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Impact of News on Volatility of Nigeria's Crude Oil Prices Using Asymmetric Models with Error Distribution Assumptions

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Abstract
This study investigates the asymmetrical volatility of crude oil prices in Nigeria using error distribution assumptions from 1982 to 2023. The study materials are from the National Bureau of Statistics (NBS) data repository. Asymmetric generalized autoregressive conditional heteroscedasticity models, such as EGARCH, PGARCH, and TGARCH, were used to investigate the leverage effect under the assumption of error distributions. After assessing many models, we determined that the PGARCH (1,1) was the best depiction of asymmetry and leverage in Nigerian crude oil price returns, assuming a normal error distribution. The serial correlation LM test and the stability diagnostic check both proved the model's resilience. The PGARCH model with normal error distribution is a valuable tool for risk management and portfolio optimization in the Nigerian crude oil market since it considers the leverage effect, heteroscedasticity, and responsiveness to news or shocks at different volatility levels.

Keywords: Volatility, Crude Oil Prices, News Impact, Asymmetry, Error Distribution

Introduction

Crude oil prices are closely monitored by everyone from producers to consumers, investors, and politicians due to its importance as a global economic indicator. Over the past decade, significant theoretical and empirical research has focused on understanding and forecasting the volatility of crude oil prices. Investors and energy policymakers must be mindful of Nigeria's volatile crude oil price. In reality, volatility is a fundamental notion in econometrics, and a variety of value-at-risk models use it to assess or anticipate market risk. To summarize, Brooks and Persand (2000) demonstrate that many common methods for estimating the risk-adjusted value of a securities business rely on evaluating the correlation and historical volatility of returns to the assets that comprise the portfolio. According to Usoro and Ekong (2022), crude oil prices have an evident influence on Nigeria, since the country's economy is significantly dependent on the petroleum industry. Stock prices, inflation rates, currency rates, crude oil prices, and other financial time series data often show volatility clustering, as noted by Deebom and Essi (2017). Deebom and Essi (2017) made Gujarati's work in 2009 more accessible by emphasizing the necessity of understanding volatility and how it pertains to a variety of different fields. Given the volatility of the global market, investors must understand when to put their money in and when to exit in order to reduce their losses and maximize their winnings. Mistakes in estimating crude oil prices, as well as the significance of forecasting, have increased in line with the weight of risk and uncertainty in economic theory (Brooks, 2014). So, based on previous data, how can we predict the return's average and standard deviation? This will be done via the use of many asymmetric generalised autoregressive conditional heteroscedasticity models, each with its own error distribution. Models with volatility dynamics enable asymmetric reactions to positive and negative shocks, which is critical for correctly modelling crude oil price behaviour.

Several studies have tried to dive into the difficult idea of modelling volatility asymmetry using generalized autoregressive conditional heteroscedasticity, as a measure of capturing uneven variance and its effects on micro and macroeconomic variables have not been extensively investigated. Engle (1982) presented the first model of conditional heteroscedasticity, which used conditional variance of white noise.

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When employing empirical ARCH models, researchers often encounter the problem of over-parameterization. Bollerslav (1986) proposed an enhanced form, generalized autoregressive conditional heteroscedasticity, as a solution to the parameterization issue. A proposal to adapt the GARCH model to solve issues with the conventional GARCH (p,q) model was accepted. These issues included an inability to account for unequal volatility consequences and practical implementation that violated the non-negativity condition. To name a few, Nelson (1991) offered the Exponential GARCH, Ding et al. (1993) suggested the Power GARCH, and Zakoian (1990) introduced the Threshold GARCH, all of which exhibit volatility asymmetry. Given the above, it is vital to investigate additional similar research with a focus on context.

