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Comparative Modelling of Price Volatility in Nigerian Crude Oil Markets Using Symmetric and Asymmetric GARCH Models

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Authors' contributions

This work was carried out in collaboration among all authors. Author DZD designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Authors MYD and CBE managed the analyses of the study. Authors RIC and GLE managed the literature searches. All authors read and approved the final manuscript.

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Abstract

The study aimed at developing an appropriate GARCH model for modelling in Nigerian Crude Oil Prices Markets using symmetric and Asymmetric GARCH models while the specific objectives of the study include to: build an appropriate Symmetric and asymmetric Generalized Autoregressive Conditional Heteroskedacity (GARCH) model for Nigerian Crude Oil Prices, compare the advantage of using Symmetric and Asymmetric GARCH. The data for the study was extracted from the Central Bank of Nigeria online statistical database starting from January, 1982 to December, 2018. The software used in estimating the parameters of the model is Econometric view (Eview) software version ten (10). Two classes of models were used in the study; they are symmetric and Asymmetric GARCH models. The results of the estimated models revealed that

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Asymmetric GARCH model (EGARCH (1,1) in student's-t error assumption gave a better fit than the first order Symmetric GARCH models. Also, Using EGARCH (1,1) models with their corresponding error distribution in estimating crude oil price was found that the larger the size of the estimated news components of the model, the higher the negative news associated with high impact of volatility. This means that conditional volatility estimated using EGARCH model has strong asymmetric characteristic which is prone to news sensitivity. Based on the above findings, recommendations were made in the study.

Keywords: Modelling; crude oil; markets; symmetric; asymmetric.

1 INTRODUCTION

1.1 Background to the study

When there is an unstable economic situation, crude oil price is usually associated with negative return and high variance. According to Dritsaki [1], the larger the risk in stock price changes in monetary policies during these unstable periods would reduce market efficiency, and is most likely to affect the consistency in macroeconomic relationships. Risks associated with instability in the returns on prices and sales of crude oil is one of the major challenges facing both oil producing countries and major buyers of crude oil in the world today. This risk took the form of response to good and bad news due to disaster, insurgency, political disorder, political agitations etc. Sequel to the occurrence of these unforeseen circumstances, crude oil market prices experienced fluctuation and becomes highly volatile. The degree of price fluctuation or volatility in crude oil markets has increasingly attracted attention in recent period. In time series, econometrics as well as other financial literature; and according to Dritsaki [1], it has been recognized as one of the most significant economic phenomena. Researchers like Zheng, et al. [2] have argued that price of crude oil is volatile, so it reduced welfare and competition by increasing consumer costs. Meanwhile, Apergis and Rezitis [3], observed that price volatility of this product makes both producers and consumers of this product to be uncertain, which most times, oligarchy see it an opportunity to take advantage of this situation to advance their selfish interest.

Although, commodity prices in general are volatile, and in particular crude oil prices and its constituents like Kerosene, Petrol, etc. are renowned for their continuous volatile nature. Returns on prices and sales of crude oil have undergone dramatic changes over the past years, the desire to formulate policy measure or intervention to prevent it from going into volatility have not been achieved due to irregularities in the market system. Findings in this area show that returns on prices and sales of crude oil in the markets still remain high. Besides, crude oil price volatility in monetary assets is still an area in which little empirical attention has been paid in Nigeria. Therefore, it appears worthwhile to devote effort in modelling price volatility in Nigerian crude oil markets using symmetric and Asymmetric GARCH models with a view to prefer solutions to the problems confronting crude oil markets

2 METHODOLOGY

2.1 Sources of data and software used in the study

Data used for this study was sourced for and extracted from the official website of the Central Bank of Nigeria [4]. The data comprise of monthly crude oil export prices, sales in Naira/Dollar per barrel. It was extracted between the month of January, 1988 and March, 2019. These make a total of 396 data points. The software used in estimating the parameter of the model was Econometric view (Eview) software version ten (10).

2.2 Data transformation

According to Tsay [5], time series data are divided into two categories; the first category is the stationeries and the second category is then on-stationary. He further explained that the Stationarity of a data set can be tested with augment Dickey-Fuller (ADF) test whereas the Non-stationary time series data can are usually transformed into stationary data by using log return transformation. Therefore, this is done by assuming CP_{Rt} to denote the data crude oil Price Return at time *t* and CRn denotes the log return of the data, the log return transformation can be written as:

$$CRn = \log\left(\frac{CP_{Rt}}{CPR_{t-1}}\right) \times \frac{100}{1} \tag{2.1}$$

Where t = 1, 2, 3 …. t-I and CRn represents the return on crude oil pieces, CP_{Rt} is crude oil export price at time t in Naira per Dollar, CPR_{t-1} represents crude oil price at lag t (t-1) or precious time at t minus one, log represents logarithms, and 100 is a constant value (Number) the data used in this study was differenced (D) in order to get rid of outlier as well as to attain stationarity of the data.

2.3 Model specification

Black [6] defined model specification as a simplified system used to simulate some aspects of the real or actual economy. It is a form or specified views of reality design to enable the researcher describe the essence or inter-relationship within the variables or condition under the study. However, in line with the objectives of this study, two classes of models used in the study are symmetric and asymmetric GARCH models.

2.3.1 The standard symmetric GARCH models

The process of developing standard symmetric GARCH commence with the autoregressive moving average (ARMA) model with (p.q) order of the log return data r_1 can be written as

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-1} - \sum_{j=1}^{q} \theta_j \alpha_{t-j} + \alpha_t \tag{2.2}$$

Where ϕ_0 denotes the constant, ρ denotes the order of autoregressive (AR) Model, $\phi_{1,2,\ldots,P}$ denotes the AR parameters, q denotes the order of the moving average (MA), $\phi_{1,2,3,\ldots,q}$ denotes the MA parameter, and α_t denotes the model residual at time (*t)*. Tsay [6] further observed that the highest MA order determined by ACF plot which cut off after the p^{th} lag while AR order determined by PACF plot which cut off after the q^{th} lag. The Heteroskedasticity effect of ARMA model can be tested with Lagrange multiplier (LM) test. Therefore, by definition the standard GARCH model used in the estimation of Crude Oil price returns , we considered the residual of the ARMA process obtained in model in equation (3.2) and the residual could written as shown below $\sigma_t = \sigma_t \varepsilon_t$ for $\varepsilon_t \sim N(0,1)$ and $\sigma_t / f_{t-1} \sim N(0, \sigma_t^2)$ (2.3)

The standard symmetric GARCH (1, 1) model can written as thus

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2.4}$$

Where$\alpha_0 \geq 0$, $\alpha_1 \geq 0$ and $\beta \geq 0$, i.e. all these parameters must be positive in order to guarantee a positive conditional variance, and where $\alpha_1 + \beta < 1$ represents the persistence of shocks to volatility [7]. Following Klaassen [8] and Haas et al. [9] the study adopted Student's-t and normal distribution for εt. Also, another example of the standard GARCH model is the Generalized Autoregressive Conditional Heteroskedasticity in means (GARCH-M). According to Brooks [10], this model suggests that the mean return of a financial data series would be related to the conditional variance or standard deviation of the economic data series itself and that this model estimate mostly high risk associated with financial time series data. The GARCH Model is written as :

Mean equation $Rcop = \mu + \lambda\sigma_t^2 + \varepsilon_t$ (2.5)

Variance Equation: $Rcop = \chi_t^T \gamma + \lambda\sigma_t^2 + \varepsilon_t$ (2.6)

Similarly, $\mu \geq 0$, $\gamma \geq 0$ and $\lambda \geq 0$ for $Rcop$, σ_t^2 are all parameters are to be estimated is called the risk premium parameter, and it is mostly not interpretable in practice. According to Brook (2006), this model captured different form influence of volatility on the conditional variance

2.3.2 Standard asymmetric GARCH models

In another development, the study considered asymmetric GARCH model and some of the examples of the asymmetric GARCH model are used TGARCH, EGARCH, PARCH and CGARCH.

