International Journal of Economic, Finance and Business Statistics (IJEFBS)
Vol. 3, No. 3, 2025: 137-152

Modified Volatility Conditional Heteroscedastic Models using Binary Variable

U A Akpan[1], U P Akra[2]*, E E Bassey[3]
[1]Department of Statistics, Trinity Polytechnic, Uyo, Mbak Ifa
[2]Department of Statistics, Akwa Ibom State University, Ikot Akpaden
[3]Department of Statistics, University of Calabar, Calabar
Corresponding Author: U P Akra ukemeakra@aksu.edu.ng

A R T I C L E I N F O

Keywords: Conditional Heteroscedastic, Volatility, Binary Variable, Modified Model

Received: 21, April
Revised: 20, May
Accepted: 30, June

A B S T R A C T

This study modified some of the existing conditional heteroscedastic models by introducing binary variable to sort out categorical data into mutually exclusive categories and compared the existing conditional heteroscedastic models with the modified conditional heteroscedastic models. Jarque-Bera statistic was used for normality test, Augmented dickey-fuller (ADF) test was used to test the stationarity of the return series, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) was used for model selection, and root mean square error was for model fitness. The parameters of these models were estimated using the Marquardt's numerical optimization algorithm in the Econometric view software. Time series behaviour of daily closing stocks returns of seven oil companies listed in the Nigerian stocks market from 4th January, 2017 to 30th June, 2023 was considered. ARCH (1), ARCH (2), GARCH (1,1), GARCH (2,1), EGARCH (1,1), EGARCH (2,1), GJRGARCH (1,1) and GJRGARCH (2,1) with generalized error distribution were used for the analysis. Results revealed that all the oil stocks returns were all stationary and not normally distributed. These shows the evidence of volatility clustering, negative skewness, leptokurtic and leverage effect which are usually observed in financial time series. Also, the modified GJRGARCH (1,1) outperformed better than other models for forecast evaluation and fitness performance respectively.

DOI: https://doi.org/10.59890/ijefbs.v3i3.56
ISSN-E: 3025-9959
https://dmimultitechpublisher.my.id/index.php/ijefbs

INTRODUCTION

Conditional heteroscedastic models are models for studying volatility in financial markets and are applicable when the standard deviations of a variable observed over a specified period of time are non-stationary. In this study, a binary variable will be imposed on the volatility models to obtain modified volatility models with a reduced root mean square error which will be used empirically in examining and proffering solutions to the possible effect of crude oil price in the international market on the volatility of the Nigerian oil stocks. Binary variable is an artificial value used to sort out categorical data into mutually exclusive categories such as low and high, stable and unstable, etc. The distribution of the binary variable is assumed to follow a Bernoulli function. If is the probability of success and is the probability of failure, clearly the likelihood function of y is called the Bernoulli probability function given as.

$$f(y) = \begin{cases} p, & if\ y=1 \\ q, & if\ y=0 \end{cases} \tag{1}$$

Where and, is called the Bernoulli probability function.

The empirical study of this research work will make use of the oil sector stocks from the Nigerian stock market. The oil stocks are considered especially now that the global oil price is dwindling in the international market. The benchmark barrel of crude oil price is the current price of crude oil price which includes: West Texas Intermediate (WTI), Bonny light, Brent, OPEC reference Basket, etc. (Kilduff, 2016). Early in this decade, the crude oil price was stable between the years 2011 and June, 2014. Then, started from July, 2014 to dwindle up to November, 2014. From December, 2014 to June, 2015 the crude oil prices started falling below the expected benchmark price. Stocks in the oil sector are the most competitive stocks on the floor of Nigerian stock exchange. This is due to how viable these stocks are, given the nature of Nigerian mono-economy which solely depends on oil.

Despite the successes recorded in handling the challenges of volatility, obtaining the best conditional heteroscedastic model with the least Root Mean Square Error (RMSE) remains open among scholars. It is in the light of this that, this study seeks to handle this problem by comparing the existing conditional heteroscedastic models with the modified conditional heteroscedastic models in terms of forecast performance evaluation and fitness.

