Volatility Modelling of Stock Returns of Selected Nigerian Oil and Gas Companies

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Abstract: Modelling volatility asset returns is a well-researched concept in financial statistics, given its significance to investment analysts, economists, risk-averse investors, policymakers and other relevant stakeholders to underpin the market and the general economic performance and resilience to shocks, domestically and internationally. Thus, this study fits an appropriate ARCH/GARCH family model to daily stock returns volatility of each of the selected five most traded assets of the oil and gas marketing companies on the Nigerian stock exchange (NSE), using daily closing prices from January 1, 2005, to December 31, 2020. First-order symmetric and asymmetric volatility models with the Normal, Student's t, Skewed Student's t and generalized error distributions (GED) were fitted to select the best model with the most appropriate error distribution using appropriate model selection criteri EGARCH (1,1) with GEDs was found to be the best-fitted models based on the Akaike Information Criterion (AIC). The results indicated the presence of a leverage effect in the series and how the volatility reacts to good news as against bad news implying that positive shock has a higher impact on the returns of the respective companies. Based on the findings it is recommended that, for enhanced precision, GARCH family models with appropriate error distribution be applied in underpinning assets volatility, which in turn would help to better understand the nature of inherent shocks characterizing asset volatility of the respective companies. With such knowledge, appropriate investment decisions are made to guide risk-averse investors in their investments.

Keywords: Volatility, Oil/Gas Industry, ARCH/GARCH Models, Leverage Effect, Nigerian Stock Exchange

1. Introduction

The stock market of any country serves as a platform and medium of exchange through, which participants such as individuals (otherwise called investors), institutions, corporations, and government, meet to trade on security assets such as stocks (or equity), derivatives and debt securities. Alternatively, a stock exchange market is an organized institution where the securities of companies listed on such market platform are traded freely, subject to the laid down regulations. The key function of a financial security market is to act as an intermediary between savers and borrowers. Thus, such a market in any country is vital to economic growth and development given its fundamental role of mobilizing domestic resources in the economy (particularly from the surplus end) and channeling them to productive investments.

The crude oil revenue has remained the pivot of the Nigerian economy since the early 1970s such that the country is currently rated as the world's seventh largest producer of oil. Generally, oil revenue has continued to account for about 40 per cent of the Gross Domestic Product (GDP). For example, between 2000 and 2,005, oil revenues accounted for an average of 27.75 per cent of total export. It also constituted an average of 38.16 per cent of the GDP over the same period [27].

Oil exploration has progressively dominated the nation's economic activities such that a chunk of the annual national budget financing is largely derived from the oil revenue indicating that the general performance of the government budget, aggregate economy and its sub-sectors will become more sensitive to the shocks characterizing oil productivity and market instability. In 2006 for example, the federally generated revenue

stood at N5, 695.1billon, which was 7.5 per cent higher than the 2005 oil proceeds. Further, according to the Central Bank of Nigeria (CBN)'s annual revenue report, about 32.7 per cent of the country's GDP was largely attributed to huge receipts from the oil sector as the prices of crude oil exceeded the budget benchmark price of US $35.99 per barrel [12]. Consequently, given the statistics presented so far and the contribution of oil to the nation's economy, it is expected that the earnings of corporate firms, and investors in the sector, especially at the exchange market would significantly be impacted.

The Nigerian Stock Exchange (NSE), like many other exchange markets, is a conduit for raising funds for individuals, corporate institutions and government, and has remained the central focus of investment analysts, economists and researchers as it is equally impacted by changes in the general economy. According to the author [26], the stock market serves as the fulcrum for capital market activities and as a barometer for measuring business or investment performance. The author [20], states that the stock market functions as a medium through which funds are transferred, from people who have amassed surplus to those who have a paucity of funds. Thus, while the savings sector (investors) needs to deploy their savings to more beneficial and productive projects, the productive sectors always explore financial sources to assist them function optimally, in the economy.

Financial time series provides a more robust analytical approach to analyzing financial assets such as stocks given the behavior and nature of the generated data collected over time. Financial data including currency exchange rate, share prices, all share index (ASI), etc. are largely non-stationary [30, 35]. Fluctuation (or volatility) in stock prices has been the object of several researches in recent years due to various global financial crises that have characterized financial markets across various developed and developing economies. According to the author [29], generalized autoregressive conditional heteroscedastic (GARCH) family models have been the most widely applied models in analyzing the inherent volatility characterizing such financial data.

The ARCH/GARCH family models are usually more robust in capturing both heteroscedasticity and persistence in the financial asset data. Further, these models have been found to be appropriate in capturing some other stylized facts such as volatility clustering, leverage effect, leptokurtosis, etc., attributed to asset data. Meanwhile, many nonlinear extensions of GARCH, such as the Exponential GARCH (EGARCH), Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), Power GARCH (PGARCH) and Threshold GARCH (TGARCH), have been proposed to handle asymmetry or leverage effect, which is another significant feature influencing the security data [17]. Thus, in handling financial data [5], opined that models with sophistication in capturing the heteroscedasticity in asset data are most appropriate for modelling inherent volatility in the data.

Dallah, H. and Ade I. [13] examined the volatility of daily stock returns of Nigerian insurance stocks using twenty-six insurance companies' daily data from December 15, 2000, to June 9, 2008, as a training data set and from June 10, 2008, to September 9, 2008, as out of sample dataset. Their result of ARCH (1), GARCH (1,1), TARCH (1,1) and EGARCH (1,1) shows that in model evaluation and out-of-sample forecast of stock price returns, EGARCH is more suitable as it performed better than other models. The author [15] aimed at fitting symmetric and asymmetric GARCH models to daily stock prices of selected securities in Nigeria using Access and Fidelity Banks daily closing share prices from April 1, 2010, to December 16, 2016. The study estimated first-order symmetric and asymmetric volatility models each in Normal, Student-t and generalized error distributions (GED) with a view to selecting the best forecasting volatility model with the most appropriate error distribution The results of the analysis showed that, $APARCH(1,1)$, $EGARCH(1,1)$ and TGARCH in that order with GED were selected to be the best-fitted models based on the Akaike Information Criterion (AIC).