The threshold Generalized Autoregressive Conditional Heteroskedasticity TGARCH (1,1) model

According to Brook [10], the TGARCH was found by Glisten et al. in 1993 the variance of the model was define as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_t^2\left[1 - I_{\{\varepsilon-1\}t} > 0\right] + \left\{\xi\varepsilon_t^2 I_{\{\varepsilon_{t-1}\}}\right\} + \beta_1\sigma_{t-1} \quad (2.7)$$

α_0, α_1, ξ and $\beta_1 \geq 0$, where $I_{\{\varepsilon_{t-1}\}}$ is an indicator function, and if $\varepsilon_{t-1} > 0$, $I_{\{\varepsilon_{t-1}\}}$ =i,j Otherwise , $I_{\{\varepsilon_{t-1}>0\}} = 0$

In equation (3.4), when $\varepsilon_{t-1}^2 > 0$ this simply multiplies good news whereas $\varepsilon_{t-1}^2 < 0$ implies bad news and under these condition, (shocks) of equal magnitude have differential effects on conditional variances [11]. Similarly, good news has an impact magnitude of α_1 while bad news has an impact magnitude of α_1 + I which in away cause increase in volatility. Also, if $I_1 > 0$, this invariably means that there is the existence of leverage effect of the 1st order. When $I_1 = 0$, then this means that news impact is asymmetric in nature. Although, given the standard GARCH model in equation (3.6) assumes that the effect of positive and negative information is symmetric which may not be completely applicable in a market situation [7]. Nelson [12] proposes the Exponential GARCH (EGARCH) model to examine the asymmetric features of asset price volatility, and which according to him the logarithm of the conditional variances of Crude Oil price returns can be stated as thus:

$$\log\left(\sigma_t^2\right) = \alpha_0 + \alpha_1\left|\frac{a_t - 1}{\sigma_{t-1}^2}\right| + \sum^{e} \frac{\Sigma_{t-1}}{\sigma_{t-1}} + \beta\log\left(\sigma_{t-1}^2\right) \quad (2.8)$$

$\alpha_0 \geq 0 1 \alpha_1 \geq 0$ Σ>0 and $\beta_1 \geq 0$. Similarly, $\varepsilon_{t-1} > 0$ simply depict good news and $\varepsilon_{t-1} < 0$ means bad news respectively whereas the total effects of bad and good news are given as $(1-\xi)[\varepsilon_{t-1}]$ and $(1+\xi)[\varepsilon_{t-1}]$ respectively.

In this case, we accept the null hypothesis that ξ = 0 which shows that there is the presence of leverage effect and this simply mean bad news have stronger effect than good news on the volatility of the return series [11].

2.3.2.1 The power ARCH (PARCH) model

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_i (|\mu_{t-i}| - \eta_i \mu_{t=i})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} \tag{2.9}$$

Where $\delta > 0,\ \eta_i \leq 1$ for t=1,……., γ, η_i =0 for $t > \gamma$, and $\gamma \leq p$ (2.10)

The components GARCH (CGARCH) model

It allows mean reversion to a varying level m_t

$$\sigma_t^2 - m_t = \varpi + \alpha(\mu_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi) \tag{2.11}$$

$$m_t = \omega + \rho_o (m_{t-1} - \omega) + \phi(\mu_{t-1}^2 - \sigma_{t-1}^2) \tag{2.12}$$

σ_{t-1}^2 is still the volatility, while m_t takes the place of ω which could also be time varying long-run volatility. The model (3.11) describes the transitory component, $\sigma_t^2 - m_t$ which converges to zero with powers of $(\alpha + \beta)$. The model (3.12) describes the long run component m_t, which converges to ω with powers of ρ .The models stated in equation (3.3) to (3.11) define the standard GARCH model.

2.3.3 Error distributional assumptions

In modelling the conditional variance of crude oil price, five conditional distributions for the standardized residuals of the price returns modernism were considered and they include; the Gaussian (Normal), student's –t, Generalized, student's –t with fixed parameter(v=3) and Generalized with fixed parameter(v=3) .

2.3.3.1The gaussian (normal) distribution

The Gaussian (Normal) error distribution assumed a log-likelihood contribution is of the form;

$$LogL(\theta_t) = \sum_{t=1}^{T} L(\theta_t) = -\frac{1}{2} Log[2\prod] - \frac{1}{2}\sum_{t=1}^{T} \log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T} \frac{(y_t - \gamma y_t)^2}{\sigma_t^2} \tag{2.24}$$

2.3.3.2 The student's –t error distribution

The student's –t error distribution assumed a log-likelihood contribution is of the form;

$$LogL(\theta_t) = -\frac{1}{2}\log\left[\frac{\prod[v-2]\Gamma\left[\frac{v}{2}\right]^2}{\Gamma\left[\frac{v+1}{2}\right]^2}\right] - \frac{1}{2} Log\sigma_t^2 - \frac{[v+1]}{2} Log\left[1 + \frac{[y_{t-} X_t' \gamma]^2}{\sigma_t^2 [v-2]}\right] \tag{2.25}$$

Where σ_t^2 is the variance at time t and the degree of freedom v>2 controls the tail behaviour.

2.3.3.4 The generalized, distribution

The Generalized (GED) likelihood function is specified as:

$$LogL(\theta_t) = -\frac{1}{2}\log\left[\frac{\Gamma\left[\frac{1}{r}\right]^3}{\Gamma\left[\frac{3}{r}\right]\left[\frac{r}{2}\right]^2}\right] - \frac{1}{2}Log\sigma_t^2 - Log\left[\frac{r\frac{3}{r}\left[y_{t-}X_t^{'}\gamma\right]^2}{\sigma_t^2\Gamma\left[\frac{1}{r}\right]}\right]^{\frac{r}{2}} \quad (2.26)$$

r >0 is the shape of the parameter which basically account for the skewed properties of the returns of the series under estimation. The higher the value of r, the heavier the weight of the tail. Omorogbe and Ucheoma [13] revealed that the Generalized (GED) turns to be a Gaussian (Normal) error distribution if r =0 and flat-tailed if r<2.

2.3.3.5 The student's –t with fixed parameter (v=3) error distribution

The student's –t error distribution assumed a log-likelihood contribution is of the form;

When v=3, we substitute the value into the model in equation (2.25)

$$LogL(\theta_t) = -\frac{1}{2}\log\left[\frac{\Pi\ \Gamma\left[\frac{3}{2}\right]^2}{\Gamma\left[2\right]^2}\right] - \frac{1}{2}Log\ \sigma_t^2 - 2\ Log\left[1 + \frac{\left[y_{t-}X_t^{'}\gamma\right]^2}{\sigma_t^2}\right] \quad (2.27)$$

Where σ_t^2 is the variance at time t and the degree of freedom v=3 controls the tail behaviour.

