relationship $\alpha_i + B_j + \dfrac{Yi}{2} N$ is valid. When p = 1 and q = 1, the GJR-GARCH(p,q) model are written as thus:

$$\sigma_t^2 = w + \alpha_1 \Sigma_{t-1}^2 + B_1 \sigma_t^2 + Y_i I_{t-1} \varepsilon_{t-1}^2 \qquad (3.13)$$

$$I_{t-1} = \begin{cases} 1 \text{ when } \varepsilon_{t-1} < 0 \\ 0 \text{ when } \varepsilon_{t-1} \geq 0 \end{cases}$$

To avoid certain challenges that may cause or lead to inappropriate modeling, the entire model specified above were subject to conditional distribution assumption as cited in Deebom and Essi (2017) and such assumptions include the normal distributional assumptions, generalized error distributional assumption, and student's-t error distributional assumption, skewed Generalized error distribution assumption set at fix degree of freedom $v = 10$, and skewed student's-t error distribution assumption set at fix degree of freedom $v = 1.5$. Deebom and Essi (2007), further suggested that the reasons why this is inco-operated into the model is that using GARCH model in the form of an ordinary least square is necessary since the error terms are independently and identically distributed iid (0,1), therefore no need to use ordinary least square method on small samples. However, in this case it will be good to use the maximum likelihood method (Greene, 2008). Also, Dritsaki (2017) posited that the parameters of GARCH models maximize the log likelihood function and this is derived through non-linear least squares using Marguardt's algorithm (Marquardt, 1963).

Normal Error Distribution in the case of standard normal error distribution the random variable (Ƶ) following log-likelihood function needs to be maximized as thus;

$$\text{In L}(Y_t), \theta) = -\frac{1}{2}\left[T \, In(2\pi) + \sum_{t=1}^{T} Z_t^2 + \sum_{t=1}^{T} In(\sigma_t^2) \right] \qquad (3.14)$$

Where θ is the vector of the parameter that will estimate with conditional mean, variance and density function such that "T" represents number of observation.

Similarly, **student-t distribution** deals with more severe leptokurtosis and it's log-likelihood function and it is define as thus:

$$In(Y_t)\theta\} = T\left[In\Gamma\left(\frac{v+1}{2}\right) - In\Gamma\left(\frac{v}{2}\right) - \frac{1}{2}In[\pi(v-2)]\right] - \frac{1}{2}\sum_{t=1}^{T}\left[In(\sigma_t^2) + (1+v)In\left(1 + \frac{Z_t^2}{v-2}\right)\right] \qquad (3.15)$$

Where $\Gamma(v) = \int_0^\infty \ell^{-x} \times v^{-1} \, dx$ the gamma function and v is the degree of freedom. Dritsaki (2017) confirmed that t-student error distribution is symmetric around zero and it incorporates the standard normal distribution as a special case when v $=\infty$. In another development, it gives a

cauchy distribution when v = 1 and when v have a lower value the distribution yields a "flatter tails".

Also, the **Generalized Error Distribution** as proposed by Nelson (1991) is more appealing in terms of fulfilling stationarity compared to the student-t distribution. Just like in the case of the student's-t error distribution the unconditional means and variances may not be finite in the EGARCH. The log-likelihood function for the standard generalized error distribution is defined

as follows; $In \, L\left[(Y_t), \theta \right\} \sum_{t=1}^{T} \left[In\left(\frac{V}{\lambda}\right) - \frac{1}{2}\left|\frac{Z_t}{\lambda}\right|^v - \left(1 + V^{-1}\right)In(2) - In\Gamma\left(\frac{1}{v}\right) - \frac{1}{2}In\left(\sigma_t^2\right) \right]$ (3.16)

Where; $\lambda = \left[2^{-2/v} \frac{\Gamma\left(\frac{1}{v}\right)}{\Gamma\left(\frac{3}{v}\right)} \right]^{1/2}$

The generalized error distribution (GED) incorporates both normal error distribution when (V = 2), laplace distribution when (v = 1), and the unique distribution for v = ∞. Dritsaki (2017) observed that when v = 2 the distribution of the random variable "Z_t" would be the standard normal distribution. Similarly, given v < 2, the distribution of the random variable Z_p will produce thicker tails than that of normal distribution. Given v = 1 the distribution of the random variable Z_t will produce double potential distribution. While when v > 2 the distribution of the random variable Z_t will produce thinner tails than normal distribution, and for v = ∞ the distribution of the random variable Z_t will produce a uniform distribution. Furthermore, the skewed student's –t error distribution with V is used where V has a shape of parameter with 2< v <∞ and λ is a skewness parameter having a range of value – 1 <λ< 1. The model is given thus

$f(Z; \mu, \sigma, v, \lambda) =$
$$\begin{cases} bc\left(1 + \frac{1}{v-2}\left(\frac{Z-\mu+a}{\frac{\sigma}{1-\lambda}}\right)^2\right)^{\frac{-V+1}{z,}} & if \ z < -a/b \\[4ex] bc\left(1 + \frac{1}{v-2}\left(\frac{b(Z-\mu)+a}{\frac{\sigma}{1+\lambda}}\right)^2\right)^{\frac{-V+1}{z,}} & if \ z. > -a/b \end{cases}$$
(3.17)

Where μ and σ2 are the mean and variance estimating the skewed student's-t error distribution.