Asemota et al. (2017) used GARCH models to investigate the volatility of stock weekly returns at six banks. The estimated model found no evidence of a leverage effect, however the findings reveal that ARCH had an impact on B2 and B3 equity returns. After estimating using conventional criteria, the best volatility models for B2 and B3 were found to be EGARCH (1,1) and CGARCH(1,1) in the context of the student's t-distribution. The research argues that for replicating stock market volatility, multiple GARCH models and other error distributions should be used. This will assist to guarantee that the findings are valid. Deebom and Essi (2017) utilized the GARCH model to anticipate volatility in the Nigerian crude oil market. The purpose of this study is to evaluate the price volatility and risk return associated with crude oil exports in Nigeria using first-order symmetric and asymmetric univariate GARCH family models with three distributional assumptions: normal, student's t, and generalized error. The study data comes from the Nigerian central banks' online statistics data source. The symmetric GARCH (1,1) model fits the student's t-distributed data better than the asymmetric model, according to the estimated results. The government was advised to diversify its economy by investing in mining, manufacturing, and agriculture. Mbwambo and Letema (2023) employed asymmetric GARCH models to estimate oil return volatility using data from Tanzania. The research anticipates the return on Brent crude oil prices from January 2002 to February 2022 using a set of asymmetric GARCH models. The most successful model for forecasting crude oil price volatility was GJRGARCH (1,1). They conducted a diagnostic examination to see if the selected model was appropriate. According to the study's suggestions, the GJRGARCH technique may be used to forecast how unexpected events will develop in the future.

Onyeka-Ubaka and Anene (2020) investigated multiple forecast asymmetry GARCH models for long-tail distributions. It predicts and forecasts variations by using asymmetric GARCH models with normal, student's t, and generalized error distributions. In terms of forecast inaccuracy for both West Texas Intermediate and Brent oil spot prices, the EGARCH and asymmetric power GARCH models outperform the other asymmetric GARCH models across the board. Victor-Edema and Wariboko (2023) investigated the effectiveness of symmetric and asymmetric GARCH models in the Nigerian crude oil market between 1999 and 2023. The study examined data from the Central Bank of Nigeria's (CBN) Statistical Database, which contained crude oil prices in Naira/Dollar from January 1999 to April 2023. The return on crude oil price using the symmetric and asymmetric GARCH models supports TGARCH as the best-fitting model under student-t, with a fixed parameter degree of freedom (df=10). The following models were considered: GARCH (1,1), EGARCH (1,1), and TGARCH (1,1). The results of the diagnostic tests revealed that TGARCH is adequate for forecasting crude oil prices in Nigeria. Among other things, the study's authors proposed that the TGARCH model might have a substantial influence on volatility, prompting market players to incorporate risk into their strategy. After reviewing multiple sources on the asymmetry in crude oil prices in Nigeria, none have successfully modelled and evaluated the associated value-at-risk (VaR). This study intends to breach this gap by addressing this issue.

Statement of the Problem

Despite the importance of Nigeria's crude oil market in the worldwide energy landscape, there has been a dearth of thorough research that considers the variance in the assumptions made regarding error distribution. Traditional symmetric models may fail to account for crucial subtleties in crude oil price behaviour, resulting in inaccurate forecasts and ineffective risk management measures. Research and analysis of the asymmetry in the volatility of Nigeria's crude oil price, under proper error distribution assumptions, it is therefore crucial for a better understanding of the underlying market dynamics and improving decision-making processes for energy sector participants.

Aim and Objectives of the Study

One may reproduce the imbalance in the volatility of Nigeria’s crude oil price by examining the assumptions of the error distribution. The objectives of the study include to;

i. Determine the trend in the movement of the crude oil price market in Nigeria

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ii. Model and evaluate crude oil price using asymmetric GARCH models in error distribution assumptions
iii. Examine volatility persistence and news impact assessment in the selected models
iv. Determine the best model for modeling the volatility of crude oil prices in error distribution assumptions in Nigeria

Materials and Methods

Using data from the National Bureau of Statistics (NBS) database, the study examines the dollar price of crude oil from 1982 to 2013. Crude oil price variance models, when fitted to conditionally compounded monthly return computation, demonstrate that;

$$RCOP = \log\left(\frac{COP_t}{COP_{t-1}}\right) * 100 \quad (1)$$

Where COP_t is crude oil price at time t, COP_{t-1} is crude oil price at time t-1.