The out-of-sample forecasting evaluation result adjudged PGARCH (1, 1) with GED as the best predictive model based on Mean Absolute Error and Theil Inequality Coefficient and EGARCH (1,1) based on root mean square error (RMSE) [2, 9-11] used the Generalized Autoregressive Conditional Heteroscedastic models to estimate volatility (conditional variance) in the daily returns of the principal stock exchange of Sudan namely, Khartoum Stock Exchange (KSE) over the period from January 2006 to November 2010. The models include both symmetric and asymmetric models that capture the most common stylized facts about index returns such as volatility clustering and leverage effect. The empirical results showed that the conditional variance process is highly persistent (explosive process), and provided evidence of the existence of risk premium for the KSE index return series which supports the positive correlation hypothesis between volatility and the expected stock returns. The findings also showed that the asymmetric models provide a better fit than the symmetric models, which confirms the presence of the leverage effect. These results, in general, explain that high volatility of the index return series is present in the Sudanese stock market over the sample period.

Other studies that have applied Garch family models to examine volatilities across different markets and have established the suitability of such models in studying financial series include but not limited to; [27] (to the Nigerian financial market during 2009 Global financial crises); [32] (applied univariate GARCH model to the Bombay stock exchange); [36]; which underpins the asymmetries in stock volatility of the Hong Kong stock market; [1] (studied Saudi Market volatility using GARCH family model); while Dallah, H. and Ade I. [13] applied GARCH models to forecast volatility of some of the Nigerian Insurance companies stocks in the Nigerian Stock Exchange.

Given the foregoing, this study focuses on the behavior of stock returns volatility of Nigeria's stock market using daily oil price data of five oil marketing companies for 15 years. To achieve the aim of this study, some specific objectives are set. We shall be investigating the data-generating process of the

stock returns of the selected companies, thereafter which appropriate GARCH family models are fitted to the stock returns of the respective companies subject to the appropriate error distribution associated with the fitted model(s); and finally, we shall examine impact of shocks on the returns of the respective companies. It is generally believed that in a volatile stock market, the value of the magnitude of the disturbance terms should fluctuate at different periods than others. Further, given the behavior of data in this study as enunciated earlier, ARCH/GARCH family models are employed to examine the volatility characterizing stock prices/returns of the various companies and it is hoped that the findings of this study will be of immense benefit for relevant stakeholders including the investors, for appropriate investment decisions on their assets.

2. Data Presentation and Methodology

2.1. Data Description

The stock returns obtained from the daily closing stock prices of five (5) most traded oil and gas companies in the stock market from 1st January 2005 to 31st December 2020 (a period of fifteen (15) years) represent the data used in this study. In this research, secondary data were collected on a daily closing price list of five oil from among the most traded companies (Mobil oil, MRS oil, Conoil, Oando oil and Total oil), with sufficient national spread, from the website (www.cashcraft.com) of a subsidiary company (named Cashcraft) to NSE in Nigeria. The data coverage ranges from January 1, 2005, to December 31, 2020, totaling 18,883 data points. Trading does not take place on Public Holidays, Saturdays and Sundays on the floor of the Nigerian Stock Exchange (NSE); thus, no data is available for these days. While Microsoft Excel was used in data entry, R-package (R-Studio), was introduced to analyze the data.

2.2. Volatility Models

2.2.1. The ARCH Model

The first model that provides a systematic framework for volatility modeling is the ARCH model [16]. The basic idea of ARCH models is that (a) the shock of an asset return is serially uncorrelated, but dependent; and (b) the dependence of a_t can be described by a simple quadratic function of its lagged values. Specifically, an ARCH (m) model assumes that.

The mean equation:

$$r_t = \mu + a_t \qquad (1)$$

The volatility equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \qquad (2)$$

Where $a_t = \sigma_t \epsilon_t$, and $\epsilon_t \sim N(0,1)$; $\{\epsilon_t\}$ is a sequence of independent and identically distributed (iid) random variables with mean zero and variance 1. In practice, ϵ_t is often assumed to follow the standard normal or a standardized Student-t or a generalized error distribution.

The ARCH (1) model is given as;

$$a_t = \sigma_t \epsilon_t, \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 \qquad (3)$$

where $\alpha_0 > 0$ and $\alpha_1 \geq 0$.

2.2.2. The GARCH Model

Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset return. Consequently, the author [6] proposes a useful extension known as the generalized ARCH (GARCH) model, which is formulated as follows:

Let the mean equation, $r_t = \mu_t + a_t$

Then, the GARCH (m, s) volatility equation (model) is given as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-1}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \qquad (4)$$

Where $a_t = \sigma_t \epsilon_t$, and $\{\epsilon_t\}$ is a sequence of independent and identically distributed (iid) random variables with mean 0 and variance 1.

$$\alpha_0 > 0,\ \alpha_1 \geq 0,\ \beta_j \geq 0\ and\ \sum_{i=1}^{\max(m,s)}(\alpha_i + \beta_i) < 1.$$

As before, ϵ_t is often assumed to follow a standard normal or standardized Student-t distribution or generalized error distribution. The α_i and β_j are referred to as $ARCH$ and $GARCH$ parameters, respectively. The $GARCH$ (1,1) model is given as;

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \qquad (5)$$

Subject to the following conditions: $0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1$.

2.2.3. The Exponential GARCH Model

To overcome some weaknesses of the GARCH model in handling leverage/asymmetric effect associated with financial time series, the author [24] proposes the exponential GARCH (EGARCH) model. In particular, to allow for asymmetric effects between positive and negative asset returns, he considered the weighted innovation.

