



## Research Article

# Modelling of Volatility in Nigeria Crude Oil Price Using symmetric and asymmetric GARCH models

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### ABSTRACT

Accurate modelling of volatility is important in finance, particularly as it relates to the modelling and forecasting of crude oil prices. This paper examines which of the model can best handle the price volatility of the Nigeria Crude Oil market. The models consider in this work are the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) and Power Autoregressive Conditional Heteroskedasticity (PARCH). The analysis displays the evaluation of the enactment of Nigerian crude oil price for GARCH (1, 1), EGARCH (1, 1) and PARCH (1, 1) models. The data used was collected from the Central Bank of Nigeria website for twelve (12) years (2010 - 2021) which make up of 2422 observations. Time Series was carried out using Eviews 9 and the result shows that the GARCH model outperforms EGARCH and PARCH models based on the value of Akaike Information Criteria.

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### INTRODUCTION

Moderate modelling of volatility is significant in finance, especially as it relates to the modelling of volatility in Nigeria's crude oil price. Financial time series data such as gross domestic products (GDP), crude oil prices, stock prices, exchange

rates, inflation rates to mention but a few are some of the variables that frequently display the features of clustering. A period then refers to volatility clustering whereby prices show widespread within an extended time and it will later show relatively

calmness. This is not only applicable to variables such as gross domestic products (GDP), crude oil prices, stock prices, exchange rates, inflation rates etc. but they are also applicable to virtually all microeconomic variables. For example, all the indicators and determinants of employment and production, consumption, investment in raising productive capacity and how much a country imports and exports. They suffered sudden fluctuation and this continual fluctuation affects so many things thus contributing to the increase in price volatility and revenue profile of these products. And these are some of the causes of economic shocks widely experienced in Nigeria as well as the world at large”.

Agenor et.al (2000) reported that macro-econometric variables and trade shocks arising from price volatility have a great significant effect on developing countries like Nigeria, Ghana etc. The economic effect that arose on the private and public saving has a high influence which arose because of the shocks in aggregate economic volatility.

Generally, “volatility can be seen as variance, and it is a proportion of dispersion of a random variable from its mean value. The study of volatility is essential in financial investment. The degree of volatility in a financial market provides a measure of risk exposure to investors on their investments. Most investors and financial analysts are concerned about the uncertainty of the variability in speculative market prices (and market risk) and the instability of business performance” Alexander (1999)

Several authors have written generally about handling volatility problems using the family of GARCH. In this research, we aimed at comparing the effectiveness of symmetric and asymmetric GARCH models in handling volatility in Nigeria crude oil price by applying the following models GARCH, EGARCH, and PARCH.

The purpose of this research work is to model the price volatility of the crude oil market in Nigeria, by relating different univariate specifications of the

GARCH type model using E-views to analyze the day-to-day observations from October 2010 to July 2021. Also, to determine which of the model can best handle the price volatility of Nigeria’s crude oil market.

### **Brief insights from extant literature**

This segment outlined some related literature in modelling volatility in a financial time series and other related areas of Nigeria’s economy. “Some popular existing models in the literature are: Autoregressive Conditional Heteroscedasticity (ARCH) model which was proposed by Engle (1982) but due to the limitations of the ARCH model there came a Generalized Autoregressive Conditional Heteroscedasticity(GARCH) model which was proposed by Bollerslev (1986), Nelson (1991) proposed Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) due to the limitation of ARCH/GARCH models that is, failure to take into account leverage effect in financial investment returns”.

Deebom and Isaac (2017) researched on “modelling volatility of Nigerian crude oil markets using GARCH model from January 1987 to June 2017. The results from the statistical analysis revealed that the markets were optimistic about their investment and other trade-related activities. It was also discovered that there were high probabilities of gains than losses. In estimation, first-order symmetric GARCH model GARCH, (1,1) in student’s-t error assumption gave a better fit than the first order asymmetric GARCH model EGARCH (1,1) in normal error distributional assumptions”. Therefore, they advised investors or marketers in this market to be mindful of trading in a highly volatile period, especially when there is evidence of high standard deviation in statistics of series return and in modelling of the volatility of price return of certain micro/macro-economic variables, the leverage effect of such variable should be appropriately estimated using asymmetric GARCH model.

Chaido (2018) observed the Stockholm Stock Exchange volatility using day-to-day stock returns. The results showed a high effect of negative shocks than positive shocks in this market.