2.3.3.6 The generalized with fixed parameter(r =3) error distribution

The Generalized (GED) likelihood function is specified as thus: When v=3 , we substitute the value into the model in equation (3.24), we have

$$LogL(\theta_t) = -\frac{1}{2}\log\left[\frac{\Gamma\left[\frac{1}{r}\right]^3}{\Gamma\left[\frac{3}{r}\right]\left[\frac{r}{2}\right]^2}\right] - \frac{1}{2}Log\ \sigma_t^2 - Log\left[\frac{r\frac{3}{r}\left[y_{t-}X_t^{'}\gamma\right]^2}{\sigma_t^2\Gamma\left[\frac{1}{r}\right]}\right]^{\frac{r}{2}} \quad (2.28)$$

$$LogL(\theta_t) = -\frac{1}{2}\log\left[\frac{\Gamma\left[\frac{1}{3}\right]^3}{\Gamma\left[\frac{3}{3}\right]\left[\frac{3}{2}\right]^2}\right] - \frac{1}{2}Log\,\sigma_t^2 - Log\left[\frac{3\frac{3}{3}\left[y_{t-}X_t^{'}\gamma\right]^2}{\sigma_t^2\Gamma\left[\frac{1}{3}\right]}\right]^{\frac{3}{2}}$$

$$LogL(\theta_t) = -\frac{1}{2}\log\left[\frac{\Gamma\left[\frac{1}{9}\right]}{\Gamma\left[\frac{9}{4}\right]}\right] - \frac{1}{2}Log\ \sigma_t^2 - Log\left[\frac{3\left[y_{t-}X_t^{'}\gamma\right]^2}{\sigma_t^2\Gamma\left[\frac{1}{3}\right]}\right]^{\frac{3}{2}} \quad (2.29)$$

r =3 is the shape of the parameter which basically account for the skewed properties of the returns of the series under estimation. The higher the value of r , the heavier the weight of the tail.

3 RESULTS

First, we present the raw data. Fig. 1 is a plot of the raw data with time (years) on the horizontal axis and Crude Oil Price (Dollar/Barrel) on the vertical axis. This portrays the direction and moving trend of the variable under study. This is followed by Table 1 which contains the results of descriptive statistics of the returns on crude oil price (Dollar/Barrel). This is carried out in order to know whether the returns on crude oil price data obey the normality assumption

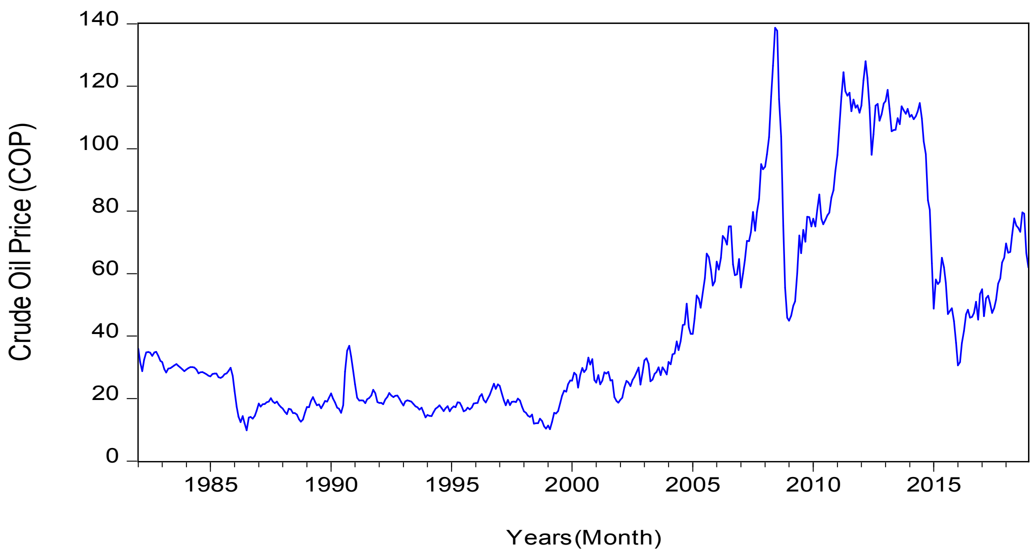


Fig. 1. Time plot on crude oil price (dollar/barrel)

Table 1. Descriptive statistic of the returns on prices and sales of crude oil

Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P-value
0.123	0.484	47.084	-32.105	8.909	-0.092	5.535	119.210	0.000

The result of the estimated ARMA Model which was done in order to obtain the residual from the ordinary linear square regression equation

$$\text{DCop} = \underset{(0.772)}{0.119} + \underset{(0.0000)}{0.230}^{*}\ \varepsilon_{t-1}^{2} \tag{3.1}$$

The model in equation 4.1 was estimated in order to obtain the residual from the Autoregressive Moving Average which was used to test for the presence of volatility clustering.

To portray the volatility clustering of Crude Oil Prices (Dollar/Barrel), a graphical representation is shown in Fig. 2. This is done in order to be sure that the variable on Crude Oil Prices (Dollar/Barrel) exhibits volatility clustering and also be good enough for GARCH Estimation.

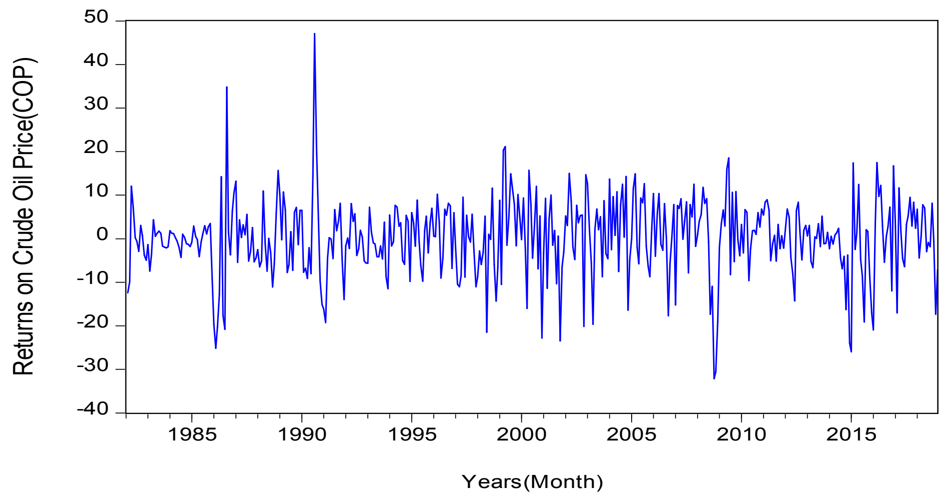


Fig. 2. Volatility clustering on crude oil prices (dollar and barrel)

An estimation of heteroskedasticity is presented in Table 2. This represents the results of the heteroskedasticity (ARCH Effect) estimation. This is done using the residual (standard error) obtained from the ARMA process and this helps in verifying that variance of the residual is constants. If it is not constant, then if it is heteroskedastic, the GARCH model will be appropriate in capturing the effect of volatility in the returns of the series.

3.1 Heteroskedasticity (ARCH effect) estimation

Table 3 shows the results obtained from the estimation of classes of symmetric GARCH model with their corresponding error distributional assumptions.The symmetric GARCH models comprises of GARCH(1, 1) and GARCH(1, 1) in Mean with their corresponding normal, students, Generalized, Student's t- with fixed degree of freedom (V=3), and GED with fixed degree of freedom(V=3).