Unlike the standard GARCH model, the EGARCH model can capture size effects as well as sign effects of shocks. The variance equation of the EGARCH model is given as;

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{m} \left\{ \alpha_i \left| \frac{a_{t-i}^2}{\sigma_{t-i}} \right| + \gamma_i \left(\frac{a_{t-i}^2}{\sigma_{t-i}} \right) \right\} + \sum_{j=1}^{s} \beta_j \ln(\sigma_{t-j}^2) \qquad (6)$$

$a_{t-i} > 0$ and $a_{t-i} < 0$ implies good news and bad news and their total effects are $(1 + \gamma_i)[a_{t-i}]$ and $(1 - \gamma_i)[a_{t-i}]$ respectively. When $\gamma_i < 0$, the expectation is that bad news would have higher impact on volatility. The $EGARCH$ model achieves covariance stationarity when $\sum_{j=1}^{s} \beta_j < 1$. Based on this representation, some properties of the $EGARCH$ model can be obtained in a similar manner as those of the $GARCH$ model. For instance, the unconditional mean of $\ln(\sigma_t^2)$ is α_0. However, the model differs from the $GARCH$ model in several ways. *First*, it uses logged conditional variance to relax the positivity constraint of model coefficients. *Second*, the model responds asymmetrically to positive and negative lagged values of a_t. The simplest form is the $EGARCH$ (1,1) model, which is specified as

$$\ln(\sigma_t^2) = \alpha_0 + \alpha \left| \frac{a_{t-1}^2}{\sigma_{t-1}} \right| + \gamma \left(\frac{a_{t-1}^2}{\sigma_{t-1}} \right) + \beta \ln(\sigma_{t-1}^2) \quad (7)$$

Meanwhile, the GARCH family equations stated above are estimated with a normal distribution by maximizing the likelihood function.

$$L(\theta_t) = -\frac{1}{2}\sum_{t-1}^{T}\left(\ln 2\pi + \ln \sigma_t^2 + \frac{a_t^2}{\sigma_t^2} \right) \quad (8)$$

2.3. Error Distributions Hypothesis

The probability distribution of stock returns often exhibits fatter tails than the standard normal distribution. The existence of heavy-tailedness is probably due to a volatility clustering in stock markets. In addition, another source for heavy-tailedness seems to be the sudden changes in stock returns. An excess kurtosis also might be originated from fat-tailedness. Mostly, in practice, the returns are typically negatively skewed and in order to capture this phenomenon (e

g., heavy-tailedness), the Generalized Error Distribution (GED), student-t, and skewed student-t distributions are also considered in this analysis [8, 14].

For the GARCH models characterized by GED, which help to capture additional kurtosis in the returns, which are not adequately captured by Normal error distribution, such models are estimated by maximizing the likelihood function below:

$$L_{(GED)}(\theta_t) = -\frac{1}{2}\ln\left(\frac{\Gamma\left(\frac{1}{v^3}\right)}{\Gamma\left(\frac{3}{v}\right)\left(\frac{v}{2}\right)^2} \right) - \frac{1}{2}\ln s_t^2 - \frac{1}{2}\left(\frac{\Gamma\left(\frac{3}{v}\right)(r_t - X'_t\theta)^2}{s_t^2\Gamma\left(\frac{1}{v}\right)} \right)^{\frac{v}{2}} \quad (9)$$

Where v is the shape parameter which accounts for the skewness of the returns and $v > 0$. The higher the value of v, the greater the weight of the tail. GED reverts to normal distribution if $v = 0$. In the case of t-distributions, the volatility models considered are estimated to maximize the likelihood function of a Student's t distribution and skewed Student's t distribution respectively as:

$$L_{(std)}(\theta_t) = -\frac{1}{2}\ln\left(\frac{\pi(d)\Gamma(d/2^2)}{\Gamma[(d+1)/2]^2} \right) - \frac{1}{2}\ln s_t^2 - \frac{(d+1)}{2}\left(1 + \frac{(r_t - X'_t\theta)^2}{s_t^2(d-2)} \right) \quad (10)$$

$$L_{(sstd)}(\theta_t) = -\frac{1}{2}\ln\left(\frac{\pi(d-2)\Gamma\left(\frac{d}{2)^2}\right)}{\Gamma\left[\frac{(d+1)}{2}\right]^2} \right) + \ln\left(\frac{2}{v+\frac{1}{v}} \right) + \ln(s) - \frac{1}{2}\ln s_t^2 - \frac{(d+1)}{2}\left(1 + \frac{(s(r_t - X'_t\theta)+m)^2}{s_t^2(d-2)}v^{-2I_t} \right) \quad (11)$$

Here, d is the degree of freedom and controls the tail behavior, $d > 2$. Other parameters, m, s and I_t are given by:

$$m = \frac{\Gamma\left(\frac{d-1}{2}\right)\sqrt{v-2}}{\sqrt{\pi}\Gamma\left(\frac{d}{2}\right)}\left(v - \frac{1}{v} \right), s = \sqrt{\left(v^2 + \frac{1}{v^2} - 1 \right) - m^2} \text{ and } I_t = \begin{cases} 1 \ if \ \left(\frac{r_t - X'_t\theta}{s_t} \right) \geq -\frac{m}{s} \\ -1 \ otherwise \end{cases}$$

2.4. Model Selection

The first-order volatility models in GARCH equations above are estimated by allowing a_t for each of the variance equations to follow normal, student's t, skewed student's t and generalized error distributions. This process generates twelve volatility models. Model selection is done using information criteria, and the model with the least information criteria value across the error distributions is adjudged the best fitted. This selection produces the best-fitted conditional variance models for stock returns.

3. Results Presentation and Discussions

3.1. Summary Statistics

The descriptive analysis of the data shown in Table 1 reveals

that the daily average returns of CONOIL, MOBIL, MRS, OANDO and TOTAL are 0.000475, -0.000057, $0.000639, 0.000893$ and 0.000093 respectively over the period under review, with standard deviations $0.041434, 0.024825, 0.027876, 0.047418$ and 0.058556 respectively. While the Oando stock return (with the highest positive skewness of 3.727079) is more skewed compared to any other companies; the Total stock return is apparently more peaked compared to other companies. Indicating that the daily stock returns of Total oil (with the highest excess kurtosis of 1340.0111), are most heavily tailed compared to other investigated companies. From the table, with all the five companies having extremely high positive excess kurtosis values, one can conclude that their stock returns are highly leptokurtic, meaning that their respective distributions tend to contain more extreme values, which is a violation of Normality assumption.

Table 1. Summary Statistics for the five companies.