Mulukalapally (2017) carried out research on “modelling and forecasting the financial volatility of daily returns of India stock market from September 17, 2007, to December 30, 2016. He applied GARCH family models to inspect the performance of stock return volatility for India stock market”. The result indicated evidence of asymmetric and leverage effect, volatility clustering and non-existence of risk premium in the Indian stock market.

Savadatti (2018) “analysed the volatility pattern of the Bombay Stock Exchange (BSE) using symmetric and asymmetric GARCH models based on the daily return series of the S and P BSE all-cap index covering 2005 to 2018. The result shows evidence for the presence of leverage effect in the day-to-day return series”.

Joseph and Eric (2006) applied the GARCH type family model to forecast the volatility on the Ghana Stock Exchange. The unique “three days a week” Databank Stock Index (DSI) was used to study the dynamics of Ghana’s stock market volatility over a 10-years period. Their output showed that the Databank Stock Index (DSI) used in representing

### Theoretical Framework

The work focused on symmetric and asymmetric GARCH models.

### ARCH

$$\sigma^2_t = a + \sum_{i=1}^q b_i e^2_{t-1} \quad (1)$$

Where  $a \geq 0$  implies the conditional variance at time  $t$ , while  $a$  is constant,  $b_i$  represents the parameters

the market returns of Ghana exhibits stylised characteristics like leptokurtosis, asymmetric effects, and volatility clustering associated with stock market returns. The result showed that GARCH (1, 1) model performed better than the other model using normal distribution as the error innovation.

Olayemi *et al.* (2021) carried out research on “Modelling the Efficiency of TGARCH Model in Nigeria Inflation Rate”. They looked at the efficiency of the GARCH and TGARCH models in terms of forecasting and best of fit by considering RMSE and AIC. The result shows that TGARCH is more efficient in terms of forecasting evaluation and best of fit.

### METHODOLOGY

The day-to-day price of Nigerian crude oil in USD over the study period (October 2010 through July 2021) was extracted from the Central Bank of Nigeria (CBN) website used in modelling the type of GARCH family in this article.

The heteroscedasticity models used in this research work include the GARCH (1, 1), PGARCH (1, 1) and EGARCH (1, 1). TGARCH and EGARCH are both asymmetric models, but literature has shown that EGARCH is superior to TGARCH in most cases. In view of this, EGARCH was used in place of TGARCH for the purpose of this research Ali (2013).

of the general order of ARCH terms and mean the lagged values of the squared prediction error.

“The GARCH method has a wide range of capital markets applications. The model is based on the assumptions that to forecast the variance changing in time which depends on the lagged variance of

capital assets. An unexpected increase or fall in the returns of an asset at time  $t$  will generate an increase in the variability expected in the period to come”.

**The GARCH ( $p, q$ ) model is given as:**

$$\sigma^2_t = a + \sum_{i=1}^q b_i e^2_{t-1} + \sum_{j=1}^p c_j \sigma^2_{t-j} + w_t \quad (2)$$

$p$  represents the degree of GARCH;  $q$  is the degree of the ARCH process; and  $w_t$  a random component with the properties of white noise”.

The commonly used model is GARCH (1,1), which can be expressed as:

$$\sigma^2_t = a + b e^2_{t-1} + c \sigma^2_{t-1} + w_t \quad (3)$$

“Such that  $\sigma^2_t, a, b$  and  $e^2_{t-1}$  are as defined in equation (1),  $c$  is the GARCH coefficient and  $e^2_{t-1}$  represents the one period lag of the fitted variance from the model. To ascertain a well-defined GARCH (1,1) model, it is required that  $b \geq 0$  and  $c \geq 0$  while  $b + c < 1$  suffices for covariance stationarity.

### EGARCH

Nelson (1991) proposed EGARCH model to inspect the asymmetric effect of the conditional volatility and was indicated as:

$$\log \sigma^2_t = a + b_1 \left| \frac{\mu_{t-1}}{\sigma_{t-1}} \right| + c_1 \log(\sigma_{t-1}) + d \frac{\mu_{t-1}}{\sigma_{t-1}} \quad (4)$$

Where  $\log$  is the natural logarithm of conditional variance,  $\log(\sigma^2_{t-1})$  is the previous day's natural log of conditional variance,  $a$  is the constant term,  $b_1$  is the parameter represents a magnitude effect;  $d$  is the parameter measures the asymmetric or the leverage effect, the parameter of importance so that the EGARCH model allows for testing of asymmetries. If  $d = 0$ , then the model is symmetric; that is with the same magnitude of shock occurring, positive shocks (good news) generate the same volatility as negative shocks (bad

news); if  $d < 0$ , there is the presence of leverage effect; that is with the same magnitude of shock occurring negative shocks generate more volatility than positive shocks”. Finally, if  $d > 0$ , the impact is asymmetric, it implies that with the same magnitude of shock occurring, positive shocks generate more volatility than negative shocks;  $c_1$  measures the persistence in conditional volatility irrespective of what is happening in the financial investment and when it is relatively large, according to Alexander (2009),