The results obtained from the estimation of classes of asymmetric GARCH model with their corresponding error distributional assumptions is shown in Table 4.

Table 5 Shows the results obtained from the estimation of classes of asymmetric GARCH model with their corresponding error distributional assumptions.

The best fitted model from the thirty estimated models based on the Schwarz information criterion (SIC) can be written as thus:

The mean Equation:

$$COP_t = -0.146 + 0.199\,\varepsilon_{t-1}^2 \quad (3.2)$$
$$(0.614) \quad (0.000)$$

Table 2. Testing for the presence of an ARCH effect

F-statistic	4.891	Prob. F(5,431)	0.0002
Obs*R-squared	23.463	Prob. Chi-Square(5)	0.0003

Table 3. Estimation of standard GARCH model (error distributional assumption)

Model(s)	Estimator(s)	Parameter(s)	Normal	Student's-t	GED	Student's t- with Fix DF (V=3)	GED with Fix Df (V=3)	Min. AIC
GARCH(1,1)	Mean (μ)	Intercept(α)	-0.144	-0.003	-0.058	0.096	-0.379	
			(0.541)	(0.989)	(0.823)	(0.706)	(0.030)	
		ARCH(β)	0.167	0.179	0.177	0.198	0.143	
			(0.00)	(0.00)	(0.000)	(0.000)	(0.000)	
	Variance(σ)	Intercept(α)	1.972	1.707	1.865	1.967	2.013	
			(0.069)	(0.105)	(0.103)	(0.247)	(0.056)	
		ARCH(β)	0.437	0.364	0.397	0.518	2.031	
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
		GARCH(σ)	0.635	0.687	0.661	0.741	0.577	
			(0.000)	(0.000)	(0.000)	(0.000)	0.000	
	Volatility Impact(ϕ)	(σ+ β)	**0.802**	**0.866**	**0.838**	**0.939**	**0.720**	
	Model Selection Criteria	AIC	6.976	**6.962***	6.970	7.001	7.063	
		SIC	7.023	**7.017***	7.025	7.047	7.109	(**6.962**)
		HQC	6.995	**6.983***	6.992	7.019	7.081	
GARCH-M	Mean (μ)	@SDRT (GARCH)(λ)	0.153	0.170	0. 157	0.131	0.106	
			(0.145)	(0.09)	(0.126)	(0.063)	(0.255)	
		Intercept	-0.942	-0.914	-0.889	-0.828	-0.946	
			(0.129)	(0.137)	(0.145)	(0.148)	(0.096)	
		ARCH	0.163	0.172	0.172	0.186	0.146	
			(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	
	Variance(σ)	Intercept	1.824	1.574	1.656	1.925	2.180	
			(0.096)	(0.140)	(0.142)	(0.253)	(0.051)	
		ARCH(β)	0.437	0.367	0.399	0.533	0.594	
			(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	
		GARCH(σ)	0.639	0.688	0.666	0.736	0.580	
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
		(σ+β)	**0.802**	**0.860**	**0.838**	**0.922**	**0.726**	
	Model Selection CRITERIA	AIC	6.973	**6.958***	6.967	6.996	7.063	
		SIC	7.029	**7.023***	7.032	7.052	7.119	(**6.958**)
		HQC	6.995	**6.983***	6.992	7.018	7.085	

Table 4. Estimation of asymmetric GARCH model (Error distributional assumption)

Model(s)	Equation**(s)**	**Parameter(s)**	**Normal**	**Student's-t**	**GED**	**Student's- with Fix DF (V=3)**	**GED with Fix Df (V=3)**	**Min. AIC**
	Mean (μ)	Intercept(α)	-0.193	-0.146	-0.151	-0.038	-0.329	
			(0.495)	(0.614)	(0.597)	(0.889)	(0.198)	
		ARCH(β)	0.191	0.199	0.195	0.214	0.197	
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
	Variance(σ)	Intercept(α)	-0.077	-0.089	-0.083	-0.106	-0.058	
			(0.586)	(0.502)	(0.567)	(0.467)	(0.678)	
		ARCH(β)	0.632	0.537	0.589	0.608	0.8227	
EGARCH (1,1)			(0.000)	(0.000)	(0.000)	(0.000)	(0.441)	
		Asymmetric(γ)	-0.068	-0.096	-0.076	-0.125	-0.029	
			(0.145)	(0.111)	(0.171)	(0.205)	0.441	
		GARCH(σ)	0.898	0.919	0.908	0.946	0.867	
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
	Volatility Impact(ϕ)	(σ+β)	1.089	1.118	1.103	1.160	1.016	
	Model Selection Criteria	AIC	6.953	**6.942***	6.950	6.989	7.028	
		SIC	7.008	**7.007***	7.015	7.045	7.084	(6.942)*
		HQC	6.974	**6.968***	6.976	7.011	7.050	
	Mean (μ)	Intercept(σ)	-0.263	-0.134	-0.175	-0.015	-0.484	
			(0.345)	(0.641)	(0.537)	(0.954)	(0.043)	
		ARCH(β)	0.175	0.196	0.188	0.219	0.147	
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
	Variance(σ)	Intercept(α)	1.888	1.569	1.741	1.628	2.018	
			(0.067)	(0.102)	(0.099)	(0.275)	(0.057)	
		ARCH(β)	0.348	0.243	0.299	0.308	0.537	
TGARCH (1,1)			(0.000)	(0.001)	(0.000)	(0.090)	(0.000)	
		Asymmetric(γ)	0.124	0.162	0.133	0.287	0.104	
			(0.235)	(0.163)	(0.251)	(0.216)	(0.313)	
		GARCH(σ)	0.656	0.719	0.688	0.773	0.587	
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
	Volatility Impact(ϕ)	((σ+ β))	1.004	0.962	0.987	1.081	1.124	
	Model Selection Criteria	AIC	6.978	**6.962***	6.972	7.001	7.066	
		SIC	7.034	**7.027***	7.036	7.056	7.121	(6.962) *
		HQC	7.000	**6.987***	6.997	7.023	7.088	

Table 5. Estimation of asymmetric GARCH model (error distributional assumption) continuation