Statistic	CONOIL	MOBIL	MRS	OANDO	TOTAL
Mean	0.000475	-0.000057	0.000639	0.000893	0.000093
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.616360	0.238202	0.642756	1.468435	2.319411
Minimum	-0.614010	-0.378483	-0.642756	-1.201488	-2.355695
Sum	1.809193	-0.214410	2.373941	3.383015	0.352821
Variance	0.001717	0.000616	0.000777	0.002248	0.003429
Std. Dev.	0.041434	0.024825	0.027876	0.047418	0.058556
Skewness	-0.108455	-0.569210	0.157115	3.727079	-0.783492
Kurtosis	70.40505	24.3146	168.1403	353.1896	1340.0111
Jarque-Bera	786946	93602	4383311	19713148	28356114

Statistic	CONOIL	MOBIL	MRS	OANDO	TOTAL
Shapiro-Wilk	0.4849	0.7189	0.4677	0.5976	0.1676
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	3,806	3,787	3,717	3,787	3,786

3.2. Time Plots for Daily Prices and Daily Returns

Figures A1 and A10 in Appendix I, display the time plots of daily closing stock prices and the daily stock returns for the five oil companies. In Figure A1, the price series (for CONOIL), as with other companies, seems to be noisy, characterized with non-stationary trend and other components that are challenging to capture. Thus, the need for return series, which is the relative changes in stock prices and has more empirical robustness in capturing the behavior of an asset data. In Figure A2, though the return series seem to be stationary at level (about the mean = 0), the variance is however non-stationary, depicting signs of heteroscedasticity (due to series of spikes at some time points). Besides, the plot further reveals a fundamental characteristic of an asset series, which is volatility clustering; a circumstance where returns of equal magnitudes move together. Going through the plots of the remaining four companies, the same behaviour as with CONOIL is observed.

3.3. Normality Test

Despite seeing non-normality behavior of the series of the respective companies given the apparent violation of normality attributes by both the skewness and kurtosis, we found it necessary to conduct empirical normality tests using, Shapiro-Wilk and Jarque-Bera Test [19], statistics for further confirmation. Reference to Table 1, The Shapiro-Wilk Normality and Jarque-Bera tests have p-values of $< 2.2e^{-16}$ each, with the respective statistic as presented in the table, implying that the distribution is not normal for the five companies.

For further examination, the Q-Q plots and the Normal Distribution curve on (Histograms) are plotted and presented in the Figures A11-A18. For example, Figures A11 and A12 present the histogram and Q-Q plots for the CONOIL. However, in Figure A11, it is apparent that the distribution of the company's returns significantly deviate from normal. Moreover, from Figure A12, it can be seen that some points are far away from both ends (of the straight line), as outliers, which is a further confirmation of non-normality. The same behavior is exhibited by the rest of the four companies as presented in Figures A11-A18. Meaning, none of the five companies returns is normally distributed, a stylized fact that is expected of financial security data across different markets of the developed and developing economies [28].

3.4. Testing for ARCH Effects

The two test statistics for checking for possible presence of ARCH effects are applied and the results presented. From the results as presented in Table 2, the two tests are apparently significant based on the accompanied p-values across the five companies. With these outcomes, fundamental conditions for applying GARCH family models have been fulfilled.

Table 2. ARCH Effect Tests Results for the Five Oil Companies.

	CONOIL	MOBIL	MRS	OANDO	TOTAL
Ljung-Box test	2960.7	90.652	898.06	800.33	945.25
p-value	2.2e-16	0.0003829	2.2e-16	2.2e-16	2.2e-16
Lagrange Multiplier test	1556	70.775	1499.9	1146.1	1732.5
p-value	2.2e-16	2.293e-10	2.2e-16	2.2e-16	2.2e-16

In fitting appropriate volatility models for each of the companies, three different candidate models were applied to capture some of the stylized facts identified with the returns of these companies. Tables 3, 4 and 5 present the results on the fitted $ARCH$, $GARCH$ and $EGARCH$ respectively. These models are intended to capture both symmetric and asymmetric behaviours characterizing volatility of each of the companies. Subsequently, AICs for the respective models were compared to select the most suitable model to describe the nature of the volatility inherent in each series.

3.5. Fitted Model Results

Table 3 presents the results of the fitted $ARCH(1)$ volatility models for the five companies' stock returns. The estimates of $\alpha_0 = 0.01052$ and $\alpha_1 = 0.2113$ with p-values of approximately 0.000, each are highly significant at the 5% level, meaning that effects due to immediate past shocks or historic information influence the current stock prices with percent contribution of about 21% for CONOIL (for example). However, when the effect of the historic information on the current volatility is not factored (not significant in predicting the current stock price), the impact of the current shock (i. e. current market information), for CONOIL is only about 1%, which is very low.

Table 3. Estimation Results of ARCH (1) Models.

Parameter	CONOIL		MOBIL		MRS		OANDO		TOTAL	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_0	$1.052e^{-03}$	$< 2e^{-16}$	$4.559e^{-04}$	$< 2e^{-16}$	$4.918e^{-04}$	$< 2e^{-16}$	$1.348e^{-03}$	$< 2e^{-16}$	$1.927e^{-03}$	$< 2e^{-16}$
α_1	$2.113e^{-01}$	$< 2e^{-16}$	$2.967e^{-01}$	$< 2e^{-16}$	$3.330e^{-01}$	$< 2e^{-16}$	$2.437e^{-01}$	$< 2e^{-16}$	$6.034e^{-02}$	$< 2e^{-16}$

Meanwhile, given the inadequacies of the ARCH model, which include: *(i.)* requiring higher orders of its kind for its inability to capture impacts of previous shocks adequately; and *(ii.)* in-ability to detect (or distinguish between) the effects of both negative and positive shocks; we fitted a more parsimonious candidate model- $GARCH$ (1,1) to address in particular, the parsimony issue. However, since both ARCH and GARCH share the same inadequacy of inability to detect asymmetric effects of the past shocks, EGARCH (an extension of the GARCH models, meant for such purpose) is thus introduced and fitted. Consequently, Table 4 presents the results of these other models with consideration of the distributions (which might follow either Normal, student-t or GED), of the inherent residuals.