Time Plot

This was inexorable, to see how the series was trending over time and to provide a visual representation of the changes.

ARCH Effect

Following the recommendation of Engle (1982), this test was used to examine if there was heteroscedasticity in the residual of the return on crude oil prices and the Lagrange Multiplier (LM) was made use of.
The test's working hypothesis is:
Ho : $\alpha_1, = \ldots. =, \alpha_q$ Absence of ARCH effect
H_1 : $\alpha_1, \neq \ldots. \neq, \alpha_q$ At least one variable has the presence of ARCH effect

Asymmetric GARCH Model Specification

The Exponential GARCH (EGARCH) Model

Accordingly, EGARCH, the conditional variance of the exponential generalized autoregressive conditional heteroscedasticity proposed by Nelson (1991), is:

$$\log(\sigma_t^2) = \varphi + \sum_{i=1}^{q} \eta_i \left|\frac{u_{t-1}}{\sqrt{h_{t-i}}}\right| + \sum_{i=1}^{q} \gamma_i \left|\frac{u_{t-1}}{\sqrt{h_{t-i}}}\right| + \sum_{k=1}^{p} \theta_k log(\sigma_{t-1}^2) \quad (2)$$

φ – Constant
η – ARCH effects
γ – Asymmetric effects
σ_t^2 – Conditional variance at time t
θ – GARCH effects

The leverage effect is determined by the log of the variance series (h_t), which is exponential rather than quadratic. This ensures that the estimates are non-negative. When $\gamma_1 < 0$, negative shocks, which are bad news, produce greater volatility than positive shocks, which are good news, implying an asymmetric model as opposed to $\gamma_1 = \gamma_2 = \ldots = 0$ for a symmetric model.

The Asymmetric Power GARCH (PGARCH) Model

Asymmetric power autoregressive conditional heteroscedasticity (PGARCH) was introduced by Ding et al. (1993). It is a relatively general model that incorporates the standard GARCH, TGARCH, and Log-GARCH models, and it enhances the conditional volatility of asset returns' dynamics. As the standard PGARCH (p,q) method is described as;

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i(|\epsilon_{t-i}| - \vartheta_i \epsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \quad (3)$$

$\epsilon_t = \sigma_t \eta_t$
where $\omega > 0$, $\delta > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, $|\vartheta_i| \leq 1$, $E(\eta_t) = 0$ and $Var(\eta_t) = 1$
ϑ- Symmetric parameter
δ- Power term parameter

As a result, choosing $\vartheta_i > 0$ on the same modulus ensures that negative innovations impact the current volatility more than positive innovations, (Francq & Zakoian, 2010). A good way to describe the common asymmetric feature of financial series is by using the limitation $\vartheta_i \geq 0$, which is also applicable to more complex APARCH models.

The Threshold GARCH (TGARCH) Model.

The threshold GARCH model put out by Glosten et al. (1993) and Zakoian (1990) is intended to capture asymmetries in relation to positive and negative shocks. To determine if negative shocks might lead to a statistically significant change, it just incorporates a multiplicative dummy variable into the variance equation.
In a TGARCH (1,1) model, the conditional variance is explicitly expressed as

$$h_t = \vartheta + \theta_1 h_{t-1} + b_1 u_{t-1}^2 + \gamma_1 u_{t-1}^2 D_{t-1} \quad (4)$$

h_t – Conditional variance at time t
γ – Asymmetry or leverage term
D – Dummy variable
b – Good news
b+ γ – Bad news
u_{t-1}^2 – First lag of squared error term
Therefore, the TGARCH (p,q) model can be specified as:

$$h_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} (b_i + \gamma_i D_{t-i}) u_{t-i}^2 \quad (5)$$

One may account for the conditional variance of the standardized residuals of return innovation by including the Gaussian normal and student's t distributions. Based on the postulates of the normal distribution, the variance in the asymmetric GARCH models is defined by the dispersion and the probability function of the residuals.