LITERATURE REVIEW

In the light of the changes or irregularity constants, variability in stock prices also called volatility. Onwukwe et al., (2011) observed that changes produce by volatility can better be explained by the used of models. Statistically, volatility refers to the variance of returns of stocks for a particular security. It covers financial markets (Engle et al., 2005), and gives the actual measure of uncertainty which is usually associated with the stock market. Volatility features are mostly observed in asset returns. These features are: volatility clusters, leverage effects, etc. Bassey and Akra (2021) studied the effect of Nigerian macroeconomic factors and also investigate the relationship between the factors for the period of 1985-2014. Krainer (2002) adduced that factors that increases volatility in stock market and level of volatility can guide investors to know whether to hold much or less stocks in their portfolio and economic forecasters to predicts the direction of the economy, policy makers in making the good policies and decision makers to make the right decisions. Business in Nigeria has the problem of where, and how to promote usually enclosed a retailer's mind which becomes the uncertainties that projected doubt whether or not to establish it. To remedy this problem, a multi-level factorial design is proposed by (Akra et al., 2025). Many say that volatility arises from factors which include change in investors' tolerance of risk, changes in economic policies, etcetera (Mala and Reddy, 2007). In modelling financial markets variables and returns, volatility determines the magnitude of the errors in it (Engle et al., 2007). According to Scott (2006), inflation volatility was found to have significant negative effect on inflation. Basher and Sardosky (2006) examine the connection that exists between developing stock market returns and the risk of the price of oil. His study used various univariate specifications of symmetric and asymmetric models. Salisu and Fasanya (2012) observed existence of leverage effects in the crude oil market and stated that overlooking these impacts in the oil price modelling will result in serious biases and inaccurate results using GARCH (1,1), GARCH-M (1,1), TGARCH (1,1), EGARCH (1,1). Samson (2015) using indicator variable noticed volatility persistence and clustering in the Nigerian insurance stocks which also exhibited positive and negative effects that had significant impact on the daily returns pattern. Agri et al. (2016) observed that the economy of Nigeria is highly vulnerable due to oil price fluctuations, as most industries in Nigeria depend on oil. Oil prices volatility has caused changes in macroeconomic variables which in turns affects other commodity prices and economic development which led to macroeconomic fluctuations sand a highly volatile real exchange rate. The study also observed that crude oil price and its volatility in the global market impacted on the features and potential of political, institutional, social and economic development in Nigeria.

Binary variable is artificial values (0,1) created to sort out categorical data into mutually exclusive categories. They are used as apparatus to sort data into mutually exclusive categories such as stable and unstable, low and high, etcetera. Alabi (2014) attached dummy variables in Regression model to obtain the mean internally Generated Revenue and wage Bill of six Geopolitical zones in Nigeria. The dummy variable which was made up of two digits 0 and 1 represented two mutually exclusive categories. According Vasudera and Kumari (2013) in their study claimed that generalized error distributions are applicable where the errors are not normally distributed.

METHODOLOGY

Data for the Study

This study considered some of the conditional heteroscedastic models which were modified by the introduction of binary variable in the models. Data for this study were obtained from Cash Craft Asset Management Limited. The data are there in the website (www.cashcraft.com). Cash Craft Asset Management Limited is one of the members of the Nigerian stock Exchange (NSE) and one of the leading stock broking firms in Nigeria.

Determination of Returns

In financial statistics, one way to obtain stationarity when a series is confirmed to be non-stationary is by taking the logarithm of the return series. The log return series, is given mathematically as:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

Tests for Stationarity and Heteroscedasticity

Stationarity of the was tested by the Augmented Dickey Fuller (ADF) statistic used for testing a unit root in a series sample. The Lagrange Multiplier in the Ordinary Least Squares regression subroutine in the Econometric view software was used to check for the existence of heteroscedasticity from the residual of the conditional mean.

Residual in the Models and Normality Test

The fitted model was analysed to confirm irregularities using GARCH model estimation. The numerical maximization of Marquardt's likelihood function's subroutine in Econometric view software was used to obtain the models parameters. Normality of the residual was checked by the Jarque-Bera test.