In like manner, skewed generalized error distribution is given as thus;

$f(Z; \mu, v, \varepsilon) = v\left[2\sigma\Gamma\left(1/v\right)\right]^{-1} \exp\left(-\frac{/z - \delta/^v}{\left[1 - sign(z-\delta)\varepsilon\right]^v_{\theta^v}}\right)$ (3.18)

Where
$\theta = \Gamma\left(1/v\right)0.5\Gamma\left(3/v\right)^{-\phi.5}\varsigma(\varepsilon)^{-1}$
$\delta = 2\,\varepsilon\,AS(\varepsilon)^{-1}$ (3.19)
$\varsigma(\varepsilon) = \sqrt{1 + 3\,\varepsilon^2 - 4A^2\varepsilon^2}$
$A = \Gamma\left(2/v\right)\Gamma\left(1/v\right)^{-1.5}\Gamma\left(3/v\right)^{-1.5}$

Supposing V>0 is the shape of the parameter controlling the height and heavy tail of the density function. Where ε is skewness parameter of the density that lies within $-<\varepsilon<1$.
In the estimation process using Eview, all parameters in the model in equation (3.17) and (3.20) are set at default value and these involve location, scale and skewness parameters are equal to 10 and 1.5 respectively. The shape of parameter is equal to 10 for student's-t with fix degree of freedom and equal to 1.5 for skewd generalized error distribution.

Data Source

Data used in this study was collected from the official website of the Central Bank of Nigeria (CBN) (www.cbn.gov.ng) (2017). It spans from the period August, 1997 – August, 2017 and comprises 240 observations. The monthly stock return on prices and sales of crude oil is

calculated thus; $\mathrm{RCOP}_t = \log\left(\dfrac{COP_t}{COP_{t-1}}\right) \times 100 = \mathrm{In}(COP_t - \mathrm{InCOP}_{t-1}) \times 100$ (3.20)

Where P_t is the monthly closing value of the stock return on prices of crude oil at time t and RCOP_t is the return on prices and sales of crude oil.

Basic Estimation Procedures

The Basic estimation procedures used in this study are as follows;

Testing the trends of the variable using Time Plot

This is done to know whether a time series data is stationary and the mean; variance and auto-covariance (at various lags) remain the same no matter at what time it is measured. According to Deebom and Essi (2017), times series plot is a square taken at successful equal spaced point on a line graph. This is followed by testing for volatility clustering and this is done to detect the presence of volatility clustering using the model transformation in equation (3.17). This process uses the residual obtained from an ARMA model.

Test for Normality

The test for normality is done using the Jarque-Bera test statistic. According to Dickko et al (2015),Jarque-Bera could be defined as points test of skewdness and Kurtosis to examine whether data series exhibit normal distribution or not. The test statistics was developed by Jarque and Bera (1980) and this is defined as

$$X^2 \sim \frac{N}{6}\left[S^2 + \frac{(K-3)^2}{4}\right]$$ (3.21)

Where S-Stands for Skewdness, K-Stands for Kurtosis and N-Stands for number of observation

This test statistic is considered under the Null hypothesis of a normal distribution has a degree of freedom of 2. Abdulkareem and Abdulhakeen (2016) once suggested that when an observation does not obey the normality test that the alternative inferential statistic to be considered is ARCH and GARCH models. This is because error distribution assumptions with fixed degree of freedom are fussed into them.

Test for ARCH Effects

This test statistic could be defined as a condition in which there exist relationship between (n) number of observation multiply by co-efficient determination (R^2) and chi-square distribution with 9 degree of freedom (Deebom and Essi, (2017). If the value of nR^2 is greater than the value of the chi-square distribution, then there is evidence of ARCH(q) effects.

GARCH Model Estimation

This is done using the Asymmetric and Asymmetry model with a view of comparing the two error distributional assumptions are incorporated into the estimation with a target of having an appropriated fitted model.

Model Selection

Model selection is done using Akaike information criteria (AIC), Schwartz information criteria (SIC). The Akaike information criteria (AIC) is define thus:

$$AIC = 2K - 2In (LL) = 2K + In\left(\frac{RSS}{n}\right)$$

Where K represents the number of parameters used in the mode.
L represents maximized value of the likelihood

$$RSS = \sum_{t-1}^{n} \varepsilon^2 n$$ is the residual sum of squares. Similarly, the Schwartz information criteria is given

as; $$SIC = \log\left(\sum\frac{\varepsilon^1}{n}\right) \times \sum \log\frac{n}{n}$$

In general the desirable is the one that minimizes the AIC or SIC of HQ on the significant tests for each parameter. However, the study will place emphasis on the Schwartz information criteria because it levies heavy penalty on models for loss of degree of freedom as revealed in Abdulkareem and Abdulhakeen (2016).