$$L(\theta_t) = \frac{1}{2}\sum_{t-1}^{T}\left(ln 2\pi + ln\sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2}\right) \quad (6)$$

The student's t-distribution is used to estimate the volatility models in order to optimize the probability function, as indicated in section 3.7.

$$L(\theta_t) = \frac{-1}{2}\log\left[\!\left[\frac{\pi(\gamma)\sqrt{r/2}}{\sqrt{\frac{(\gamma H)^2}{2}}}\right]\!\right] - \frac{1}{2}\log \sigma_t^2 - \frac{(\gamma H)}{2}\log\left(1 + \frac{(Y_t - X_t^1\theta)^2}{\sigma_t^2\,(\gamma-2)}\right) \quad (7)$$

γ is the degree of freedom that controls the characteristic of the tail $\gamma > 2$

Results

Test for Volatility Clustering (Time Plot)

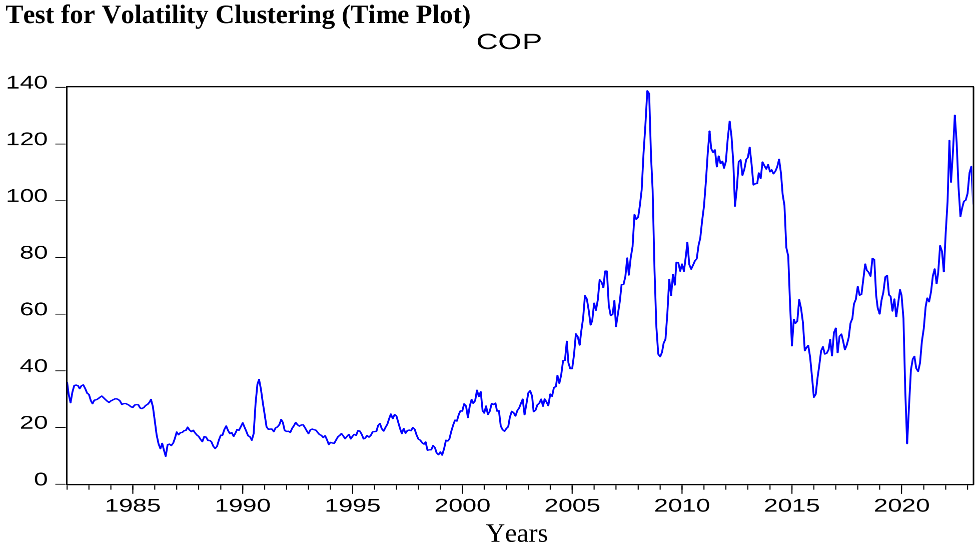

Figure 1: Time plot of Monthly Price of Nigeria Crude Oil (US Dollar/ Barrel) From January 1982 to April 2023.

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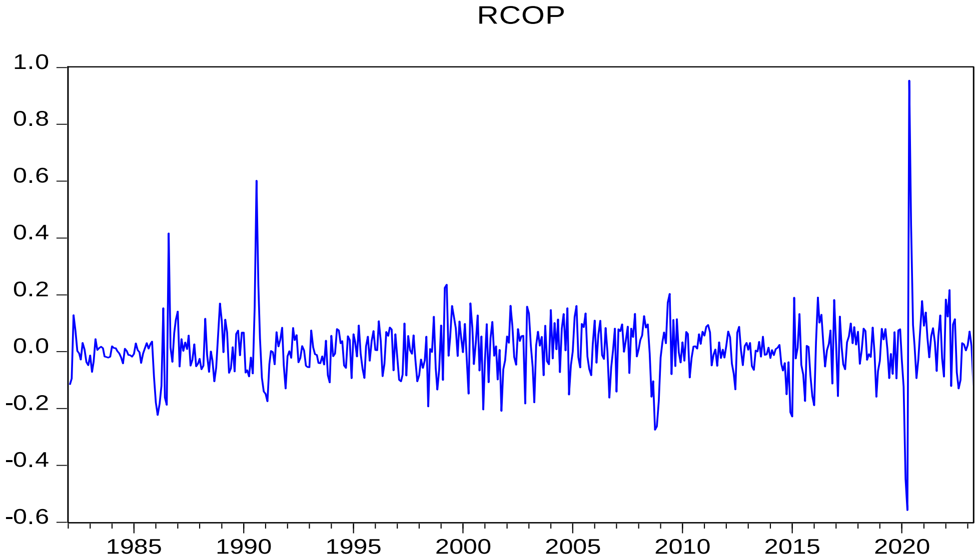

Figure 2 shows the monthly return on the price of Nigerian crude oil (in US dollars per barrel) from January 1982 to April 2002.