### PARCH

The PARCH model is an extension then “volatility takes a long time to die out” following a shock in

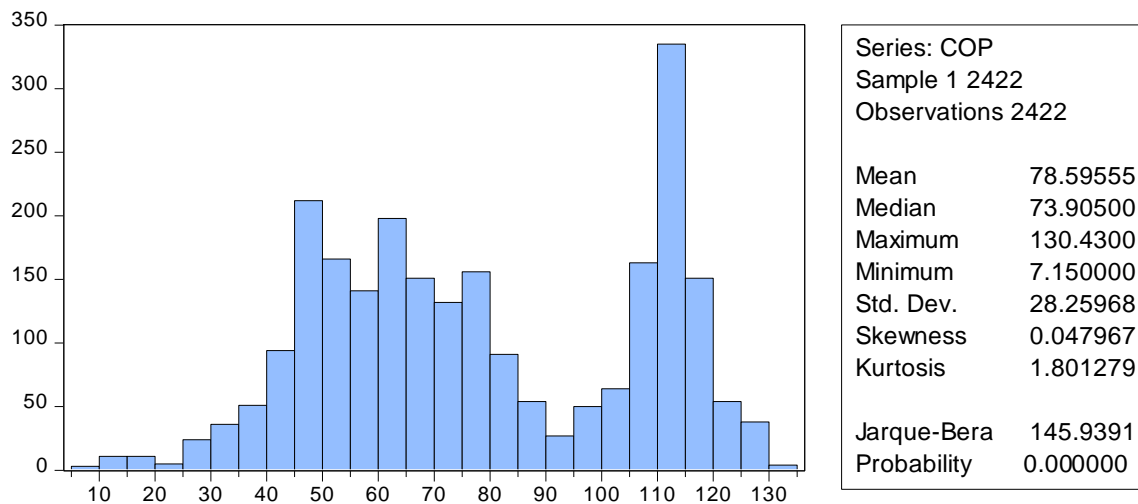
the financial investment of GARCH with an extra term added to account for possible asymmetric and it can be expressed in this way

$$\sigma^2_t = a + b e^2_{t-1} + c \sigma^2_{t-1} + d \mu^2_{t-1} I_{t-1} \quad (5)$$

**RESULTS AND DISCUSSION**

In this section, a summary of the descriptive statistics of the time series data was discussed. Also, the Augmented Dickey-Fuller Test for unit

root was carried out, and the performance of the volatility models was estimated.



**Figure 1:** Descriptive statistics of Nigeria’s daily crude oil price in USD

Figure 1, gives a summary of the descriptive statistics of the time series data collected from the Central Bank of Nigeria on Nigerian crude oil.

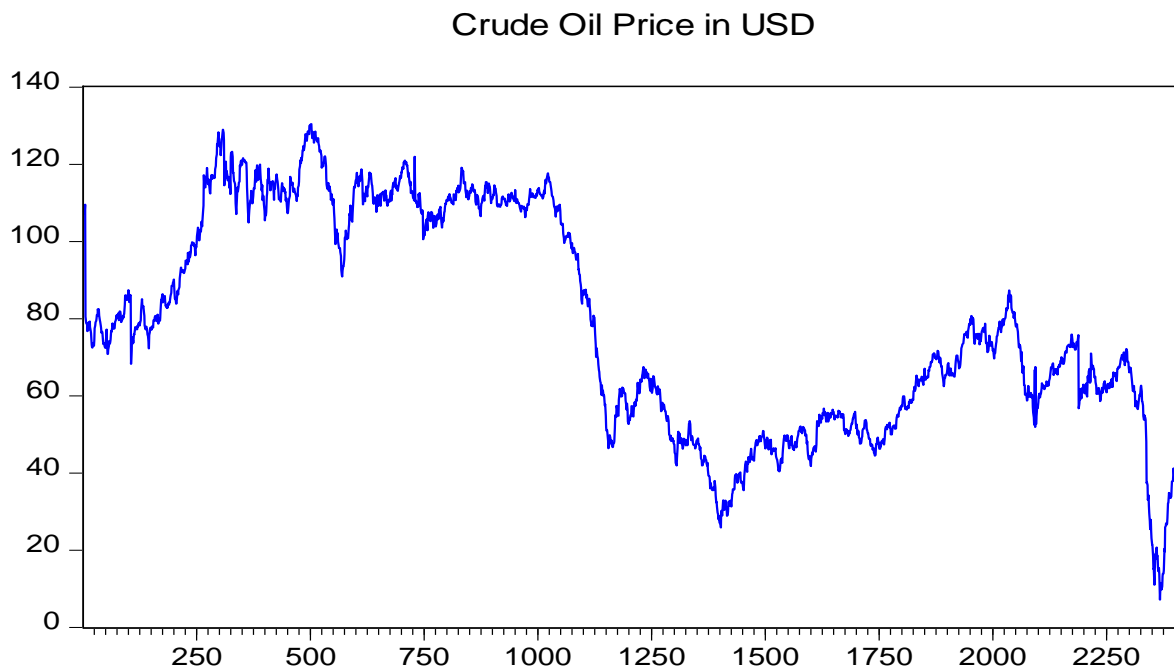
**Table 1:** Augmented Dickey-Fuller Test for unit root