Model Parameter Estimation

This is done on the basis of the coefficients of the selected model. The news impact assessment and test for volatility persistence will be done under model parameter estimations.

Model Diagnostic Check

In order to be sure that the model selected are test fitted and good enough for estimation, the following confirmatory test shall be carried out. They include ARCH-LM test, serial correlation test and Q – q plots for selected model.

Results

YEARS
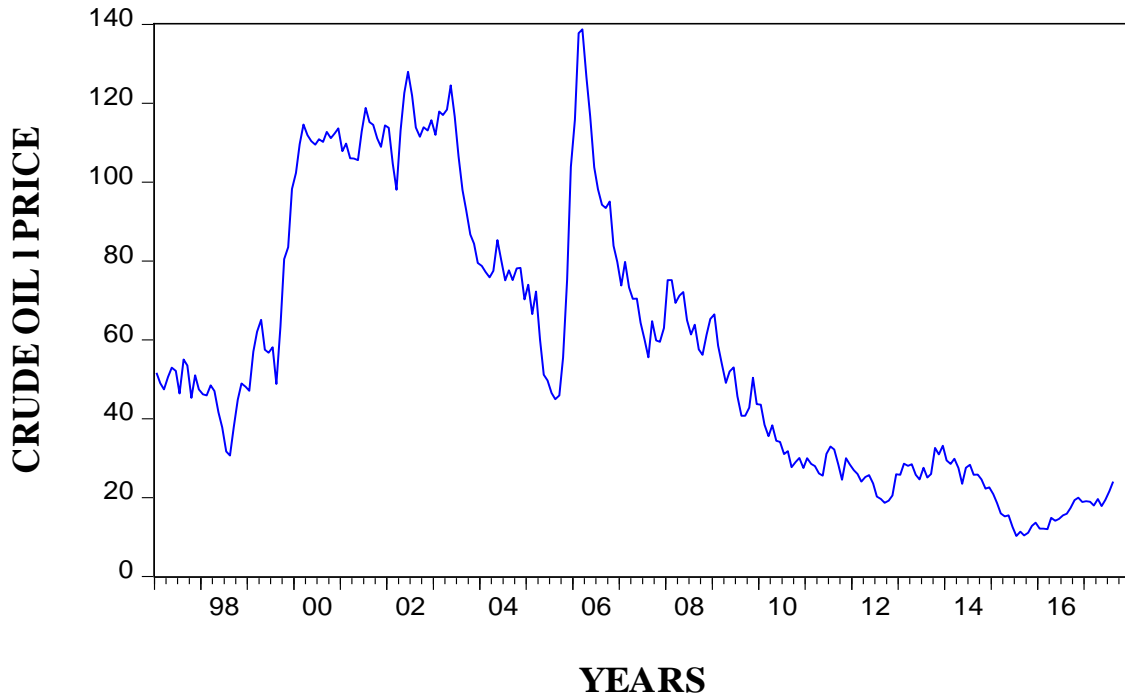
Figure 4.1: Time Plot on the Returns on Prices and sales **of Crude Oil**
Time plot to investigate the direction and moving trend of the variable under the study, at its
normal state (raw form)

Table 4.1: Descriptive Statistic of the Returns on Prices of Crude Oil

| Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P-value
7.18e-15	-0.409	28.795	-12.286	5.446	1.376	7.622	297.809	0.000

Source: Researcher's Calculation, 2018 using Eviews, Version 10. It is all tested Significant at
1 and 5% respectively.

Table(4.1) above investigate descriptive statistics of the returns on prices and sales of crude oil.
This is carried out to know whether the returns on prices and sales obey the normality assumption.
The ARMA Model as contained from the linear regression equation

Cop   =   0.4996   + 0.99 * $\varepsilon_{t-1}^2 + \mu_t$ (4.1)

The model as shown above is estimated in order to obtain the residual of the Autoregressive
moving average that will be used in the transformation on the return on prices and sales.