Conditional Heteroscedastic Models

The ARCH (1) Existing Model

Engle (1982) proposed the ARCH model for volatility modelling. Mathematically expressed as:

$$\sigma_t^2 = \psi_0 + \sum_{i=1}^{m} \psi_i \varepsilon_{t-i}^2 + \varepsilon_t \tag{3}$$

$$\sigma_t^2 = \psi_0 + \psi_1 \varepsilon_{t-1}^2 + \varepsilon_t \tag{4}$$

Modified ARCH (1) Model

$$\sigma_t^2 = \psi_0 + \psi_1 \varepsilon_{t-1}^2 + \varphi P + \varepsilon_t \tag{5}$$

Where $\varepsilon_t = \sigma_t x_t$, x_t is white noise process, $\psi_0 > 0$, $\psi_i > 0$ for $i = 1, 2, \ldots, m$, $\psi_0, \psi_1, \ldots, \psi_m$ are parameters of the model, P is a binary variable, φ is the coefficient of the binary variable. Thus

$$P = \begin{cases} 0, & stable \\ 1, & unstable \end{cases}$$

The GARCH Existing Model

Bollerslev (1986) proposed the ARCH (q) model of (Engle, 1982) to GARCH (p, q) in which they introduced q lag of previous conditional variance. This combines the Autoregressive and moving average components in the Heteroscedastic variance. The GARCH (p, q) model is express mathematically as:

$$\sigma_t^2 = \psi_0 + \sum_{i=1}^{m} \psi_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 + \varepsilon_t \tag{6}$$

Where $\varepsilon_t = \sigma_t x_t$ is white noise, $\psi_0 > 0$, $\psi_i > 0$, $\beta_j > 0$ are parameters of the model and $\sum_{i=1}^{\max(m,s)} (\psi_i + \beta_j) < 1$. Here, $\psi_i = 0$ for $i > m$ and $\beta_j = 0$ for $j > s$, $i = 1,2,...,m$ *and* $j = 1,2,...,s$

Modified GARCH Model

$$\sigma_t^2 = \psi_0 + \sum_{i=1}^{m} \psi_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 + \varphi P_i + \varepsilon_t \tag{7}$$

Where $\varepsilon_t = \sigma_t x_t$, x_t is white noise process, $\psi_0 > 0$, $\psi_i > 0$ for i=1,2,...,m, $\psi_0, \psi_1, ..., \psi_m$ are parameters of the model, P is a binary variable, φ is the coefficient of the binary variable. Thus

$$P = \begin{cases} 0, & stable \\ 1, & unstable \end{cases}$$

EGARCH Existing Model

Nelson (1991) proposed the EGARCH model that captured asymmetric impact between positive and negative asset returns. It is expressed as mathematically

$$\ln \sigma_t^2 = \psi_0 + \sum_{i=1}^{s} \left[\psi_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} + \gamma_i \left(\frac{/\varepsilon_{t-i}/}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] + \sum_{j=1}^{m} \beta_j \ln(\sigma_{t-j}^2) \tag{8}$$

where $\psi_0, \psi_i, \beta_j, \gamma_i$ are parameters of the models and $E(\varepsilon_t) = \sqrt{\frac{2}{\pi}}$, $x_{t-i} = \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$. and γ_i coefficient thus denotes the leverage effect of ε_{t-i}

Modified EGARCH Model

$$\ln \sigma_t^2 = \psi_0 + \sum_{i=1}^{s} \left[\psi_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} + \gamma_i \left(\frac{/\varepsilon_{t-i}/}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] + \sum_{j=1}^{m} \beta_j \ln(\sigma_{t-j}^2) + \varphi P_i \tag{9}$$

Where $\psi_0, \psi_i, \beta_j, \gamma_i$ are parameters of the models and $E(\varepsilon_t) = \sqrt{\frac{2}{\pi}}$, $P = \begin{cases} 0, & stable \\ 1, & unstable \end{cases}$ an γ_i coefficients thus denotes the leverage effect of ε_{t-i}

GJRGARCH Existing Model

GJRGARCH model is introduced to capture asymmetry in the ARCH process. It is defined mathematically as;

$$\sigma_t^2 = \psi_0 + \psi_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 \mathrm{I}_{t-1} \tag{10}$$

Where $\psi_0, \psi_1, \beta, \gamma$ are parameters of the model, $\mathrm{I}_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$ and $\mathrm{I}_{t-1} = 1$ if $\varepsilon_{t-1} < 0$.