Figure 2 clearly demonstrates a clustering of volatility in the return of Nigerian crude oil prices, with periods of high volatility followed by periods of low volatility, and vice versa.

Summary Statistics of Nigeria's Crude Oil Price Return

Table 1: Descriptive Statistics for Crude Oil Price Return

Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
47.06871	31.06500	138.7400	9.82000	32.93633	0.931378	2.659945	74.10034	0.000

Source: Researcher's Computation, 2024

Table 1 includes summary statistics for the raw data from January 1982 to April 2023. A slightly long right tail exhibits some asymmetry, with a positive skewness of 0.931378. Also rejected is the notion that data has a normal distribution.

Test for Heteroscedasticity/Arch Effect

Table 2: Results of Test for ARCH Effect

Heteroscedasticity Test: ARCH	Lag 1
F-Statistic	440.7868
Prob. F(1.492)	0.0000
n^*R^2	233.4389
χ^2 (1)	0.0000

Source: Researcher's Computation, 2024 at 5% significant level.

The F-statistic and n*R2 tests in Table 3 demonstrate the influence of heteroscedasticity (ARCH) on the crude oil price series. Deebom and Essi (2017) suggest that while the test at lag 1 is adequate for recreating the asymmetry in crude oil price volatility investigated in this work, the test for larger lags was not performed. Table 3 illustrates the assumption of error distribution in the first-order asymmetric GARCH model.

Table 3: Estimation Results for First Order Asymmetric GARCH Family Models with Error Distribution Assumptions.

Model(s)	Model Parameter(s)	Normal Distribution		Student's - t Distribution		Error Model with Minimum AIC & SIC	
		Coefficients	P-Value	Coefficients	P-Value	Coefficients	P-Value
	Mean						
	Intercept	-0.001367	0.6163	-0.001277	0.6541		
	RCOP(-1)	0.195361	0.0000	0.203440	0.0000		
EGARCH(1,1)	Intercept(3)	-1.161537	0.0000	-0.915682	0.0000		
	Variance						
	ARCH(4)	0.734476	0.0000	0.579387	0.0000		
	Asymmetry(5)	-0.119717	0.0076	-0.155637	0.0076		
	GARCH(6)	0.881651	0.0000	0.906558	0.0000		
	AIC	-2.157664		-2.175621		-2.175621	
	SIC	-2.106621		-2.116071		-2.116071	
	ARCH+GARCH	1.616133		1.48594			
Model	Model Parameter(s)	Normal Distribution		Student's t- Distribution		Error Model with Minimum AIC & SIC	
		Coefficients	P-Value	Coefficients	P-Value	Coefficients	P-Value
	Mean						
	Intercept	-0.001521	0.5386	-0.001561	0.5769		
	RCOP(-1)	0.189978	0.0000	0.204599	0.0000		
PGARCH(1,1)	Intercept(3)	0.010565	0.1716	0.009344	0.2472		
	Variance						
	ARCH(4)	0.349686	0.0000	0.299583	0.0000		
	Asymmetry(5)	0.287805	0.0016	0.332979	0.0240		
	GARCH(6)	0.661308	0.0000	0.706638	0.0037		
	AIC	-2.139470		-2.159470		-2.159470	
	SIC	-2.116091		-2.091413		-2.116091	
	ARCH+GARCH	1.010994		1.006221			
	Mean						
	Intercept	-0.001440	0.6003	-0.000677	0.8125		
	RCOP(-1)	0.182474	0.0001	0.193804	0.0000		
TGARCH(1,1)	Intercept	0.00334	0.0344	0.000287	0.0521		
	Variance						
	ARCH	0.384756	0.0000	0.243162	0.0025		
	Asymmetry	0.311800	0.0122	0.348404	0.0117		
	GARCH	0.560356	0.0000	0.651325	0.0000		
	AIC	-2.126659		-2.145839		-2.145839	
	SIC	-2.075616		-2.086289		-2.086289	
	ARCH+GARCH	0.954112		0.894487			