Model(s)	Equation**(s)**	**Parameter(s)**	**Normal**	**Student's-t**	**GED**	**Student's- with Fix DF (V=3)**	**GED with Fix Df (V=3)**	**Min. AIC**
	Mean (μ)	Intercept(α)	-0.177 (0.487)	-0.144 (0.628)	-0.125 (0.662)	-0.049 (0.859)	-0.100 (0.000)	
		ARCH(β)	0.166 (0.000)	0.192 (0.000)	0.186 (0.000)	0.212 (0.000)	0.148 (0.000)	
	Variance(σ)	Intercept(α)	0.353 (0.077)	0.402 (0.178)	0.403 (0.152)	0.450 (0.410)	0.247 (0.007)	
PARCH (1,1)		ARCH(β)	0.281 (0.001)	0.275 (0.000)	0.286 (0.000)	0.335 (0.007)	0.261 (0.001)	
		Asymmetric(γ)	0.697 (0.000)	0.729 (0.000)	0.709 (0.000)	0.777 (0.000)	0.665 (0.000)	
		GARCH(σ)	0.674 (0.000)	0.882 (0.018)	0.810 (0.019)	1.058 (0.056)	0.337 (0.018)	
	Volatility Impact(ϕ)	(σ+ β)	0.955	1.107	1.019	1.393	0.597	
	Model Selection Criteria	AIC	6.969	**6.957***	6.965	7.005	7.057	
		SIC	7.034	**7.031***	7.039	7.065	7.121	(6.957)*
		HQC	6.995	**6.986***	6.994	7.026	7.082	
CGARCH (1,1)	Mean (μ)	Intercept(α)	-0.068(0.809)	0.071 (0.801)	-0.006 (0.983)	0.309 (0.304)	-0266 (0.322)	
		ARCH(β)	0.181(0.000)	0.191 (0.000)	0.185 (0.000)	0.187 (0.000)	0.187 (0.000)	
	Variance(σ)	Intercept(α)	5567. (0.889)	406.471 (0.845)	8811.27 (0.759)	52576 (0.459)	5121.91 (0.000)	
		ARCH(β)	1.000 (0.000)	0.993 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	
		Asymmetric(γ)	0.035 (0.781)	-0.143 (0.003)	0.361 (0.010)	0.075 (0.327)	0.511 (0.004)	
		GARCH(σ)	0.582 (0.000)	0.573 (0.227)	0.616 (0.000)	-0.800 (0.000)	0.454 (0.027)	
	Volatility Impact(ϕ)	(σ+ β)	1.582	1.566	1.616	0.200	1.454	
	Model Selection Criteria	AIC	6.970*	6.974	6.967	7.035	7.045	
		SIC	7.035*	7.057	7.041	7.100	7.110	(6.970)*
		HIQ	6.995	7.000*	6.996	7.061	7.070	

Table 6. Model selection criteria for symmetric and asymmetric GARCH Model

GARCH Model	Selection criteria	Error Distribution Assumptions					MinSIC	Overall Min SIC
		Normal	Student's-t	Generalized	Student's-t(v=3)	Generalized (v=3)		
GARCH	AIC	6.976	**6.962***	6.970	7.001	7.063		
	SIC	7.023	**7.017***	7.025	7.047	7.109		
	HIQ	6.995	**6.983***	6.992	7.019	7.081	(**6.962**)	
GARCH-MEAN	AIC	6.973	**6.958***	6.967	6.996	7.063		
	SIC	7.029	**7.023***	7.032	7.052	7.119		
	HIQ	6.995	**6.983***	6.992	7.018	7.085	(**6.958**)	
EGARCH	AIC	6.953	**6.942***	6.950	6.989	7.028		
	SIC	7.008	**7.007***	7.015	7.045	7.084		6.942 *EGARCH in
	HIQ	6.974	**6.968***	6.976	7.011	7.050	(6.942)*	Student's-t
TGARCH	AIC	6.978	**6.962***	6.972	7.001	7.066		
	SIC	7.034	**7.027***	7.036	7.056	7.121		
	HIQ	7.000	**6.987***	6.997	7.023	7.088	(6.962) *	
PGARCH	AIC	6.969	**6.957***	6.965	7.005	7.057		
	SIC	7.034	**7.031***	7.039	7.065	7.121		
	HIQ	6.995	**6.986***	6.994	7.026	7.082	(6.957)*	
CGARCH	AIC	**6.970***	6.974	6.967	7.035	7.045		
	SIC	**7.035***	7.057	7.041	7.100	7.110	(6.970)*	
	HIQ	**6.995**	**7.000***	6.996	7.061	7.070		
	BIC	2496.413					(249.4163)	

The variance Equation:

$$\text{Log (GARCH)} = -0.089 + 0.537\left|\frac{\varepsilon_{t-1}^{2}}{\sigma_{t-1}^{2}}\right| - 0.096\left(\frac{\alpha_{t-i}}{\sigma_{t-1}}\right) + 0.919\log\left(\sigma_{t-j}^{2}\right)$$

(0.502) (0.000) (0.111) (0.000)

Schwarz Information Criteria (SIC) = 6.942

Results for Model Diagnostic Check are presented in Table 7, Fig. 6 and Table 8.

3.2 Heteroskedasticity test for model fitness

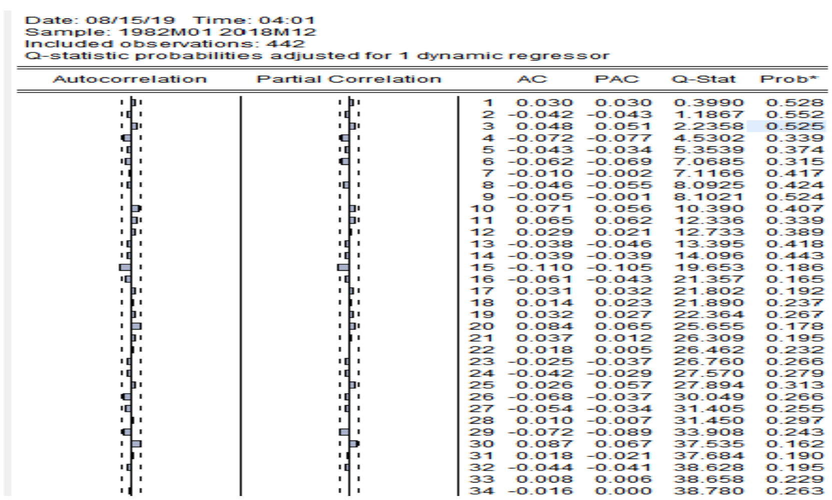
Table 7 contains the results of the Heteroskedasticity Test to confirm the Fitness of the selected GARCH Model. The below results revealed that from the null hypothesis for the test of ARCH there is no ARCH effect should be accepted even at the 5% level of significance while the alternative hypothesis of there is ARCH effect should be rejected.

Table 7. Heteroskedasticity test for the best fitted GARCH family model

Models	Heteroskedasticity Test: ARCH	Lag 5	Lag 10
EGARCH(1,1) in student's-t Error	F-statistic	0.962097	0.644732
Distribution	Prob. F((5,431,10,421)	4.823617	6.515986
	n*R^2	0.4407	0.7753
	X^2(5,10)	0.4378	0.7702

3.3 Correlogram Q-statistics test for model fitness

Fig. 5 shows serial test correlation using Correlogram Q-statistics in order to validate the fitness of the model selected. Since the calculated probability values are greater than that of the standard probability value (0.05),then the null hypothesis for test correlogram Q-statistics is accepted while the alternative is rejected and this mean that the estimated model is confirmed to be appropriate.