Null Hypothesis: Crude Oil Price has a unit root			
Exogenous: Constant, Linear Trend			
Lag Length: 1 (Automatic - based on SIC, maxlag=26)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.884150	0.6624
Test critical values:	1% level	-3.961837	
	5% level	-3.411665	
	10% level	-3.127708	

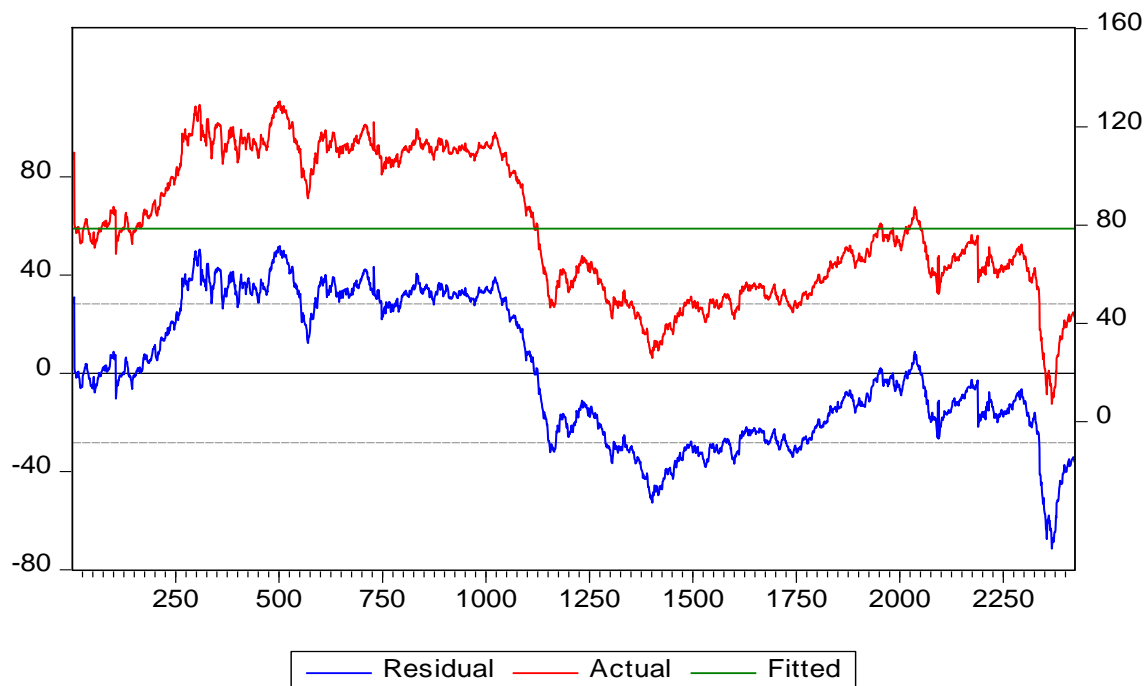
Sample: October 2010 to July 2021

Test for the possible unit roots in the returns series, the augmented Dickey-Fuller (ADF) statistic is calculated. The result in Table 1 suggests that the

null hypothesis of unit root can be rejected at a 1% level of significance.