For example, Table 4 displays the results of the eight volatility models for each company's stock returns. While parameter estimates of some of the models are significant at 5%, others are not. Among these, we have $EGARCH(1,1)$ for

CONOIL, $EGARCH(1,1)$ for MRS, $GARCH(1,1)$ for OANDO and $EGARCH(1,1)$ for TOTAL oil, with all the four error distributions having all their parameters significant. In these models, we observe all the GARCH terms in the models are positive, highly significant and are higher than the ARCH terms, indicating that higher candidate models outperform ARCH model.

For EGARCH models, the asymmetric term γ_1 is positive and statistically significant for each of the companies; indicating there is possible presence of leverage effect in the series. Implying that volatility reacts differently to bad news with respect to good news, but with the relative effect of positive shock having higher impact on stock returns of the respective shock, compared to negative shocks across periods covered by the data. When such behavior occurs, it shows good news characterized volatility more than bad news; thereby encouraging the risk-averse investors in the companies to be optimistic about their investments across the five companies.

Table 4. *Estimation Results of First Order GARCH Family Models.*

COMPANY	MODEL	PARAMETER	ERROR DISTRIBUTION							
			NORMAL		STUDENT-T		SKEWED STD		GED	
			Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
CONOIL	GARCH(1,1)	α_0	0.000116	0.00000	0.00000	1.00000	0.000000	1.00000	0.00002	0.00000
		α_1	0.093471	0.00000	0.51770	0.00000	0.746293	0.00000	0.05000	0.00000
		β_1	0.80515	0.00000	0.03263	0.00000	0.027227	0.00000	0.90000	0.00000
		ν			2.12710	0.00000	2.039939	0.00000	2.00000	0.00000
		ς					1.052806	0.00000		
	EGARCH(1,1)	α_0	-0.47906	0.00000	-2.851204	0.00000	-5.466697	0.00000	-1.0455	0.00000
		α_1	-0.06914	0.00000	-0.062917	0.00000	-0.047069	0.00000	0.24924	0.00000
		β_1	0.921586	0.00000	0.812964	0.00000	0.676569	0.00000	0.88122	0.00000
		γ_1	0.187458	0.00000	0.070395	0.00000	0.050785	0.00000	0.14458	0.00000
		ν			2.100000	0.00000	2.010000	0.00000	0.10012	0.00000
		ς					1.016839	0.00000		
MOBIL	GARCH(1,1)	α_0	0.000092	0.00000	0.000000	1.0000	0.000000	1.00000	0.00001	0.35573
		α_1	0.196962	0.00000	0.805207	0.0000	0.806563	0.00000	0.05229	0.00000
		β_1	0.673153	0.00000	0.065158	0.0000	0.074323	0.00000	0.89067	0.00000
		ν			2.120792	0.0000	2.067894	0.00000	0.11356	0.00000
		ς					1.005167	0.00000		
	EGARCH(1,1)	α_0	-1.35957	0.00001	-0.568723	0.0000	-0.479418	0.00000	-0.94274	0.00000
		α_1	0.01772	0.18544	-0.100188	0.0000	-0.259983	0.00000	-0.17277	0.00000
		β_1	0.80618	0.00000	0.951344	0.0000	0.952198	0.00000	0.90314	0.00000
		γ_1	0.33919	0.00000	0.242607	0.0000	0.624444	0.00000	0.67236	0.00000
		ν			2.100000	0.0000	2.010000	0.00000	0.20932	0.00000
		ς					1.007583	0.00000		
MRS	GARCH(1,1)	α_0	0.000073	0.0000	0.00000	1.00000	0.00000	1.00000	0.00001	0.06379
		α_1	0.283908	0.0000	0.20302	0.0000	0.25970	0.0000	0.05000	0.0000
		β_1	0.715092	0.0000	0.08611	0.0000	0.10482	0.0000	0.90000	0.0000
		ν			2.14860	0.0000	2.05119	0.0000	2.00000	0.0000
		ς					1.05966	0.0000		
	EGARCH(1,1)	α_0	-0.79290	0.0000	-6.842660	0.0000	-1.419505	0.0000	-1.21379	0.0000
		α_1	-0.17105	0.0000	-0.000956	0.0000	0.000021	0.0000	-0.01239	0.00001
		β_1	0.87304	0.0000	0.783013	0.0000	0.955722	0.0000	0.91514	0.0000
		γ_1	0.35201	0.0000	0.000946	0.0000	0.000025	0.0000	0.08989	0.0000
		ν			2.103067	0.0000	2.021086	0.0000	0.15479	0.0000
		ς					0.904751	0.0000		
OANDO	GARCH(1,1)	α_0	0.000174	0.0000	2.248e-09	0.9870	2.249e-09	0.9860	0.00002	0.0000
		α_1	0.389273	0.0000	1.00000	0.0000	1.0000	0.0000	0.05000	0.0000
		β_1	0.532364	0.0000	0.56390	0.0000	0.56430	0.0000	0.90000	0.0000
		ν			2.73700	0.0000	2.73600	0.0000	2.00000	0.0000
		ς					0.98440	0.0000		
	EGARCH(1,1)	α_0	-1.14642	0.0000	-0.48932	0.0000	-0.23682	0.0000	-0.35963	0.0000
		α_1	0.030342	0.09029	0.21469	0.00095	0.71928	0.00003	2.01615	0.0000
		β_1	0.826516	0.0000	0.89370	0.0000	0.89561	0.0000	0.90112	0.0000
		γ_1	0.449786	0.0000	2.38291	0.0000	7.17068	0.0000	3.46138	0.0000
		ν			2.10001	0.0000	2.01000	0.0000	0.11959	0.0000
		ς					0.98300	0.0000		