Date: 08/15/19 Time: 04:01
Sample: 1982M01 2018M12
Included observations: 442
Q-statistic probabilities adjusted for 1 dynamic regressor

	AC	PAC	Q-Stat	Prob*
1	0.030	0.030	0.3990	0.528
2	-0.042	-0.043	1.1867	0.552
3	0.048	0.051	2.2358	0.525
4	-0.072	-0.077	4.5302	0.339
5	-0.043	-0.034	5.3539	0.374
6	-0.062	-0.069	7.0685	0.315
7	-0.010	-0.002	7.1166	0.417
8	-0.046	-0.055	8.0925	0.424
9	-0.005	-0.001	8.1021	0.524
10	0.071	0.056	10.390	0.407
11	0.065	0.062	12.336	0.339
12	0.029	0.021	12.733	0.389
13	-0.038	-0.046	13.395	0.418
14	-0.039	-0.039	14.096	0.443
15	-0.110	-0.105	19.653	0.186
16	-0.061	-0.043	21.357	0.165
17	0.031	0.032	21.802	0.192
18	0.014	0.023	21.890	0.237
19	0.032	0.027	22.364	0.267
20	0.084	0.065	25.655	0.178
21	0.037	0.012	26.309	0.195
22	0.018	0.005	26.462	0.232
23	-0.025	-0.037	26.760	0.266
24	-0.042	-0.029	27.570	0.279
25	0.026	0.057	27.894	0.313
26	-0.068	-0.037	30.049	0.266
27	-0.054	-0.034	31.405	0.255
28	0.010	-0.007	31.450	0.297
29	-0.072	-0.089	33.908	0.243
30	0.087	0.067	37.535	0.162
31	0.018	-0.021	37.684	0.190
32	-0.044	-0.041	38.628	0.195
33	0.008	0.006	38.658	0.229
34	-0.016	0.000	38.780	0.263

Fig. 5. Correlogram Q-statistics Test for fitness of the model

3.4 Normality Test

Table 8 shows the results of descriptive statistic test for normality. This is done to know whether the model obtained follow a normal distribution order. From all indicators the results show that the hypothesis of normality should be rejected while the alternative hypothesis should be accepted. This means that the model is not normal.

Fig. 6 shows the Quantile Plot for Normal Distribution and Quantile of EGARCH Model in student's Distribution. In the graph below in Fig. 5, lie on a straight line which reveal that the residual follows a standardized order of a normal distribution

Table 8. Descriptive statistic normality test

Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P-value
-0.0070	0.0105	3.3886	-2.5325	0.7564	-0.3626	4.1891	35.726	0.000

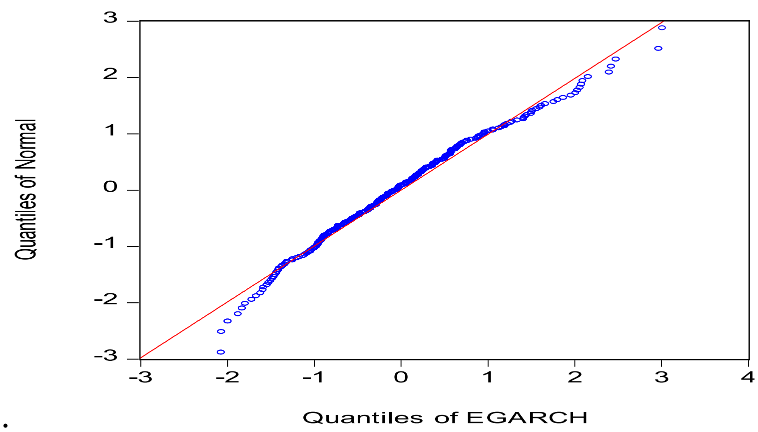


Fig. 6. Quantile plot for normal distribution and quintile of EGARCH Model in student's distribution

4 DISCUSSION

The descriptive statistics in the Table 1 as reported from the result of the analysis reveals a positive mean value of 0.123, indicating that the data series have positive mean-reverting. This means that at a certain level of volatility, the data, when subjected to constraint, will return to its favourable position [14]. Also, the standard deviation is 8.909, which is simply referred to as the risk measure associated with the series under investigation. The result also confirmed that the returns on the crude oil price series is negatively skewed with the value (-0.092) which means that the left tail of the distribution was longer indicating that the mass of the distribution was shifted to the left. Meanwhile, the distribution Kurtosis is reported to be 5.535, which means it is greater than the kurtosis of a normal distribution. This also that it is leptokurtic and has a flatter tail. This is a standard characteristic behaviour mostly exhibited by financial assets. Also, the Jarque-Bera test statistic gives the value 119.210 with a corresponding probability value of 0.000 confirming that the fact that the data is not normally distributed. Therefore, for the data to satisfy this condition, it means that the null hypothesis of normality would be rejected while the alternative of non-normality should be accepted. According to Abdulkaremet al. [15], this is one of the conditions to be satisfied before we can apply an alternative inferential statistic like the GARCH and Markov-Switching GARCH model. The result reported from the estimated descriptive statistics test corroborates Deebom & Essi's [11] result. In modelling price volatility of Nigerian crude oil market between 1987 and 2017 using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The result presented in this study also agrees with Moujieke and Essi's (2019) findings in modelling returns on prices and sales of crude oil between 1997 and

2017 using the GARCH model. The result of this present study also confirms Minoo and Shahram [16] findings in comparing regime-switching GARCH models and GARCH models in developing countries (a case study of Iran). The data is also fitted to an Autoregressive Moving Average (ARMA) model, the estimation was done to obtain the residual for the test of volatility clustering and ARCH effect. The result reported in the model (4.1) confirms that the ARCH component in the model was significant at 5 per cent level of significance. However, the residual obtained from the estimation, as in Fig. 2 as the plot of return on monthly crude oil prices (Dollar/Barrel) confirmed the presence of volatility clustering. Meanwhile, the result in Table 2 also indicates evidence of the existence of ARCH effect. We notice that the number of observations (n) multiplied by the coefficient of regression (R^2), i.e. (nR^2) was higher than the probability value of the chi-square (X^2) distribution. Therefore, it was confirmed that the null hypothesis which states that there is no presence of ARCH effect should be rejected, and the alternative hypothesis that there is ARCH effect, be accepted. The result reported here concerning the test for ARCH effect agreed with Cruicui and Luis [17] findings in risk modelling in the crude oil market: a comparison of Markov-switching and GARCH models. In Cruicui and Luis [17], it was found that the coefficient of the regression model multiplied by the number of observations (nR^2) was more significant than the probability value of the chi-square (X^2) distribution satisfying the presence of ARCH effect. Results obtained here is also in line with Veysel and Caner [18] findings in estimating the impact of oil price volatility to oil and gas company stock returns and emerging economies. In Veysela and Caner [18], it was observed that there is the presence of heteroskedasticity before GARH models used to fit the model in the study. This confirmed Abdulkarem and Abdulkarem [15] assertion about when to apply the GARCH model in estimating a financial data series. Abdulkarem and Abdulkarem [15] asserted that before GARCH model can be fitted to financial data series, there must be the presence of ARCH effect which is one of the key conditions that GARCH model used in removing ARCH during the process of estimation.