Modified GJRGARCH Model

$$\sigma_t^2 = \psi_0 + \psi_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 \mathrm{I}_{t-1} + \varphi P \tag{11}$$

Where $\psi_0, \psi_1, \beta, \gamma$ are parameters of the model, $\mathrm{I}_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$, $\mathrm{I}_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, P is a binary variable, and φ is the coefficient of the binary variable. $\hat{\sigma}_t$ and σ_t

Models Selection and Diagnostic Checks

The model's selection was done using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

RESULT AND DISCUSSION

Descriptive Statistics

From Table 1 below, the mean of the return series for four of the oil stocks has minus signs meaning indicating that these oil stocks operated at a loss during the period under study. Yet, three of the oil stocks gained with positive signs for the returns. The values of the standard deviation for all the returns showed evidence of volatility clustering, where CON is the most volatile. Four of the stocks were negatively skewed while three were positively skewed. The values of the kurtosis were very high which showed evidence of leptokurtic. But, the result of Jarque-Bera statistic from the analysis showed that the p-values were less than 1% and 5% respectively which implied that all the oil stocks returns were not normally distributed.

Table 1. Descriptive Statistics of the Returns of the Nigerian Oil Stocks

OC	Mean	Max	Min	SD	Skewness	Kurtosis	JB	PV
CON	0.1914	0.4255	-0.8723	0.2019	-1.1568	6.3436	929.262	0
ETERNA	-0.0004	0.0484	-0.0513	0.01548	-0.3133	9.0480	2078.09	0
FORTE	0.0027	1.4398	-0.6927	0.05535	12.8481	3697075	7685784	0
MOBIL	0.0001	0.2350	-0.2350	0.02093	-0.7637	37.2864	66698.2	0
MRS	-0.0005	0.6428	-0.6428	0.03048	0.0131	294.130	4799332	0
OANDO	-0.0017	1.2015	-1.4684	0.06259	-4.2088	323.848	5815038	0
TOTAL	-0.0002	0.3717	-0.3717	0.02396	0.0046	89.4362	423057	0

OC (Oil companies), SD (Standard deviation), JB (Jarque – Bera), PV (P – value)

Tests for Stationarity

The Augmented dickey-fuller (ADF) test was used to test the stationarity of the return series. From the result of analysis in Table 2 below, the ADF test statistic is less than the critical values at 1%, 5% and 10% significance level. This implies that the returns were all stationary and there is no unit root.

Table 2. ADF Test of Stationarity for the Returns of Nigerian Oil Stocks

OC	ADF TS	PV	1% CV	5% CV	10% CV	REMARKS
CON	-4.765589	0.0001	-3.434969	-2.863467	-2.67845	STATIONARY
ETERNA	-12.47465	0	-3.474874	-2.880987	-2.577219	STATIONARY
FORTE	-9.31894	0	-3.473096	-2.880211	-2.576805	STATIONARY
MOBIL	-9.880984	0	-3.474874	-2.880987	-2.577219	STATIONARY
MRS	-12.03264	0	-3.472534	-2.879966	-2.576674	STATIONARY
OANDO	-11.32072	0	-3.472534	-2.879966	-2.576674	STATIONARY
TOTAL	-14.78561	0	-3.472259	-2.879846	-2.57661	STATIONARY

OC (Oil companies), TS (Test Statistic), CV (Critical value)

Heteroscedasticity Test

The oil stocks residuals were tested for heteroscedasticity by the Lagrange Multiplier test statistic from the least squares method in the Econometric view software. The results of the analysis are given below in Table 3. The p-value results showed that there was presence of heteroscedasticity in six of the oil stocks (p-value < 0.05) while there was no heteroscedasticity in FORTE (p-value > 0.05).

Table 3. Lagrange Multiplier Test for Heteroscedasticity

OIL COMPANIES	F-STATISTIC	P-VALUE
CON	1953.708	0
ETERNA	161.4979	0
FORTE	2.613166	0.1062
MOBIL	51.52787	0
MRS	279.6202	0
OANDO	162.719	0
TOTAL	346.3182	0

Parameters Estimate for the Conditional Heteroscedastic Models with Binary Variable