In order to be sure that the variable returns on price and sales of crude oil will be good for GARCH
modeling, the residual obtained from the ARMA model was plotted on a time graph as shown
above and from visual examination, it reveals volatility clustering.
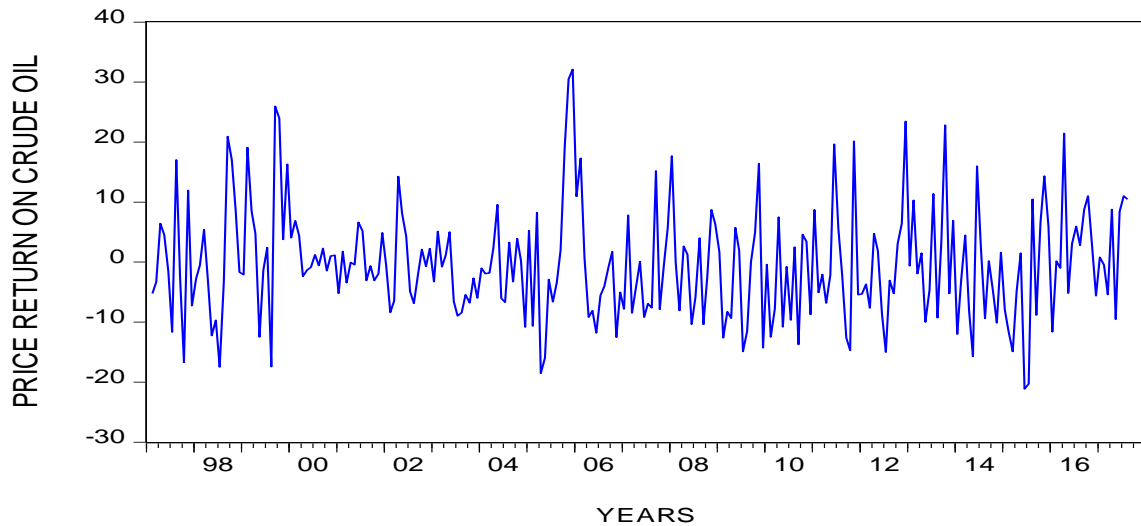
Figure 4.2: Volatility Clustering on the Returns on Prices of Crude Oil.

Test for Heteroskedasticity (ARCH Effect)
Table 4.2: Testing for the Presence of an ARCH Effect

Estimator	Lag 5	Lag 10
F-statistic	19.584	9.881
Prob. F (5,10)	0.000	0.000
n x R^2	70.966	72.097
X^2 (5,10)	0.000	0.000

Source: Researcher's Calculation, 2018 using Eviews Version 10. It is all Tested Significant at 1 and 5% respectively.

Test for heteroskedasticity (ARCH effect) was carried out to know whether the residual (standard error) obtained from the ARMA process will be biased leading to model misspecification. If it is biased then GARCH model will be used to capture the effect of volatility in the returns of the series.

Table 4.3: Estimation of Symmetric GARCH Model with their ErrorDistributional Assumption

Model(s)	Estimator(s)	Parameter(s)	Normal	Student's-t	GED	Student's-with Fix DF (V=10)	GED with Fix Df (V=1.5)	Min. SIC
GARCH(1,1)	Mean Equation	Constant	0.936 (0.395)	0.174 (0.881)	0.130 (0.905)	-0.145 (0.894)	-0.065 (0.951)	
		ARCH	-0.019 (0.289)	-0.014 (0.441)	-0.014 (0.416)	-0.012 (0.894)	(0.486)	
	Variance Equation	Intercept	11.542 (0.137)	22.387 (0.141)	150.922 (0.000)	28.203 (0.137)	24.074 (0.181)	
		ARCH	0.209 (0.006)	0.223 (0.017)	0.094 (0.013)	0.241 (0.018)	0.230 (0.028)	
		GARCH(-1)	0.672 (0.000)	0.530 (0.008)	-0.857 (0.000)	0.455 (0.063)	0.510 0.030	
	Volatility Impact	ARCH GARCH(-1)	0.881	0.753	-0.763	0.696	0.740	
	Model Selection Criteria	AIC	7.272	7.278	7.303	7.271	7.270*	
		SIC	7.343	7.363	7.388	7.342	7.341*	(7.341)
		HQC	7.301	7.313	7.338	7.300	7.299*	
		@SDRT (GARCH)	1.008 (0.249)	0.934 (0.252)	0. 918 (0.271)	0.893 (0.245)	0.807 (0.290)	
GARCH-M	Mean Equation	Intercept	-8.913 (0.261)	-8.707 (0.262)	-8.451 (0.262)	-8.589 (0.223)	-7.761 (0.267)	
		ARCH	-0.010 (0.605)	-0.006 (0.735)	-0.007 (0.695)	-0.005 (0.7884)	-0.005 (0.771)	
	Variance Equation	Intercept	40.813 (0.022)	40.196 (0.024)	40.355 (0.033)	40.372 (0.627)	40.100 (0.052)	
		ARCH	0.177 (0.038)	0.192 (0.065)	0.184 (0.167)	0.201 (0.055)	0.193 (0.077)	
		GARCH(-1)	0.333 (0.141)	0.332 (0.143)	0.334 (0.167)	0.335 (0.143)	0.342 (0.187)	
	Model Selection criteria	AIC	7.270	7.275	7.274	7.274	7.269	
		SIC	7.356	7.374	7.373	7.353	7.354	7.353)

Source: Researcher's Calculation, 2018 using Eview Software Version 10

Table 4.3 shows the results obtained from the estimation of classes of symmetric GARCH model with their corresponding error distributional assumptions.