Table 3 contains results reported from the analyses of standard GARCH model with their direct error distribution assumptions which include; normal, student's –t, generalized, student's–t with a fixed degree of freedom (V=3) respectively. As it was reported in Table 3, co-efficient of ARCH (1) model is significant at 5 per cent level of significance in all the GARCH (1,1) models which suggest that the present returns on crude oil prices are predicted by its past return. The positive coefficient of (0.167) in normal (0.179) of (student 's–t), (0.177) (generalized), (0.198) (students with fixed degree of freedom V =3) and (0.143) (generalized with fixed degree of freedom) error distribution shows that current return will be 16.7%, 17.9%, 17.9%, 17.7%, 19.8% and 14.3% respectively more than the previous months return. Similarly, in the variance equation, the ARCH (1) model are all significant at 5% level of significance. This indicates that the previous month's innovations are capable of explaining the current volatility. Also, the positive coefficient of ARCH in all the variance equation shows that this month volatility will be higher. However, the estimation of the GARCH (1,1) process also accounts for past period volatility in the analysis of these months' volatility. These models captured the persistence of last period volatility. It merely means that these months' conditional volatility is majorly governed by prior month's innovations of the ARCH term as well as previous period volatility (GARCH) condition. The degree of volatility persistence in all the model with respect to their corresponding error distribution assumptions are in the following ascending order of magnitude, and they include; GARCH (1,1) in generalized error distribution with fixed degree of freedom (V=3) having volatility persistence of (0.746) as the highest, followed by GARCH (1,1) in student's –t with fixed degree of freedom (V=3) (0.716), next was GARCH (1,1) in normal error (0.604), GARCH (1,1) in generalized error (0.574) and GARCH (1,1) in student' s-terror distribution (0.543). In all, this means that the estimator that has the highest volatility persistence was GARCH (1,1) in generalized error distribution with a fixed degree of freedom (V=3). However, from the result reported in the analysis, it then means that the previous month's crude oil price information has an impact on this next month returns which has 74.6%, 71.6%, 60.4%, 57.4% and 54.3% volatility respectively of last month transfers to the next month. Comparing the five models on the basis of their fitness and performance with respect to the basic two common selection criterion (AIC and SIC), then GARCH (1,1) in student's-t distribution has the least Akaike and Schwartz information criterion. Therefore, the GARCH (1,111) model in student's –t distribution outperforms the other models. GARCH (1,1) in Mean (GARCH-M) distribution was also estimated, and the results were reported in Table 3, as shown in chapter four of this study. According to Deebom and Essi [11], this model measure perceived risk and perceived risk mostly account for on higher return on the average of the overall estimation. However, Table 3 as reported shows that all the ARCH (α) terms in the mean equations are significant at 5% level of significance which suggests that last month's returns on crude oil prices in the crude oil market are predicted by this month volatility. It was also implied that 1 per cent increase in this present volatility causes 16.28%, 17.24%, 17.24%, 18.56% and 14.607% respectively as shown in the result as an increase in these current month crude oil prices returns. Also, it was reported from the results of the analysis that all the co-efficient of the GARCH terms have positive signs, and they are all significant at 5% level of significance. This means that the risk premium parameters (0.639, 0.688, 0.666, 0.736 and 0.580) determine these months' conditional volatility. Also, confirmed the fact that in all the estimated models and the volatility of crude oil prices is capable of providing the much need information on the series returns. However, the degree of persistence and volatility of impact were estimated as follows: GARCH (1,1) - mean in generalized error distribution with a fixed degree of freedom (V=3) has the highest volatility persistence of (0.740) , follow by GARCH (1,1) -mean in student's –terror distribution with fixed degree of freedom (V=3) (0.718), next was GARCH (1,1)-mean in normal error distribution assumption (0.600), also, GARCH (1,1)- mean in generalized error with volatility persistence of (0.571) was the next and the last but the least model was GARCH (1,1)-mean in student's –t error distribution with persistence volatility of (0.539). This simply means that the percentage of their impactis74.0%, 71.8%, 60%, 57.1% and 53.90% respectively comparing the five models on the basis of fitness and performance with respect to the basic two common selection criterion (AI &SIC), GARCH (1,1)- Mean in student' s-t distribution has the least Akaike and Schwartz information criterion, therefore, GARCH (1,1) –mean model in student' s-t error distribution outperforms the other models.

Table 4 contains the results of the analysis of standard asymmetric GARCH (1,1) models as reported from the three classes of the asymmetric GARCH models estimated in the study. The first model on the table was the Exponential Generalized Autoregressive conditional Heteroskedasticity (EGARCH) models of order 1. According to Vina, Abdul and Bezon [19], this model accounts for asymmetric responses of conditional variance to all kinds of shocks, and this is determined by the magnitude as well as the sign of news (which could be positive or negative). In all the estimated models, ARCH in the mean equations shows that they all have positive co-efficient (0.191, 0.199, 0.195, 0.214 and 0.195) and they are all significant at the 5 per cent levels of significance. This means that there is no leverage effect as it was suggested in Vina et al. [19]. In Vina et al. [19], it was suggested that when ARCH co-efficient in a GARCH model has a positive sign, and it is significant, it means that the positive leverage effect is not effective and it does not have any significant effect on the system. Similarly, all the asymmetric co-efficient have negative signs, but they are significant at the 10 and 5 per cent level of significance, respectively. Also, it was confirmed from the results of the analysis as it was reported in this study that all the asymmetric co-efficient (-0.007, -0.096, -0.776 and -0.125) were less than zero and this simply means that negative shocks increases as estimated the increased volatility is more than positive shocks of the same magnitude. The degree of volatility persistence in all the models estimated with their corresponding error distribution assumptions are in the following ascending order of magnitude, and they include; EGARCH (1,1) in normal error distribution (108.9%) as the highest followed by EGARCH (1,1) in student's–t distribution (1.118%), next was EGARCH(1,1) in generalized error distribution (110.3%), EGARCH (1,1) in student' s-t with fixed degree of freedom (116.0% and EGARCH (1,1) in generalized error distribution with fixed degree of freedom (V=3) (106.4%).This means that the model with the highest volatility persistence was EGARCH (1,1) in normal error distribution. However, from the results reported from the analysis, it then means that the persistence of past volatility explained the current volatility of persistence. Comparing the five models estimated on the basis of their fitness and performance efficiency EGARCH (1,1) in student's –t was considered the best since it has the least Akaike and Schwartz information criterion. From the results obtained using EGARCH (1,1) models with their corresponding error distribution, it was found that the larger the size of the estimated news components, the negative news revealed were highly associated with greater volatility. Conditional volatility also was discovered to have asymmetric characteristic behaviour which was prone to good news sensitivity. This finding corroborates Vina et al. [19] assertion in estimating financial forecasting power of ARCH family model: a case of Mexico. The results obtained here agree with Charan et al. [20] studied in Modelling Stock Indexes Volatility: Empirical Evidence from Pakistan Stock Exchange. In Charan et al. [20] studied it was found that EGARCH or GARCH models are the best fit for all the series as decision making criterion Akaike information criterion (AIC) and Schwarz criterion (SC) are least in these models.