COMPANY	MODEL	PARAMETER	ERROR DISTRIBUTION							
			NORMAL		STUDENT-T		SKEWED STD		GED	
			Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
TOTAL	GARCH(1,1)	α_0	0.00005	0.0000	0.000000	1.0000	3.429e-09	0.9720	0.00003	0.0000
		α_1	0.053286	0.0000	0.711104	0.0000	1.0000	0.0000	0.05000	0.0000
		β_1	0.919118	0.0000	0.084983	0.0000	0.02666	0.0000	0.90000	0.0000
		ν			2.104779	0.0000	2.0330	0.0000	2.00000	0.0000
		ς					0.9984	0.0000		
	EGARCH(1,1)	α_0	-2.06444	0.0000	-2.18455	0.0000	-1.98609	0.0000	-0.8955	0.0000
		α_1	-0.08898	0.0000	-0.26713	0.0006	-0.67824	0.0000	-0.05759	0.0000
		β_1	0.720697	0.0000	0.81461	0.0000	0.80433	0.0000	0.93213	0.0000
		γ_1	0.238488	0.0000	0.31191	0.00038	0.77575	0.0000	0.19613	0.0000
		ν			2.10000	0.0000	2.01000	0.0000		
		ς					0.99943	0.0000		

3.6. Model Selection

Having fitted the various GARCH models subject to different error distributions, the selection of the most suitable model in each case comes next. To achieve this, Akaike Information Criterion (AIC) is employed [3]; and in choosing the appropriate model, the model with the least AIC is chosen in each case. Table 5 displays the results on this for the four error distributions considered. Examining the seventh column of the table, we have that $EGARCH$ (1,1) with GED is the best model for CONOIL, MRS, OANDO and TOTAL Oil; whereas, GARCH (1, 1), with GED was best for MOBIL.

Table 5. Selection of model based on AIC with respective error distributions for the five companies.

COMPANY	MODEL	ERROR DISTRIBUTION				BEST
		NORMAL	STUDENT'T	SKEWED STD	GED	
CONOIL	GARCH (1,1)	-4.1290	-11.487	-11.792	-3.1301	*EGARCH (1,1) with GED*
	EGARCH (1,1)	-4.0671	-6.3431	-6.5824	-16.071	
MOBIL	GARCH (1,1)	-4.7374	-9.4919	-9.4299	-16.019	*GARCH (1,1) with GED*
	EGARCH (1,1)	-4.7392	-6.1094	-6.1695	-11.295	
MRS	GARCH (1,1)	-4.7183	-18.095	-18.040	-3.2694	*EGARCH (1,1) with GED*
	EGARCH (1,1)	-4.8100	-14.392	-13.766	-18.995	
OANDO	GARCH (1,1)	-4.0377	4.7125	-4.71246	-2.3197	*EGARCH (1,1) with GED*
	EGARCH (1,1)	-4.0440	-4.3377	-4.3409	-5.9581	
TOTAL	GARCH (1,1)	-4.7183	-9.2912	-7.88565	-2.0116	*EGARCH (1,1) with GED*
	EGARCH (1,1)	-4.7947	-6.3031	-6.3913	-15.872	

4. Summary, Conclusion and Recommendation

In this section, the overall summary of the results findings, conclusion and recommendations are made based on the analyses results presented in the previous section.

4.1. Summary of the Findings

Subject to the set objectives in this study, the analyses conducted so far have succeeded in answering all the accompanying research questions intended for this research. With the results obtained, we have been able to establish that the returns of the respective companies are characterized by normality, volatility clustering and conditional heteroscedasticity. The characteristics that have been researched widely and established [28, 17]; thereby affirming the appropriateness of the application of ARCH/GARCH family models in modelling volatility of financial asset returns. The results of our findings where asymmetric GARCH family models were found to be most appropriate in line with the findings [4, 18, 33, 34]. Consequently, the results of the fitted models showed that asymmetric GARCH ($EGARCH$ (1, 1)) models with GED, were the most suitable models, except for Mobil Oil.

The findings of this research have further established the importance of volatility modelling in assessing and understanding the performance of financial assets across exchange markets of developed and developing economies. There have been many researches in this respect in recent times given the easy accessibility and availability of researchable data and more sophisticated software packages with higher precision, one of which (R-software) was applied. The popularity and traction of various GARCH family models in financial asset modelling with their unique ability in capturing time-varying characteristics of financial asset returns. Although every model has its specific strengths and weaknesses, many scholars suggest that the GARCH family model provides better results compared with any other non-heteroscedastic models [21, 22].

4.2. Conclusion and Recommendation

Referenced to the findings of this study, we hereby conclude that prospective risk-averse investors wanting to identify which companies' asset to settle for, his/her need to understand the past behavior of a particular company asset by investigating the behavior of volatility characterizing returns of such asset [23]. That the financial analyst and brokers are expected to investigate various assets' volatility behavior for them to provide real-time and favourable investment decisions to their prospective investors. Researchers and empirical

analysts need to be guided by considering models with adequate error distributions for them to get results as much unbiased as possible in predicting the future volatility of a particular asset of interest based on the history of the given asset's volatility.

Given the data coverage for this research, we suggest that asymmetric GARCH models with generalized error distributions should be adopted in modelling the volatility of various oil companies' stock returns, listed on the NSE because they performed better than those with either Normal or Student's t error distributions. However, other asymmetric GARCH models such as GJR-GARCH, TGARCH, and APACRH could be explored besides EGARCH to capture further stylized facts (for example long memory), whose presence was not factored in this study.

Finally, we recommend that each company's asset returns should be examined independently for a better understanding of the nature of shocks characterizing returns of such companies for more guided and favourable investment decisions by the investors.

Conflict of Interest

The authors declare no conflict of interest.