Table 4.4: **Estimation of Asymmetric GARCH Model with Specific ErrorDistributional Assumption**

Model(s)	Estimator(s)	Parameter(s)	Normal	Student's-t	GED	Student's-with Fix DF (V=10)	GED with Fix Df (V=1.5)	Min. SIC
EGARCH (1,1)	Mean Equation	Intercept	0.882 (0.426)	0.856 (0.442)	0.804 (0.472)	0.529 (0.017)	0.375 (0.719)	
		ARCH	-0.020 (0.134)	-0.020 (0.138)	-0.019 (0.146)	-0.017 (0.182)	-0.15 (0.224)	
	Variance Equation	Intercept	0.027 (0.857)	00.280 (0.863)	0.027 (0.863)	0.066 (0.692)	0.045 (0.802)	
		ARCH	0.209 (0.001)	0.295 (0.011)	0.294 (0.002)	0.272 (0.008)	0.291 (0.010)	
		ASYMMETRIC	-0.178 (0.005)	-0.178 (0.007)	-0.178 (0.007)	-0.188 (0.008)	0.1805 0.016	
		GARCH(-1)	0.940 (0.000)	0.940 (0.000)	-0.940 (0.000)	0.938 (0.000)	0.938 0.000	
	Volatility Impact	ARCH GARCH	1.235	1.235	1.234	1.201	1.230	
	Model Selection Criteria	AIC	7.234	7.242	7.242	7.243	7.244	
		SIC	7.319	7.341	7.341	7.328	7.329	(7.319)*
		HQC	7.268	7.282	7.283	7.277	7.279	
TGARCH (1,1)	Mean Equation	Intercept	-0.703 (0.468)	0.696 (0.512)	0.652 (0.545)	0.652 (0.753)	0.205 (0.840)	
		ARCH	0.000 (0.982)	-0.018 (0.158)	-0.018 (0.168)	-0.016 (0.220)	-0.01 (0.266)	
	Variance Equation	Intercept	2.058 (0.313)	2.773 (0.863)	2.791 (0.236)	3.352 (0.236)	3.075 (0.283)	
		ARCH	0.025 (0.399)	0.030 (0.313)	0.030 (0.340)	0.026 (0.481)	0.029 (0.463)	
		ASYMMETRIC	0.366 (0.010)	0.355 (0.013)	-0.356 (0.015)	0.385 (0.0205)	0.384 (0.032)	
		GARCH(-1)	0.821 (0.000)	0.802 (0.000)	0.802 (0.000)	0.803 (0.00)	0.384 0.032	
	Volatility Impact	ARCH +GARCH =Volatility Impact	0.846	0.832	0.832	0.829	0.830	
	Model Selection Criteria	AIC	7.235	7.232	7.232	7.235	7.236	
		SIC	7.320	7.332	7.332	7.320	7.322	7.320

Source: Researcher's Calculation, 2018 using Eview Software Version 10

Table 4.4 shows the results obtained from the estimation of the three classes of asymmetric GARCH models with their corresponding error distributional assumptions.

Table 4.5: Estimation of Model Fitness

Model Selection Criterion	MODEL WITH LEAST SCHWARZ INFORMATION CRITERION					
	GARCH (1,1) with FIX DF (V = 1.5)	GARCH-M Student's-t with FIX DF (V = 10)	EGARCH	TGARCH	TGARCH	Least SIC Across Error Dist.
SIC	7.341	7.353	7.319	7.320	7.320	**7.319**

Source: Researcher's Calculation using Eviews Version 10

Table 4.5 contain the results of the least Schwartz information criterion obtained from each of the estimated GARCH model in table 4.3 and 4.4. The best fitted model from the twenty estimated models based on the Schwarz information criterion (SIC) can be written as thus:

The mean Equation: $RCOP_t = 0.882 - 0.020 * \varepsilon_{t-1}^2$ (4.1)

The variance Equation: $\text{Log (GARCH)} = 0.027 + 0.295 \left| \dfrac{\varepsilon_{t-1}^2}{\sigma_{t-1}^2} \right| - 0.177 \left(\dfrac{\alpha_{t-i}}{\sigma_{t-1}} \right) + 0.940 \log \left(\sigma_{t-j}^2 \right)$ (4.2)

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

Models	HETEROSKEDASTICITY TEST: ARCH	Lag 5	Lag 10	Lag 15
EGARCH(1,1) in Normal Error Distribution	F-statistic	1.9860	1.8321	1.3211
	Prob. F(5,10,15,1234)	0.0815	0.0563	0.1910
	$n*R^2$	9.7714	17.7718	19.4961
	$X^2(5,10,15)$	0.0820	0.0589	0.1921