In another development, Threshold Generalized Autoregressive Condition Heteroskedasticity (TGARCH) models were also estimated in the study. According to Vina et al. [19], the TGARCH (1, 1) models account for impacts of good or bad news on the conditional volatility by introducing a dummy variable. The results obtained revealed shows that ARCH coefficients of all the estimated models show the present of bad news (since Yi < 0 i.e 0.175, 0.196, 0.188, 0.219 and 0.147) and the asymmetric co-efficient (such as 0.124, 0.162, 0.133, 0.287 and 0.104) are all less than zero. Also, they are not all significant at 5% level of significance, and so, this suggests that leverage effect is absent. It also means that bad news does not increase volatility existence. In like manner, the co-efficient of the GARCH is significant at the 5% level of significance, and so, these suggest that the past month's variance have no impact on the conditional volatility of these present months. The speed of reaction of volatility to market shocks could be rated as thus; 65.65%, 71.89%, 68.76%, 77.32% and 58.75% respectively. Also, Power Autoregressive Conditional Heteroskedasticity (PARCH) models were also estimated in the study and according to Omorogbe and Ucheoma [13], the power Autoregressive Conditional Heteroskedasticity (PARCH) models also measures leverage and asymmetric effects. The results obtained from the analysis shows that all the coefficients of the ARCH, asymmetric and GARCH terms were all significant at the 5% levels of significance. This means that the speed of reaction of the conditional variance in the crude oil market is high and volatility persistence is high. The degree of persistence as reported from the results of the analysis are given as, 95.6%, 115.8%, 109.67%, 139.38%,and 59.83% respectively. This means that the model with the highest volatility persistence was PARCH (1,1) in Students'-terror distribution with fixed degree of freedom (v=3). However, from the results reported from the analysis, it then means that the persistence of past volatility explained the current volatility of persistence. Comparing the five models estimated on the basis of their fitness and performance efficiency PARCH (1,1) in student's –t was considered the best since it has the least Akaike and Schwartz information criterion (6.957 and 7.031) respectively. The results obtained here agree with Alhassan and Abdulhakeem [15] findings. In Alhassan and Abdulhakeem's [15] analyzed oil price –macroeconomic volatility in Nigeria and from the results of the study, it was found that there is persistence volatility in PARCH (1, 1) in students'-t. Although, the little variations in the two studies is that the present study confirmed that persistence volatility occurs in PARCH (1, 1) in students'-terror distribution with fixed degree of freedom (v=3) whereas the formal found in PARCH (1, 1) in students'-terror distribution not with fixed degree of freedom at v=3. Component GARCH (CGARCH) Model was also estimated in the study and according to Omorogbe and Ucheoma [13], considered volatility as the time vary in the long-run. The results obtained from the analysis shows that all the coefficients of the ARCH, asymmetric and GARCH terms were all significant at the 5% levels of significance. This means that both ARCH and GARCH terms representing Short-run and Long run persistence are significance. The degree of persistence as it was reported from the results of the analysis were given as, 158.18%, 156.67%, 161.54%, 179.94%,and 145.31% respectively. This means that the model with the highest volatility persistence was CGARCH (1,1) in students'-terror distribution with fixed degree of freedom (v=3) (179.94%) and comparing the five models on the basis of fitness and performance with respect to the basic two common selection criterion (AIC and SIC) CGARCH (1,1) in normal error performance best. The results obtain from this findings was synonymous with Omorogbe and Ucheoma(2017) studied in the application of asymmetric GARCH models on volatility of Banks Equity in Nigeria's Stock Market.In Omorogbe and Ucheoma(2017) studied, it was found that CGARCH (1, 1) in students'-terror distribution outperform others. The little variations in the two studies is that the present study confirmed that persistence volatility occurs in CGARCH (1, 1) in students'-terror distribution with fixed degree of freedom (v=3) whereas the formal found in CGARCH (1, 1) in student's-terror distribution. Although, the formal studied by Omorogbe and Ucheoma [13] on volatility of Banks Equity in Nigeria's Stock Market whereas this study was done in crude oil market. The result in Table 6 contain model Selection Criteria for both symmetric and asymmetric GARCH Model on the basis of AIC, SIC and HQ. However, the final result was restricted to model with the least Schwarz criterion (SIC). This was done because Schwarz criterion (SIC) penalized models for loss of degree of freedom. Therefore, From the results obtained it was found that the overall best fit model for decision making using Schwarz criterion (SIC)was the EGARCH in student's – t error distribution assumption. The decision obtains concerning model with the least Schwarz criterion (SIC) in this study agree with the following studies; Charan*,* et al. [20] studied in Modelling Sectoral Stock Indexes Volatility: Empirical Evidence from Pakistan Stock Exchange. In Charan et al. [20] studied, it was found that EGARCH or GARCH models are the best fit for all the series as decision making criterion Akaike information criterion (AIC) and Schwarz criterion (SC) are least in these models. Also, the findings of the study corroborate Deebom and Essi's [11] findings in modelling price volatility of Nigerian crude oil markets between 1987- 2017 using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. In Deebom and Essi's [11], after comparing the results of both symmetric and asymmetric GARCH it was found that 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. Similarly, this present study is also similar to Moujieke and Essi's [21] study on modelling Returns on Prices/ Sales of Crude Oil Using GARCH Model between1997-2017. In Moujieke and Essi's [21] study, it was found that 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. After estimation, there is need to do several models diagnostic and performance confirmatory test. This will enhance the study to be sure that the model is okay, reliable in terms of performance efficiency and predictability. Therefore, the selected model was subject to the following model diagnostic and performance confirmatory and this include, heteroskedasticity test for model fitness, Correlogram Q-statistics test for model fitness, Normality Test and Quantile Plot [11]. From the findings of the study, heteroskedasticity test for model fitness revealed that there is no ARCH effect and this mean that it is does not violates the homoskedasticity assumption for line model [22]. In Gujerati [22] textbook titled Basic Econometrics, it is clearly stated in basic econometrics that any model that violates the homoskedasticity assumptions suffered from heteroskedasticity problems and this can be eliminated using the GARCH models. This result reported from this estimation agrees with Deebom and Essi [11] and Moujike and Essi [11]. The result obtained for model fitness using Correlogram Q-statistics test in this study also agree with Atoi [23] findings using Q-Q – plot. Similarly, Normality and Quantile Plot were all in line with Abduikareem and Abdulhakeem [15] recommendation in analyzing oil price – macroeconomic Volatility in Nigeria. In Abduikareem and Abdulhakeem [15] it was recommended that in examining GARCH models that it is necessary that normality and Quantile Plot validated to be sure that the model are well fitted.

5 Conclusion

Based on the results the asymmetric behaviour of the data, the study applied EGARCH, GJR-GARCH, PARCH, and CGARCH models, so that it can investigate if there is a various effect of good and bad news on the future volatility in crude oil price dynamics. However, much emphasis was on EGARCH model since it was considered best fit and an appropriate model. Therefore, the expected outcome for the existence of asymmetric effect in the data was related to the estimated gamma (γ) co-efficient of the model to have negative significant, and since the results in this study was positively significant this shows that; there is no support to the existence of leverage effect in crude oil price dynamics. Thus, crude oil price dynamics return was considered to be volatile. Hence, whether there is good news (positive)or bad news (negative), shocks are of the same magnitude, they will have the same impact on the future volatility. The results of this findings in particular is consistent with few studies in regards to detecting the asymmetric effect in the data, the study applied EGARCH (1, 1) model, so that it can investigate if there is a various effect of good and bad news on the future volatility in Amman Stock Exchange (ASE). Therefore the expected outcome for the existence of asymmetric effect in the data is related to having negative significant gamma (γ) and since the results in our study is positively significant this indicates that; there is no support to the existence of leverage effect in Amman Stock Exchange. Thus, the stock return is considered to be volatile. Hence, whether the shocks are positive (good news) or negative (bad news) of the same magnitude, they will have the same impact on the future volatility.

6 Recommendations

Considering the level of risk associated with trading commodity like crude oil in foreign markets with its corresponding prices return series, investors, financial analysts and Government should observe the following recommendations:

1. Financial analysts, investors, and those doing empirical studies, given the level of risk associated with the returns and other investment, should consider variants of GARCH models with alternative error distributions, for example fixed degree of freedom with parameter (v=3) for robustness of results.
2. Also, investors, Marketers and Government that wants to invest in crude oil and its constituents as lucrative business option should do so base on the advice of an empirical result of a GARCH model with the lowest AIC and SIC as in the case EGARCH model in this study. This is because EGARCH model recommends that when there is low leverage effect its means that investing in such sector will rely on the value of the shares issued by an oil producing company as a way to attract the investors to invest in crude oil business in order get more returns with lesser risks.
3. The study also recommends an adequate regulatory effort by the highest financial institution in the country like the Nigeria central Bank over currency operations to enhance efficiency of markets performance and reduce volatility aimed at boosting investors' confidence in foreign trading operations.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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