Source: Researcher's Computation, 2024. Test conducted at 5% significant level

Model Selection & Fitness

Using the six approximated asymmetric models in Table 3, the model selection process made use of the Schwarz information criteria. Deebom & Essi (2017) prioritize the Schwarz Information Criteria (SIC) when selecting the best model for volatility prediction because it imposes a penalty for the maximum number of logically independent values that can vary in a data sample (see Table 4).

Table 4: Model Selection

First Order	Error Distribution Assumptions		Minimum SIC
Asymetric Models	**Normal Distribution**	**Student's t-Distr**	
EGARCH(1,1)	-2.106621	-2.116071	-2.116071
PARCH(1,1)	-2.116091	-2.091413	**-2.116091**
TGARCH(1,1)	-2.075616	-2.086289	-2.096289

Source: Researcher's Computation, 2024.

By plugging the values of PGARCH (1,1) into the normal error distribution equation, which is derived from the equation for the lowest SIC, the mean and variance equation is constructed.

Mean Equation

RCOP = -0.001243 + 0.203391*RCOP(-1)

Variance Equation

$SQRT(GARCH)^{0.831836} = 0.010562 + 0.349686*ABS(RESID(-1)) – 0.287805*RESID(-1)^{0.831836} + 0.661308*@SQRT(GARCH(-1)^{0.831836}$

ESTIMATED PARAMETERS OF THE SELECTED ASYMETRIC GARCH MODELS

Table 5 shows the influence of news on the volatility of crude oil prices as well as the volatility persistence from the three chosen models based on their estimated parameters.

Table 5: Test for Volatility Persistence and News Impact Assessment

Parameter Estimates of GARCH	Asymmetric GARCH Family Models		
	EGARCH	**PGARCH**	**TGARCH**
Distribution Assumptions	Student's t-distribution	Normal distribution	Student's t-distribution
Good News	0.579387	0.349686	0.243162
Bad News	0.42375	0.061881	-0.105242
Volatility Persistence	1.48594	1.010994	0.894487

Source: Researcher's Computation, 2024

Model Diagnostic Test

The models thus chosen based on SIC would have to undergo some tests to ensure the absence of ARCH effect or autocorrelation in the residuals as indicated in table 4.6 if the chosen models are sufficient.

Table 6: Diagnostic Test for Heteroscedasticity for the Three Best-Fitted Models.

Model	Heteroscedasticity Test: ARCH	Lag 1
EGARCH(1,1) in Student's	F-statistic	0.394045
t-Error Distribution	Prob. F(1,491)	0.5305
PGARCH(1,1) in	F-statistic	0.597316
Normal Distribution	Prob. F(1,491)	0.4400
TGARCH(1,1) in Student's	F-Statistic	0.315827
t-Error Distribution	Prob. F(1,491)	0.5744