Noticing heteroscedasticity in the returns, eight conditional heteroscedastic models with Binary variable were fitted to check the level of significance of on each of the models. These includes: ARCH (1), ARCH (2), GARCH (1,1), GARCH (2,1), EGARCH (1,1), EGARCH (2,1), GJRGARCH (1,1) and GJRGARCH (2,1) respectively. From Tables 4a and 4b below, the parameters of the different models were mostly significant at 1% and 5% except EGARCH (2,1) t, GJRGARCH (1,1) GED, GJRGARCH (2,1) t and GJRGARCH (2,1) GED for CON. Also, the values of some of the binary variables were negative with respective models, showing negative effect of the dwindling oil prices on the oil stocks. For ETERNA, some of the parameters were significant at 1%. Most of the parameters of the binary variable were negative showing also negative effect. For MOBIL, most of the parameters were not significant. But the binary variable was mostly positive showing that the stocks were not affected negatively. For MRS, parameters and leverage effect were mostly significant. And the values of the binary variable showed that the stocks were affected. For OANDO, the parameters and leverage effect were not all significant but, the values of the binary variable showed that the dwindling oil price did not really affect the oil stocks. For TOTAL, the parameters and the leverage effect were mostly significant while that of the binary variable were mostly significant.

Table 4. Summary of Parameters Estimate of the Conditional Heteroscedastic Models with Binary Variable for CON, ETERNA and OANDO

		PARAMETERS ESTIMATE					
OIL COMPANIES	MODELS	Ψ_0	Ψ_1	Ψ_2	β_1	γ_1	φP_{Dw}
CON	ARCH (1)	0.0484 ^^	6.4307				0.1089
	ARCH (2)	0.0023	4.3766	4.723			-0.0020

		^		8 ^			^
	GARCH (1,1)	0.0005 ^	1.8928 ^	0.0526			0.0009 ^^
	GARCH (2,1)	0.0026	6.0716 ^^	1.9518	-0.3219		-0.001031
	EGARCH (1,1)	-1.768 ^	20.7851 ^		3.3142	0.1974 ^^	1.2842 ^
	EGARCH (2,1)	-1.072 ^	4.5589 ^	-2.4872^	0.02703	0.8800 ^	0.1046 ^^
	GJRGARCH (1,1)	0.0017 ^	7.413715		4.94543	0.02648	0.000998
	GJRGARCH (2,1)	0.28714	7.3684	2.86896	1.4295	0.0292	-0.054195
ETERNA	ARCH (1)	0.0002 ^	0.2279 ^				-0.00019 ^
	ARCH (2)	0.0002 ^	0.2051 ^	0.0947 ^			0.00018 ^
	GARCH (1,1)	0.0001 ^	0.2081 ^		0.4648 ^		0.00012 ^
	GARCH (2,1)	0.0001 ^	0.18291^	0.11032	0.3913 ^		-0.00012 ^
	EGARCH (1,1)	-6.9260	1.3397		0.4770	-0.4476	-0.6701
	EGARCH (2,1)	-6.299 ^	1.2106	1.3786	0.3262	-0.7750 ^	-0.6303
	GJRGARCH (1,1)	0.0001 ^	0.1964 ^		0.082	0.4585 ^	0.00011 ^
	GJRGARCH (2,1)	0.0001 ^	0.1850 ^^	0.0791	0.125 ^^	0.3578 ^	-0.00012 ^
OANDO	ARCH (1)	0.0005 ^	0.8570 ^				0.0010 ^^
	ARCH (2)	0.0004 ^	0.6226 ^	0.2534 ^			0.0009 ^^
	GARCH (1,1)	0.0001 ^	0.0098 ^		-0.105 ^		0.00088 ^
	GARCH (2,1)	0.00384	0.0873 ^	-0.04937	0.5258		-0.002764
	EGARCH (1,1)	-3.882 ^	0.6616 ^		0.5040 ^	0.1497 ^^	0.4184 ^
	EGARCH (2,1)	-3.727 ^	0.6488 ^	-0.015	0.5245 ^	0.1346 ^^	0.4002 ^^

				2			
	GJRGARCH (1,1)	0.0039	0.0866 4	0.007 8	0.595 3	0.0078 25	- 0.00224
	GJRGARCH (2,1)	0.0039	0.0894	- 0.028 9	0.530 16	0.0151 34	-0.0032

^ Significance at 1%, ^^ Significance at 5%, GED – Generalized Error Distribution

Table 5. Summary of Parameters Estimate of the Conditional Heteroscedastic Models with Binary Variable for MOBIL, MRS and TOTAL