*Source: Researcher's Computations,2018 using Eviews Software Version10.*

The above results revealed that from the hypothesis for the test of ARCH confirmed that there is no ARCH effect (Null Hypothesis) even at the 5% level of significance
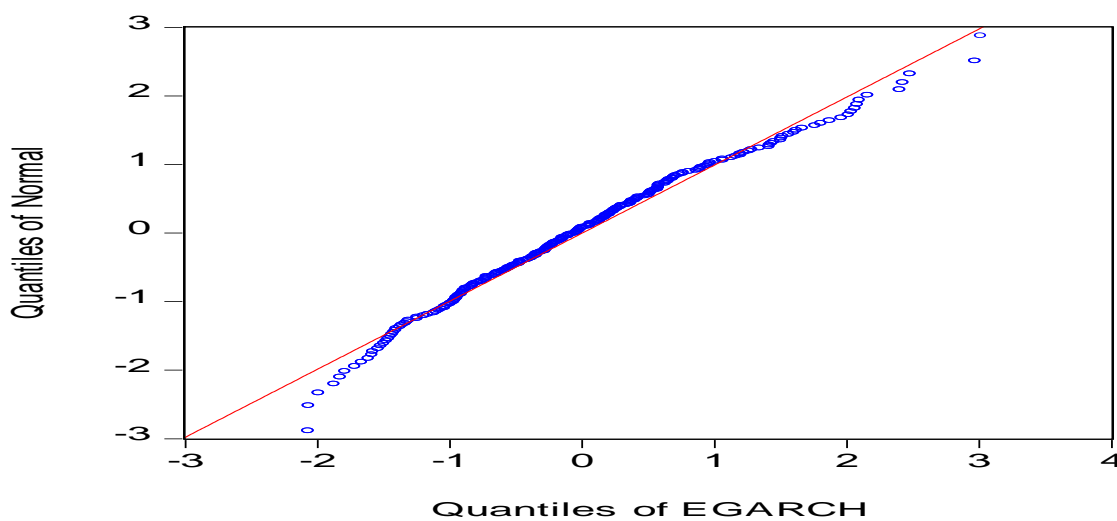
Figure 4.3: Quantile Plot of Normal Distribution and Quantile of EGARCH Model in Normal Error Distribution

In the graph above in figure 4.8, lie on a straight line which revealed that the residual follow a standardized order of a normal distribution. This is also confirmed Atoi (2014) findings about Q-Q – plot.

Correlogram of the Square Residual
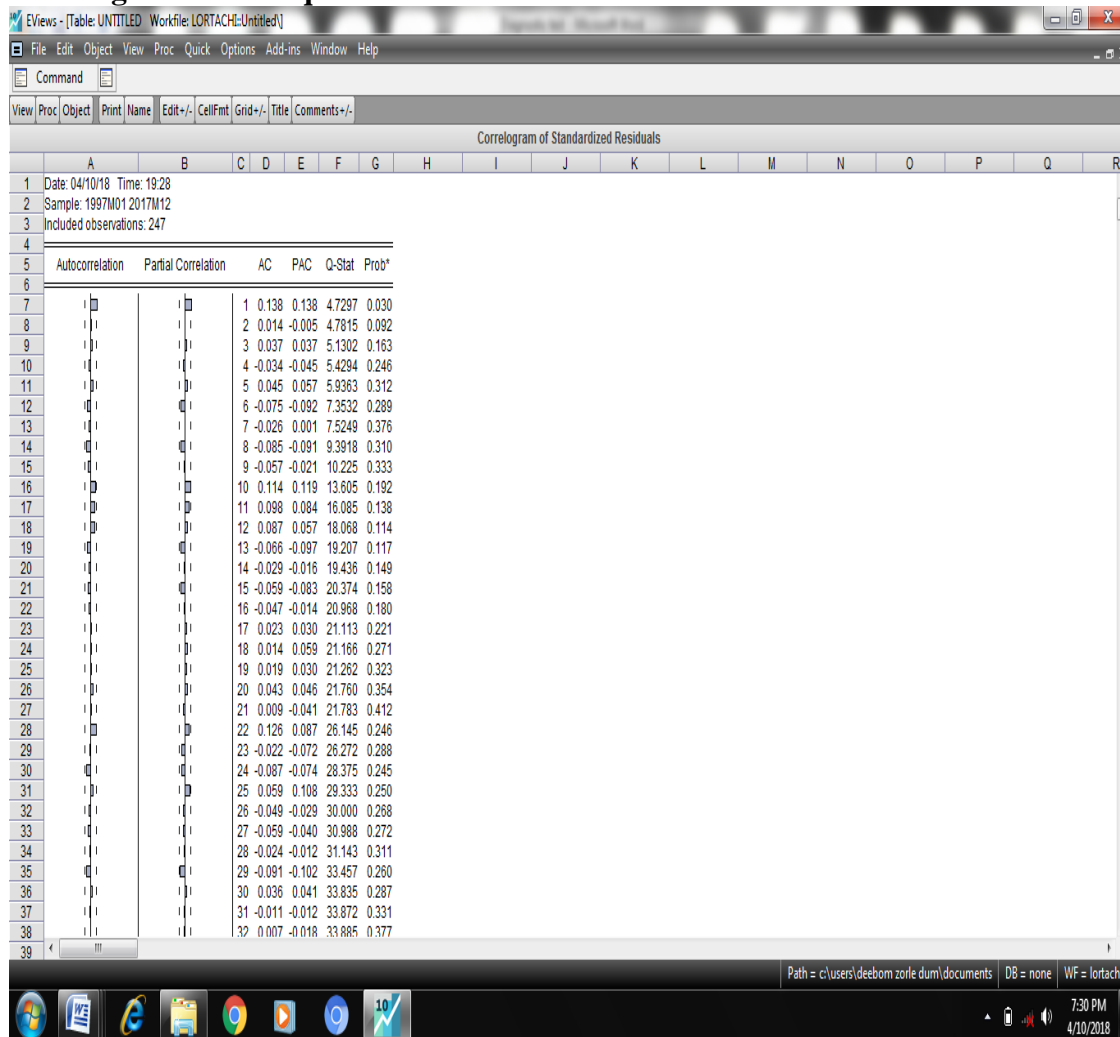
Correlogram of the square residual examined whether there exist serial correlation in the residual 0f the estimated GARCH model.