Source: Researcher's Computation, 2024

Discussion

The monthly crude oil price range for this research spans from January 1982 to April 2023, with a total of 496 data points. Six models might be projected using the asymmetric GARCH-type family model and two error assumptions. The estimated findings were based on preliminary research that included time series plots, summary statistics, heteroscedasticity tests, asymmetric model estimation, and diagnostic confirmation. Figure 1 depicts the dynamic behaviour of crude oil prices from 1982 to 2024; it shows that there was an increasing trend in 2007, a downward trend in 2009, and then an upward trend in 2010. According to Asemota and Ekejiuba (2017), the return on crude oil prices is mean reverting because, as seen in Figure 2, the return series oscillates around the mean. There is also evidence of volatility clustering, with periods of relative calm followed by significant fluctuations over long periods of time. Gujarati's Time Series Econometrics: Forecasting (2013) supports this conclusion. Before getting into regression analysis, it is critical to have a sense of the data. Descriptive statistics were used to investigate the features of the crude oil price series. The findings revealed that the series does not follow a normal distribution, as the null hypothesis was rejected, and the Jarque-Bera statistics (74.101) with a matching probability (0.000000) support this. The standard deviation, 32.93633, represents the level of uncertainty associated with crude oil prices. As the standard deviation increases, so does the portfolio's volatility and risk, since the weight of the standard deviation influences the volatility of the crude oil price. Given that the mean is 47.06817, which is positive, the series must be flipped. The raw series on crude oil price exhibits positive skewness with the right tail, indicating asymmetry in the series when values exceed the sample mean.

The matching probability chi-square value is 0.0000, which is less than the 5% threshold of significance, and the Obs*R-square value is 233.4389, as given in Table 2. Therefore, the results cannot show the lack of an ARCH effect. As a consequence, the ARCH effect is visible in the crude oil price data. Therefore, information from the previous month's crude oil price may influence the return for the current month. Table 3 shows the results of an evaluation of six models, as well as the assumptions made regarding their error distributions, to assess the usefulness of asymmetric GARCH family models in measuring crude oil price volatility in Nigeria. Table 3 shows that the EGARCH estimates with the normal distribution assumption have a positive and statistically significant arch coefficient of 0.734476, whereas the student's t-distribution assumption has a positive and statistically significant arch coefficient of 0.579387, both at the 5% level of significance. This indicates that the student's t-distribution and the normal distribution of the previous month's crude oil price return both have a direct influence on the current month's return. To put it another way, at the 5% level of significance, both the asymmetry factor (-0.119717) in the normal distribution model and (-0.155637) in the student's t-distribution model are negative. According to the findings, there is a negative relationship between the return on previous crude oil prices and future volatility. As a result, both the normal distribution and the student's t-distribution models predict that negative shocks increase volatility in the crude oil price market more than positive shocks. For EGARCH (1,1), the ARCH(α) and GARCH(β) terms add up to 1.616133 (161.6133%) in the normal distribution model and 1.616133 (161.6133%) in the student's t-distribution model. This indicates that price movements in crude oil are unexpected since their volatility is only temporary. As a result, when the return on investment for crude oil is simulated using EGARCH (1,1) in a normal error distribution, volatility persistence is larger than with the student's t-distribution. With a normal error distribution, the Schwarz information criterion for EGARCH (1,1) is -2.106621, whereas the student's t-distribution is -2.116051. EGARCH (1,1) was shown to be the best-fitting model in the student's t-error distribution, with the lowest SIC.

Table 3 shows the variance equation for the PGARCH (1,1) estimate; however, the intercepts (0.010565) and (0.009344) are positive but do not meet the statistical criteria for significance, despite the fact that the ARCH coefficient in the normal error distribution (0.349686) and the student's t-distribution (0.299583) are positive and significant at the 5% level. Thus, the return on investment in crude oil in the past affects the return on investment in crude oil now. The statistically significant and positive coefficient of asymmetry in the normal error distribution (0.287805) and the student's t-distribution (0.332979) indicate a strong relationship between the price of delayed crude oil and future volatility in Nigeria's crude oil market. It goes without saying that good news has a favourable impact on crude oil prices, while negative news has a reverse effect. The ARCH terms add up to 1.010994 in the normal distribution and 1.006221 in the student's t-distribution, demonstrating that the models are mean reverting when exposed to persistent shocks. In particular, the levels of sustained volatility in the student's t-distribution is 100.6221% and the normal distribution is 101.0994%. In a normal error distribution, the Schwarz information criteria (SIC) for PGARCH (1,1) are -2.116091, while for the student's t-distribution is -2.091413. The best fitting model to describe the asymmetry in crude oil prices in Nigeria is PGARCH (1,1) in normal error distribution, which has the lowest SIC

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value. According to the results of Deebom et al. (2021), the Schwarz information criterion should be utilized since it discourages the decrease of degrees of freedom.