		PARAMETERS ESTIMATE					
OIL COMPANIES	MODELS	Ψ_0	Ψ_1	Ψ_2	β_1	γ_1	$\varphi P_{DWINDLING}$
MOBIL	ARCH (1)	0.2288 ^^	131.02				0.1572
	ARCH (2)	3.9092	59.079	1.327 1			6.6145
	GARCH (1,1)	0.0000 1	37.961		0.9270 ^		0.0235
	GARCH (2,1)	0.5820	0.6635	- 0.443 2	0.3885		0.0836
	EGARCH (1,1)	-4.697 ^	0.8128		- 0.2130	0.524 4	0.3574
	EGARCH (2,1)	-0.610 ^	1.4849	1.870 0	0.8578 ^	1.490 7	-0.1033
	GJRGARCH (1,1)	0.2126	18.263 3		0.8635 ^	- 15.29 2	0.1109
	GJRGARCH (2,1)	0.0000 04	19.596 0	8.029 5	0.9214 ^	- 2.617 1	0.0369 ^^
MRS	ARCH (1)	0.0001 ^	0.6577 ^				0.00008 ^
	ARCH (2)	0.0009 ^	0.2709 ^	0.126 5 ^			0.00002 ^
	GARCH (1,1)	0.0001 ^	0.3969 ^		0.5725 ^		0.00002 ^
	GARCH (2,1)	0.0002 ^	0.2296 ^	0.027 48	0.1823 8		-0.00005 ^
	EGARCH (1,1)	-9.924 ^	0.0817 ^		0.1486 ^	0.089 5 ^	0.8817 ^
	EGARCH (2,1)	-8.935 ^	0.0992 ^	0.198 4 ^	0.0014	0.097 3 ^	0.1262
	GJRGARCH (1,1)	0.0008 ^	0.1207 ^^		0.4192 ^^	0.031 1	-0.0006 ^
	GJRGARCH	0.0002	0.5744	0.144	0.1435	-	-0.00005 ^

	(2,1)	^	^^	7	3	0.2674	
TOTAL	ARCH (1)	0.0001 ^	0.3062 ^				0.00017 ^
	ARCH (2)	0.00001 ^	0.1835 ^	0.2053 ^			0.00023 ^
	GARCH (1,1)	0.00005 ^	0.2613 ^		0.4774 ^		0.00007 ^
	GARCH (1,1)	0.0002 ^	0.2148 ^		0.2483 ^^		-0.00006 ^
	GARCH (2,1)	0.00026	3.6826	1.0359	0.5243 ^		0.00131
	EGARCH (1,1)	-7.135 ^	0.3984 ^		0.1455	0.3827 ^	1.5614 ^
	EGARCH (2,1)	-7.250 ^	-0.0866	0.8647	-0.791 ^	0.5978 ^	1.27065 ^
	GJRGARCH (1,1)	0.0004 ^	0.098 ^^		0.4916 ^	0.0478	0.0003 ^
	GJRGARCH (2,1)	0.00045	0.0985	0.0451	0.4648	0.0451	-0.00026

^ Significance at 1%, ^^ Significance at 5%, GED-Generalized Error Distribution

Goodness of Fit, Model Selection and Diagnostic Check for the Modified Models

The analysis of the selected models, fitness and efficiency was checked as provided in Tables 5a and 5b below. As it should be, for CON, ETERNA and MOBIL, the log-likelihood is mostly negative which gave a good fit. Log-likelihood for MRS, OANDO AND TOTAL was all negative which showed a very good fitness. And the (AIC) and (BIC) were compared to choose the model with the smallest value in each of the stocks. For CON, ETERNA, MOBIL, MRS, OANDO AND TOTAL is AIC the best. The diagnostic check was performed by the Lagrange Multiplier test to observe if the ARCH effect is removed or not. This helped to detect errors due to misspecification, which showed how efficient the selected models are. The p-values of the models were mostly insignificant indicating complete removal of heteroscedasticity in the models.

Table 6. Goodness of Fit, Model Selection and Diagnostic Check for the Modified Models for CON, ETERNA and OANDO

		Goodness of Fit	Model Selection Criteria		Diagnostic Check for Arch Effect	
Oil Companies	Models	Log Likelihood	AIC	BIC	F-Statistic	P-Value
CON	ARCH (1)	898.3272	-1.334813	-1.327066	1.122122	0.289653
	ARCH (2)	-4063.478	6.054323	6.062071	0.05868	0.808632
	GARCH (1,1)	-5032.147	7.496869	7.504616	0.378519	0.538501