**Figure 2:** Monthly Price of Nigeria Crude Oil Export Market (US Dollar/Barrel) – Clustering Effect



**Figure 3:** The residual plot Crude Oil Price

Day 1 to day 1200, a period of high volatility is followed by a period of high volatility for a

prolonged period. From 1200 days until 2100-day, a period of low volatility is followed by another

period of low volatility for a prolonged period. Again from 2100 days to 2250 days, a period of high volatility is followed by a period of high

volatility for a prolonged period. With this, there is justification for running the ARCH model.

**Table 2:** Test of ARCH effect

Heteroskedasticity Test: ARCH				
F-statistic	131837.1	Prob. F(1,2419)	0.0000	
N*R-squared	2377.379	Prob. Chi-Square(1)	0.0000	
Test Equation :				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample (adjusted): 2 2422				
Included observations: 2421 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.325161	2.924015	2.505172	0.0123
RESID^2(-1)	0.991054	0.002729	363.0938	0.0000
R-squared	0.981982	Mean dependent var	798.2536	
Adjusted R-squared	0.981975	S.D. dependent var	714.8679	
S.E. of regression	95.97685	Akaike info criterion	11.96692	
Sum squared resid	22282751	Schwarz criterion	11.97170	
Log-likelihood	-14483.95	Hannan-Quinn criteria.	11.96866	
F-statistic	131837.1	Durbin-Watson stat	2.035281	
Prob(F-statistic)	0.000000			

Sample: October 2010 to July 2021

This can be achieved by using ARCH Model to test for the EGARCH model or not.  $P = 0.0000$

Null hypotheses: There is no ARCH effect

Alternative hypotheses: There is ARCH effect

Since the p-value is less than 5%, we, therefore, have enough evidence to reject null hypotheses and accept the alternative hypothesis. Also, the F statistic and

$N \cdot R^2$  shows that there is ARCH in the data. This totally justifies the use of GARCH, EGARCH and PARCH models. Next, we specify the GARCH (1, 1), EGARCH (1,1) and PARCH (1,1) models and carry out the analysis. This analysis was carried out using the e-views software.

**Table 3:** Normal Distribution for EGARCH

Dependent Variable: COP				
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)				
Sample: 1 2422				
Included observations: 2422				
Convergence achieved after 54 iterations				
Coefficient covariance computed using the outer product of gradients.				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)				
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	62.28164	0.082048	759.0844	0.0000
Variance Equation				
C(2)	-0.984081	0.113418	-8.676578	0.0000
C(3)	1.356876	0.159637	8.499732	0.0000
C(4)	0.035295	0.080906	0.436251	0.6627
C(5)	0.939238	0.025945	36.20173	0.0000
R-squared	-0.333396	Mean dependent var		78.59555
Adjusted R-squared	-0.333396	S.D. dependent var		28.25968
S.E. of regression	32.63224	Akaike info criterion		8.554848
Sum squared resid	2578033.	Schwarz criterion		8.566806
Log-likelihood	-10354.92	Hannan-Quinn criteria.		8.559196
Durbin-Watson stat	0.002797			

Sample: October 2010 to July 2021

The model for the EGARCH model for the Nigeria crude oil price can be expressed as follows:

$$\begin{aligned}
 \text{LOG}(\text{GARCH}) = & -0.984081 + 1.356876 \times \text{ABS}\left(\frac{\text{RESID}(-1)}{\text{@SQRT}(\text{GARCH}(-1))}\right) \\
 & + 0.035295 \times \frac{\text{RESID}(-1)}{\text{@SQRT}(\text{GARCH}(-1))} + 0.939238 \times \text{LOG}(\text{GARCH}(-1)) \quad (6)
 \end{aligned}$$

**Table 4:** GARCH/TARCH Test with normal Distribution

Dependent Variable: COP				
Method: ML ARCH - Normal distribution" (BFGS / Marquardt steps)				
Sample: 1 2422				
Included observations: 2422				
Convergence achieved after 48 iterations				
Coefficient covariance computed using the outer product of gradients.				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	65.25981	0.090751	719.1055	0.0000
"Variance Equation"				