The output above is the correlogram of the square residual use in testing the validity of the model, otherwise called diagnostic test.

Discussion

This section discusses the results of the estimated data used in the study, which spans from August, 1997 – August, 2017. This gives a total data a point of 240, volatile conditional variance models was fitted to the continually compounded monthly crude oil price. From the results in the tables in chapter four twenty (20) models were estimated using the first order symmetric and asymmetric GARCH model in all the error distribution assumptions. In estimating the model, most critical conditions were duly considered and these conditions were incorporated into the system to capture some of the basic characteristics of returns on prices and sales. These include the following time series econometrics approach: time series plot, descriptive test statistic, test

for heteroskedasticity, symmetric GARCH models, asymmetric GARCH models and the model selection test.

Figure (4.1) shows the movement of returns on prices and sales of crude oil. The characteristic which shows that there exhibit a rise and later decline in price in the end of the year 2014 – 2016.

Similarly, figure (4.2) as it is shown in chapter four revealed volatility clustering in the returns on prices and sales series of the Nigerian/American crude oil markets. This confirmed Abdulkareem and Abdulhakeen (2016) and Deebom and Essi (2017) results in modeling of price volatility in Nigerian/American crude oil markets.

Furthermore, when the variable was subjected to normality test as revealed in the descriptive test statistic, the mean (1.7e-15) shows a positive sign and this simply means it is mean reverting. This according to Engle and Patton (2001) shows that there is a normal level of volatility to which it will eventually return. It is an indication that current information has no effect on the long run forecast. Similarly, the standard deviation (5.446) captured the level of risks involved returns on prices and sales under considerations, which is about 54.46% by percentage rating. The difference between the maximum and minimum return is 16.51 and this shows that the level of price fluctuation is fair to trading in this markets within the sample period.

In another development, the co-efficient of Skewdness (1.376) which is greater than zero and this shows that it is positively skewed to right. Although, this contradicts Deebom and Essi (2017) which indicated that the co-efficient of skewedness is negatively skewed to the left. The variation may be occasioned by difference within the sample period and points, while the Kurtosis have the value (7.622) which is greater than three against the Kurtosis of a normal that is also 3. The Jarque-Bera gives the value (297.809) followed by a probability value of (0.000), therefore, the null hypothesis of normality is rejected against the alternative hypothesis of non-normality. In a situation like this, Abdulkarem and Abdulhakeem (2016) suggested that the alternative inferential statistic to be employed should be GARCH with their respective error distributional assumptions and fixed degree of freedom fussed into the ARCH and GARCH models. Also, the Autoregressive (ARMA) model shows that the intercept (i) is 0.4996, which the ARCH co-efficient is 0.99 plus the disturbance term (μ_t). However, the error (disturbance) term is subjected to further test to verify the presence of heteroskedasticity. Table (4.2) shows that the value of the f-statistic (19.584) is higher that its corresponding value of the chi-square statistic (0.000), similarly, number of observation multiplied by the regression co-efficient (nxR^2) is greater than the probability chi-square.

Therefore, the null hypothesis that there is no presence of ARCH is rejected while the alternative hypothesis that it is stated that there exist heteroskedaticity (ARCH) effect is accepted. This result agreed with Deebom and Essi (2017) findings on the test for the presence of ARCH in their crude oil price return series as it is used in their study. This also agree with Abdulkarem and Abdulhakeem (2016) assertion about data that can be modeled using GARCH.