	GARCH (2,1)	-3617.047	5.389497	5.397244	0.495674	0.48153
	EGARCH (1,1)	2156.785	-3.208912	-3.201165	0.53846	0.4632
	EGARCH (2,1)	-3093.289	4.609514	4.617262	2.165973	0.14133
	GJRGARCH (1,1)	-3562.499	5.308264	5.316012	0.423038	0.515536
***	GJRGARCH (2,1)	3153.12	-4.692658	-4.68491	11.50152	0.909
ETERNA	ARCH (1)	-3170.092	4.72389	4.731637	6.703671	0.726
	ARCH (2)	-3091.568	4.606952	4.614699	9.438192	0.168
	GARCH (1,1)	-2492.995	3.715555	3.723303	19.04729	0.834
	GARCH (2,1)	-2471.9	3.68414	3.691888	22.72839	0.089
	EGARCH (1,1)	1592.988	-2.369304	-2.361556	45.70758	0.789
***	EGARCH (2,1)	2986.014	-4.443804	-4.436056	35.82035	0.899
	GJRGARCH (1,1)	-2492.389	3.714653	3.7224	16.19244	0.768
	GJRGARCH (2,1)	-2597.406	3.871044	3.878791	37.14564	0.777
OANDO	ARCH (1)	-7834.642	11.54995	11.55764	0.001133	0.973148
	ARCH (2)	-8266.807	12.18689	12.19458	0.000962	0.975265
	GARCH (1,1)	-7176.918	10.58057	10.58825	6.478399	0.911029
	GARCH (2,1)	-4606.217	6.791771	6.799454	1.967983	0.160891
	EGARCH (1,1)	-7686.412	11.33148	11.33917	0.002251	0.962166
	EGARCH (2,1)	-7720.955	11.38239	11.39008	0.002209	0.96252
***	GJRGARCH (1,1)	-4381.467	6.460526	6.468209	1.609368	0.2048
	GJRGARCH (2,1)	-4578.224	6.750515	6.758198	1.098045	0.294882

*** Indicates the best models for the different stocks.

Table 7. Goodness of Fit, Model Selection and Diagnostic Check for the Modified Models for MOBIL, MRS and TOTAL

		Goodness of Fit	Model Selection Criteria		Diagnostic Check for Arch Effect	
Oil Companies	Models	Log Likelihood	AIC	BIC	F-Statistic	P-Value
MOBIL	ARCH (1)	6090.684	-9.07405	-9.066293	1.534937	0.21559
	ARCH (2)	9751.436	-14.5297	-14.52196	73.22273	0.045
	GARCH (1,1)	-4340.125	6.471125	6.478877	0.000762	0.977977
	GARCH (2,1)	7758.711	-11.5599	-11.55217	60.81772	0.997
	EGARCH (1,1)	2702.008	-4.0239	-4.016105	32.77166	0.887
	EGARCH (2,1)	2760.797	-4.1115	-4.103718	9.257035	0.002392
***	GJRGARCH (1,1)	8491.612	-12.6522	-12.64443	63.50458	0.967
	GJRGARCH (2,1)	-5262.543	7.845817	7.853569	0.000594	0.980566
MRS	ARCH (1)	-8776.359	12.92836	12.93604	0.002802	0.957789
	ARCH (2)	-8379.197	12.34344	12.35112	0.001319	0.971029
	GARCH (1,1)	-9391.079	13.83369	13.84137	0.001224	0.972092
	GARCH (2,1)	-7163.193	10.55257	10.56026	0.001208	0.972277
	EGARCH (1,1)	-14143.68	20.83311	20.84079	33.50358	0.975
	EGARCH (2,1)	-8319.633	12.25572	12.2634	440.6368	0.67
***	GJRGARCH (1,1)	-4797.061	7.067837	7.075515	1.071671	0.3008
	GJRGARCH (2,1)	-7060.64	10.40153	10.40921	0.00095	0.975412
TOTAL	ARCH (1)	-6852.08	10.10181	10.1095	0.018734	0.891154
	ARCH (2)	-6903.925	10.17822	10.18591	0.0021215	0.972197
	GARCH (1,1)	-5477.675	8.07616	8.083843	0.061196	0.8047
	GARCH (2,1)	-2493.148	3.677448	3.685131	0.172616	0.677863
	EGARCH (1,1)	-5796.189	8.5456	8.553283	348.4618	0.8977
	EGARCH (2,1)	-2194.419	3.23716	3.244852	97.46797	0.889