C	0.779815	0.260884	2.989123	0.0028
RESID(-1)^2	0.865830	0.158685	5.456289	0.0000
GARCH(-1)	0.144858	0.051439	2.816146	0.0049
R-squared	-0.222781	Mean dependent var		78.59555
Adjusted R-squared	-0.222781	S.D. dependent var		28.25968
S.E. of regression	31.24940	Akaike info criterion		8.533669
Sum squared resid	2364167.	Schwarz criterion		8.543235
Log-likelihood	-10330.27	Hannan-Quinn criteria.		8.537148
Durbin-Watson stat"	0.003050			
<b>Sample: October 2010 to July 2021</b>				
<b>Variance Equation:</b>				
$\sigma_t^2 = 0.779815 + 0.865830e_{t-1}^2 + 0.144858\sigma_{t-1}^2 + w_t \quad (7)$				
Coefficients of the constant variance term, the ARCH and GARCH parameters are positive and statistically significant at 1% level.				
This gives the result of the GARCH model. The time-varying volatility includes a constant (0.779815) plus its past (0.865830 $e_{t-1}^2$ ) and a component that depends on the past error (0.144585 $\sigma_{t-1}^2$ )				
<b>Table 5:</b> PARCH Test with normal Distribution				
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)				
Sample: 1 2422				
Included observations: 2422				
Convergence achieved after 58 iterations				
Coefficient covariance computed using the outer product of gradients.				
Presample variance: backcast (parameter = 0.7)				
@SQRT(GARCH)^C(6) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(-1))^C(6) + C(5)*@SQRT(GARCH(-1))^C(6)				
Variable				
Coefficient				
Std. Error				
z-Statistic				
Prob.				
C	62.34112	0.104357	597.3841	0.0000
Variance Equation				
C(2)	1.168035	0.498201	2.344504	0.0191
C(3)	0.984173	0.232328	4.236134	0.0000
C(4)	-0.004378	0.070444	-0.062151	0.9504
C(5)	0.005285	0.069015	0.076582	0.9390
C(6)	1.658908	0.626585	2.647540	0.0081
R-squared	-0.330970	Mean dependent var		78.59555
Adjusted R-squared	-0.330970	S.D. dependent var		28.25968
S.E. of regression	32.60253	Akaike info criterion		8.535501
Sum squared resid	2573341.	Schwarz criterion		8.549850
Log-likelihood	-10330.49	Hannan-Quinn criteria		8.540718
Durbin-Watson stat	0.002802			

Sample: October 2010 to July 2021

$$PARCH = 1.168035 + 0.984173 \times (ABS(RESID(-1))) + 0.004378 \times RESID(-1))^{1.658908} \\ + 0.005285 \times @SQRT(GARCH(-1))^{1.658908} \quad (8)$$

**Table 6:** Summary of the results

	<b>GARCH</b>	<b>PGARCH</b>	<b>EGARCH</b>
<b>Akaike Information Criterion</b>			
<b>(AIC)</b>	8.533669	8.535501	8.554848
<b>Schwarz Criterion (BIC)</b>	8.543235	8.549850	8.566806
<b>Hannan-Quinn Criterion (HQ)</b>	8.537148	8.540718	8.559196

**Sample:** October 2010 to July 2021

The table above shows that comparing the three models using AIC; it was discovered that GARCH (1,1) model outperformed the EGARCH (1,1) and PARCH (1,1) models in terms of best fit because it

has the least Akaike Information Criterion (AIC) of 8.533669. Likewise, looking at the EGARCH (1,1) and PGARCH (1,1), the finding shows that PARCH (1,1) is better than EGARCH (1,1).

## CONCLUSION AND RECOMMENDATION

Three different models were reflected in this empirical work. “The price volatility of Nigeria crude oil market was modelled by applying the generalized autoregressive conditional heteroscedasticity (GARCH) models including symmetric and asymmetric models that capture most common stylised facts about Crude oil price in Nigeria markets such as volatility clustering and leverage effects. These models are GARCH (1,1), exponential GARCH (1,1) and power GARCH (1,1). The first model implies a symmetric effect of past shocks, whereas the last two EGARCH and PGARCH models captured asymmetric effects. While comparing the three models using AIC, it was discovered that GARCH (1,1) model outperformed EGARCH (1,1) and PGARCH (1,1) models because

it has the least Akaike info Criterion (AIC) of 8.533669. The EGARCH (1,1), GARCH (1,1) and PARCH (1,1) models are given as seen in equations 6,7 and 8, respectively.

The AIC for the EGARCH (1,1) and PARCH (1,1) models is 8.554848 and 8.535501 respectively, while that of the GARCH (1,1) is 8.533669. Many other areas can be considered, such as combining the GARCH with the EGARCH and or with the PARCH to form a model that is the GARCH-EGARCH or the GARCH-PARCH models and compared the result with the GARCH, EGARCH, and PARCH models to see the efficiency of the combine symmetric and asymmetric models on the set of data. This aspect can be studied in future research to get an improved result.

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