In like manner, Table (4.3) estimates as well model symmetric GARCH model with their error distributional assumptions such as normal, student's-t, generalized error distribution, student's-t with fix degree of freedom when it is set at default (v = 10) and generalized error distribution with fix degree of freedom when it is set at default (V = 10) and generalized Error distribution with fix degree of freedom when it is set a default (V = 1.5). In the first estimated model GARCH, the ARCH co-efficient in the mean equation in all the error distribution assumptions are all negative and not even statistically significant at the 0.05 level of significance whereas in the variance equation model, the ARCH co-efficient are all positive with corresponding probability values significant at 0.05 level of significance. The implication for this is that the previous month's price returns in formation actually have an impact on this next present month returns on

prices and sales of crude oil. This confirmed Deebom and Essi (2017) results from their findings that Crude Oil export price volatility is influenced by its own volatility the return in the price. The percentages of persistence as well as their volatility impact are as thus: GARCH in normal error distribution (88.1%) student's-t error distribution (75.3%) GED (-76.3%), student's –t with fix degree of freedom (V=10) (69.6%) and GED with fix degree of freedom (V=1.5) (74.0%). Considering model GARCH with GED with fix degree of freedom set at V=1.5 was chosen to be the best, since it has the least Schwartz information centurial (7.341). Also it was clear that the co-efficient of @ SQRT (GARCH) in GARCH-M are not statistically significant at any level of significance. This confirmed Deebom and Essi(2017) of results of their findings. The implication for this is that from the estimation volatility of the price return does not provide much needed information on the price return series similarly, the addition of the ARCH and GARCH Co-efficient are all less than one.

The statistical implication for this is that modeling price return of Crude Oil price in Nigerian/American Crude Oil markets the Characteristics demonstrated by their volatility within the sample period reveal a mean reverting condition considering the percentage of persistence as well as their volatility impact, the degree of effects are thus: GARCH-M in normal error distribution (51.0%) Student's-t error (52.4%), GED (51.8%), Student's-t with fix degree of freedom (V = 10) (53.6%) and GED with fix degree of freedom (V = 1.5) (53.5%). This reveals that volatility persistence estimated for all the models are on the average percentage Level. Considering model selection criteria student's-t with fix degree of freedom (V=10) was chosen since it has the least Schwartz information criteria.

Table4.4reveals the results from the estimation of asymmetric GARCH model with their corresponding error distributional assumption as shown in equation (3.8), (3.9), (3.10), (3.11), (3.12) and (3.13). The EGARCH (1, 1) model as it is estimated in that (4.4), the mean component of the model shows that all the Co-efficient of the ARCH terms are negative signs and their corresponding probability value (P-value) are not significant at the 0.05 level of significance. This confirmed Deebom and Essi (2017) *findings* and this also revealed that there exists the presence of leverage and ARCH effect. According to Deebom and Essi (2017), a situation like this suggested negative correlation between the past return of Crude Oil price and future volatility. Similarly, Atoi (2014) also confirmed that bad news has more impact on the volatility of the returns sense than the positive news. Table 4.4, it was reveals that the asymmetric component in the TGARCH estimation shows positive signs in all the estimator and their corresponding probability value less than 0.05. This means that they are all statistical significance and there is the presence of leverage effect which is synonymous to Abudulkarem and Abdulhakeem (2016) findings. Also the percentages of the persistence as well as their volatility impact are thus: TARCH in normal distribution (84.6%) while TGARCH in student (83.2%), the same in TGARCH in GED with fix degree of freedom set at V=10 (83.2%) and TGARCH in GED with fix degree of freedom set at (V=1.5) while the estimator with the least AIC value were TGARCH in student with fix degree of freedom set at (10) and TGARCH in Generalized error distribution with degree of freedom set at (V=1.5).

Conclusions

In conclusion, in examining the proportionality movement of other macroeconomic variables to oil shocks within the sampled period, it can be concluded that crude oil prices volatility might not be necessarily heightened interest rate, external reserves and Nigerian/American trade as a result of the recent fall in the rate of return on crude oil price exported to American (highest demander of 40%) most especially because American now fully utilize shale oil and other alternative sources of energy generation as it is even conformed in Agbede (2013). It can also be concluded that

within the sample period returns on prices/sales of crude oil and its associated volatility affects money supply and policy respond to changes in the returns on prices and sales.

Recommendations

This study has provided several important tips on modeling returns on prices and sales of crude oil as a commodity. Looking at the level of risk that is associated with external trade and investment in stocks, and price of an asset with their corresponding returns on prices and sales of crude oil, financial analyst trades, investors, companies and Government are advised to be careful while trading or doing business in this market. Therefore, the following recommendations were made thus;

i. An in-depth understanding of the returns on prices and sales of crude oil price is essential for marketers, investors, companies, users of crude oil and Government to address the importance of considering the sub-national factors in making laws and policies about commodity prices.

ii. Exchange rate between Nigeria and America as trading partners should be checked against variability which may have an adverse effect on other economic indicators.

iii. There should be need to diversify the economy from the sole economy of oil to other known-oil sectors for example Agriculture, manufacturing etc.

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