			8			
***	GJRGARCH (1,1)	-3590.334	5.294524	5.302207	4.875905	0.027401
	GJRGARCH (2,1)	-3576.978	5.274838	5.282521	4.524409	0.788

*** Indicates the best models for the different stocks.

Comparison of the Modified Models with the Existing Conditional Heteroscedastic Models

To determine the best conditional heteroscedastic models, the selected models from the modified volatility models for each of the stocks is compared with the same models from the existing volatility models to find out which of them has the least root mean square error. The ones that have the least RMSE will be adjudged as the most appropriate model and will be recommended. Hence, from the Table 6 below, for CON, MOBIL and OANDO, the modified GJRGARCH (1, 1) has the least RMSE. For ETERNA, the GJRGARCH (2, 1) GED root mean square error for the modified model is better than that of the existing model. The ARCH (2) RMSE for the modified model is less than that of the existing model for MRS. Again, modified GJRGARCH (1,1) GED is better than that of existing model.

Also, the log-likelihood values were compared for goodness of fit. Table 7 below shows that GJRGARCH (2,1) gives the best fit for CON, EGARCH (2,1) for ETERNA, ARCH (2) for MOBIL, GJRGARCH (1,1) for MRS, GJRGARCH (1,1) for OANDO and GARCH (2,1) for TOTAL respectively.

Table 8. Goodness of Fit, Model Selection and Diagnostic Check for the Selected Models

		Existing Models					Modified Models				
		Goodness of Fit	Model Selection		Heteroscedasticity		Goodness of Fit	Model Selection		Heteroscedasticity	
STOCKS	Models	Log-Likelihood	AIC	BIC	F-Statistic	P-V	LOG-Likelihood	AIC	BIC	F-STAT	P-V
CON	GJRGARCH (2,1)	646.748	-0.9602	-0.9524	0.0004	0.9840	3153.12	-4.693	-4.684	11.50152	0.909
ETERNA	EGARCH (2,1)	1811.783	-2.6951	-2.6874	93.2084	0.794	2986.014	-4.4438	-4.4361	35.8204	0.899
MOBIL	ARCH (2)	3115.068	-4.6395	-4.6317	17.1129	0.00004	8491.612	-12.652	-12.644	63.505	0.967
MRS	GJRGARCH (1,1)	-7373.92	10.8924	10.9001	0.000008	0.9977	-4797.061	7.068	7.076	1.076	0.3008
OANDO	GJRGARCH (1,1)	-11423.5	17.0215	17.0138	345.444	0	-4381.467	6.461	6.468	1.609	0.2048

TOTAL	GARCH (2,1)	-2625.67	3.8727	3.8804	51.3916	0	-2194.419	3.237	3.237	97.468	0.788

The results in Table 8 revealed that all the returns were stationery and Table 8 showed the presence of heteroscedasticity in six of the stocks except FORTE. The results showed leverage effects presence in the daily return series of all the Nigerian Oil stocks in Tables 4a and 4b respectively. The leverage effects mean that there is positive and negative news on the returns of the Nigerian Oil stocks and the distribution of the returns is asymmetric in nature. This result is in agreement with studies conducted in other countries like Saudi, Pakistan and India by Suliman (2012) and (Ali and Afzal, 2012) respectively. The GJRGARCH (1,1) was adjudged to be the best from the results of Tables 6 in terms of forecast performance evaluation which is consistent with the study of (Onwukwe et al.,2011). Hence, the need for asymmetric models. The binary variable in Tables 4a and 4b absorbed the dwindling effect and denoted low and high periods of volatilities. This research is also supporting the study (Vasudeva and Kumari, 2013) that where error is not normally distributed as assumed, other error distribution like the generalized error distribution be applied.

CONCLUSIONS AND RECOMMENDATIONS

From the results of analysis obtained, it is seen that the objectives of this study are greatly accomplished. The modified models used are the best in terms of forecast performance and fitness. The modified GJRGARCH (1,1) model is adjudged as the most suitable conditional heteroscedastic model for forecasting the volatility of the Nigerian oil stock market. Therefore, these findings will be beneficial to economic forecasters to make a right choice of best volatility models and investors to take the right and timely decision about their investments.

FURTHER STUDY

This research still has limitations so further research is still needed on this topic "Modified Volatility Conditional Heteroscedastic Models using Binary Variable

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