Appendix

Appendix I: Plots of Stock Prices and Stock Returns
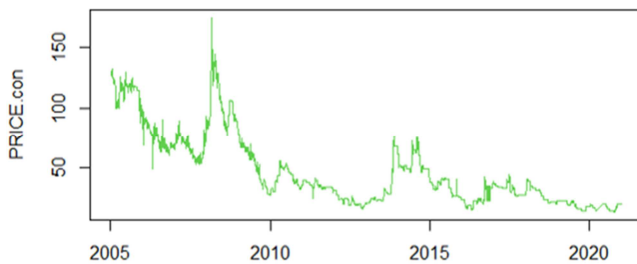
Figure A1. Time Plot for CONOIL Daily Stock Prices.
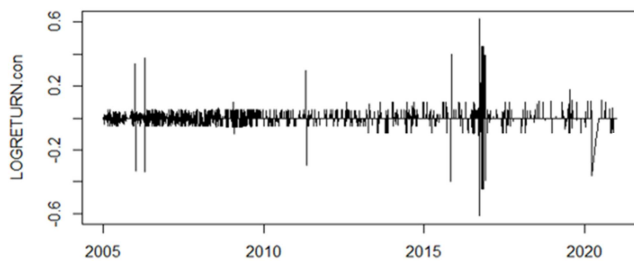
Figure A2. Time Plot CONOIL Daily Stoc k Returns.
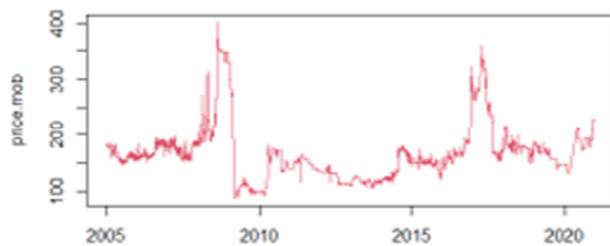
Figure A3. Time Plot for MOBIL Daily Stock Prices.
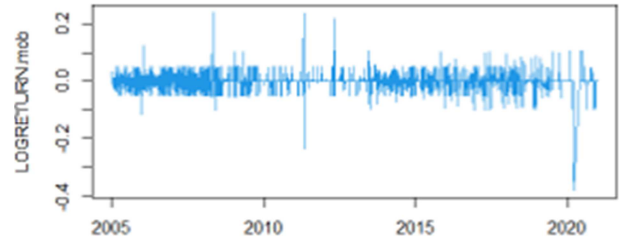
Figure A4. Time Plot for MOBIL Daily Stock Returns.
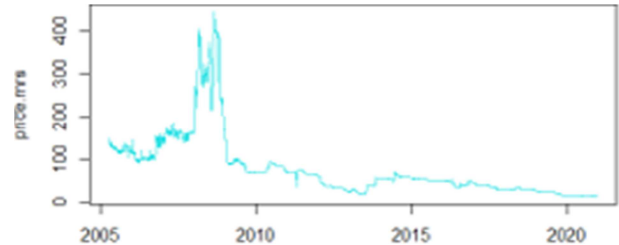
Figure A5. Time Plot for MRS Daily Stock Price.
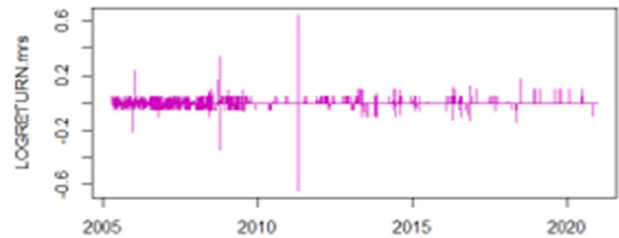
Figure A6. Time Plot for MRS Daily Stock Returns.
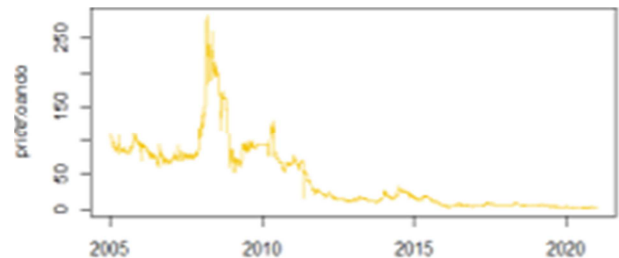
Figure A7. Time Plot for OANDO Daily Stock Price.
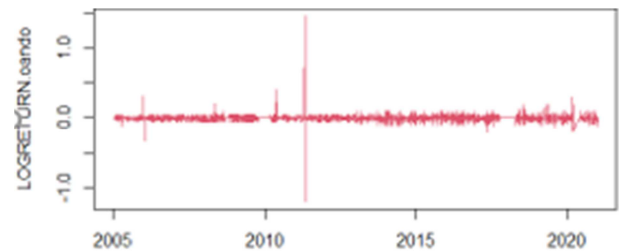
Figure A8. Time Plot for OANDO Daily Stock Returns.
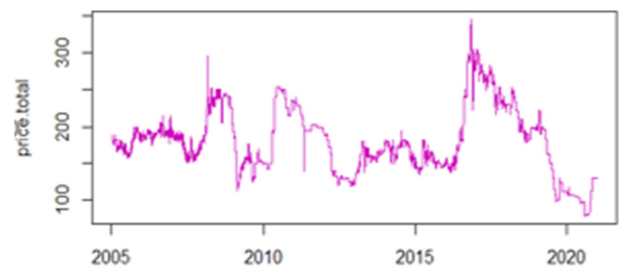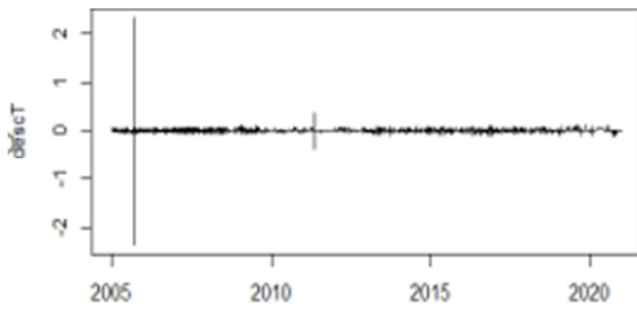

Figure A9. Time Plot for TOTAL Daily Stock Price.

Figure A10. Time Plot for TOTAL Daily Stock Returns.
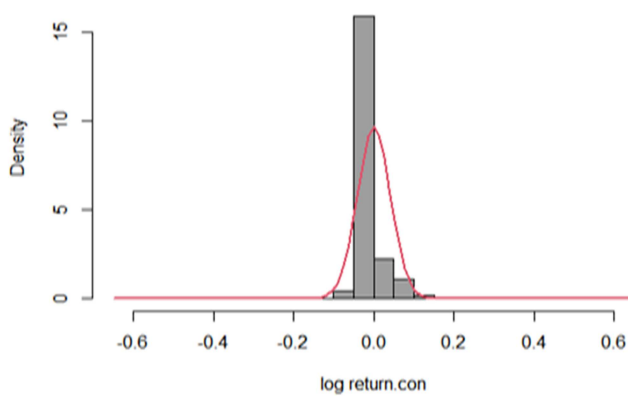
Appendix II: Normality Tests

Figure A11. Histogram with Normal Curve for CONOIL.
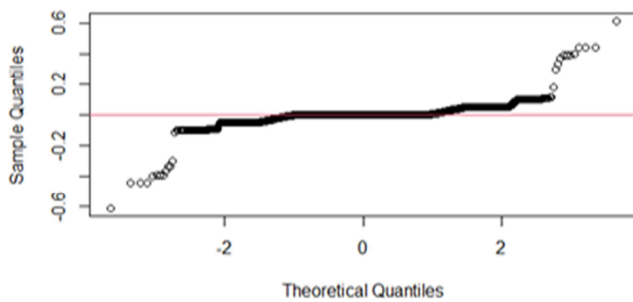
Figure A12. Quantile-Quantile Plot for CONOIL.
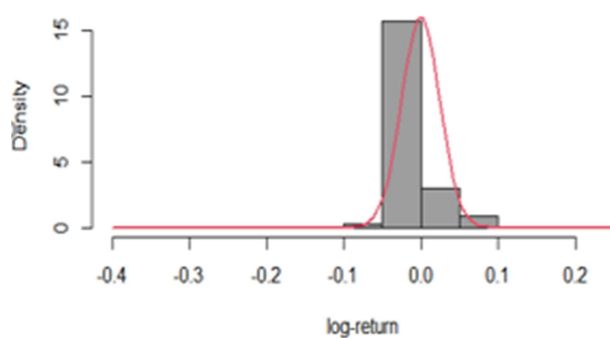
Figure A13 Histogram with Normal Curve for MOBIL.
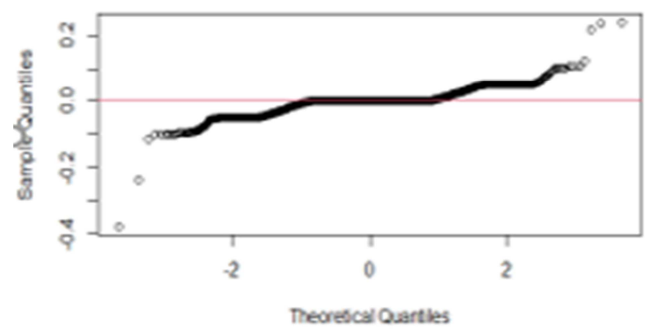
Figure A14. Quantile-Quantile Plot for MOBIL.
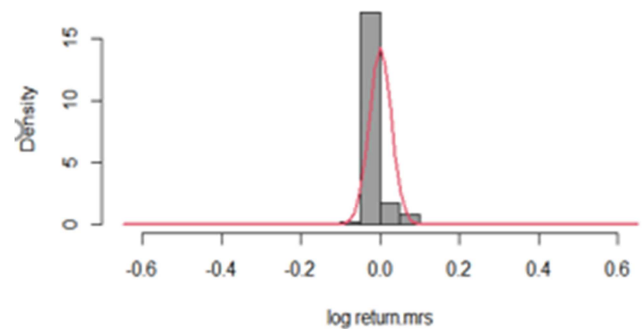
Figure A15. Histogram with Normal Curve for MRS.
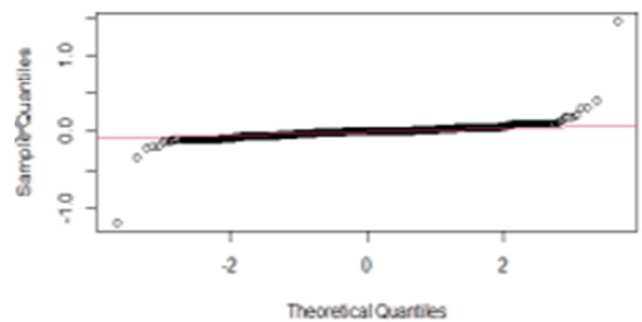
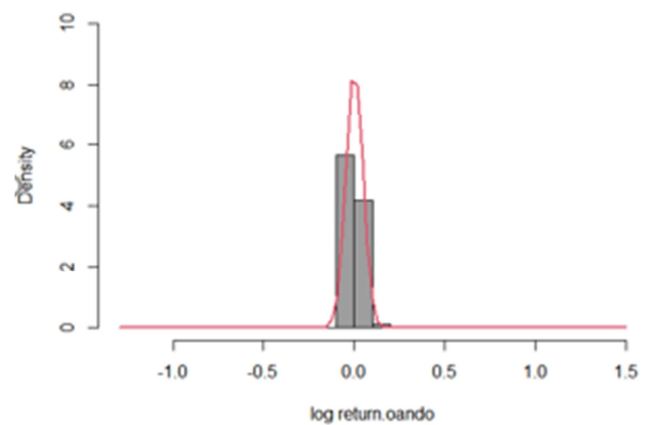*Figure A16.* Quantile-Quantile Plot for MRS.
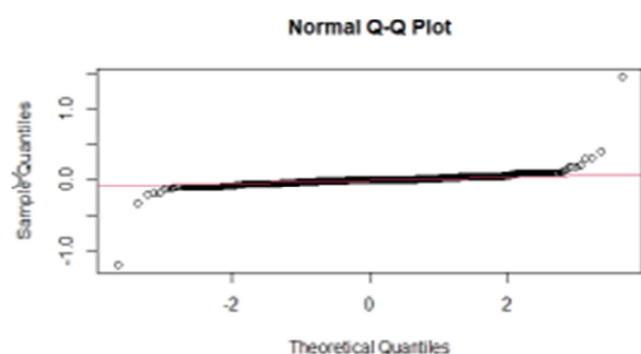

Figure A17. Histogram with Normal Curve for OANDO.

Figure A18. Quantile-Quantile Plot for OANDO.

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