Table 3 shows that the ARCH coefficient in the normal error distribution is 0.384756, whereas in the student's t-distribution it is 0.243162. These numbers are positive and statistically significant, respectively. As a result, knowing the return of crude oil prices from the previous month influences the return of crude oil this month. When positive news emerges, crude oil prices recover with less volatility than when negative news breaks. In both the normal distribution and the student's t-distribution, the leverage coefficient is positive and statistically significant, at 0.311800 and 0.348404, respectively. The inclusion of the ARCH and GARCH components in the normal error distribution and student's t-distribution, respectively, does not satisfy the condition for a mean reverting variance process since the values are less than one. It considers the length of the shock effect and how it affects the volatility of crude oil price returns. However, in a normal distribution, the degree of volatility persistence is 954.99 percent, but in a student's t-distribution, it is 894.48 percent. As a result, when replicating the volatility of crude oil price returns in Nigeria over time, the TGARCH (1,1) distribution produces more consistent volatility than the student's t-distribution. Similarly, the Schwarz information criterion (SIC) for the TGARCH (1,1) model follows a normal distribution (-2.075616) and a student's t-distribution (-2.086289). According to the student's t-distribution, TGARCH (1,1) was the best match, with the lowest SIC score.

Table 4 shows the results of the model selection and fitness analysis for the asymmetric GARCH models used in this research. The EGARCH (1,1) model best suited the students' t-distribution, PGARCH fitted the normal error distribution, and TGARCH fitted the student's t-distribution assumptions. PGARCH (1,1) with SIC (-2.1160) was found to have the best fit under the normal error distribution assumption. The news effect evaluation for the chosen asymmetric GARCH models in table 5 shows that negative news has a considerably greater influence on volatility than good news. When simulating the price of crude oil over time using the student’s t-distribution, EGARCH (1,1) shows the greatest consistent volatility. To put it another way, a lengthy memory affects its volatility and durability. To determine the fitness of the asymmetric models, a battery of diagnostic tests was applied, including a heteroscedasticity test and a correlogram of standardized squared residuals as shown in table 6 and a confirmatory test using the correlogram of standardized squared residuals revealed that all models were serially uncorrelated, indicating that the residuals had no serial correlation.

Conclusion

This study used six models to model and investigate the asymmetry of conditional variance in crude oil price returns in Nigeria. According to the findings of all asymmetric models tested, the PGARCH (1,1) model is the best volatility model for crude oil price return under the normal error distribution assumption. The findings of this study are useful in directing investment decisions in terms of portfolio optimization and risk management strategies, as indicated by Asemota et al. (2017). Furthermore, the leverage crude oil market shown by the PGARCH (1,1) model is statistically significant at the 5% level with a positive sign, implying that positive shocks have a higher next-period conditional variance than negative shocks with a comparable sign. In contrast to the PGARCH model, the leverage crude oil price provided by the EGARCH (1,1) model is statistically significant, with a negative sign at the 5% level, meaning that negative shocks produce a bigger next-period conditional variance than positive shocks. The kind of return on the crude oil price index is therefore defined by its leverage effect. The leverage effect in crude oil prices may exacerbate the impact of minor fluctuations in market conditions on crude oil prices. Analyzing these assumptions allows us to have a better understanding of the factors that influence the volatility of this key commodity market.

Recommendations

This research is pertinent and topical as policymakers, investors, and energy industry players depend on an awareness of the volatility of crude oil price returns.

1. In modelling the asymmetry in Nigeria crude oil price returns it is advised to use the PGARCH (1,1) model with normal error distribution.
2. Using the PGARCH (1,1) model in normal error distribution to investigate asymmetry in volatility of Nigeria crude oil price returns helps in risk management and portfolio optimization strategies for investors as it allows different specifications of volatility to account for leverage effect, heteroscedasticity and response to news or shocks.
3. Before putting any plan into operation in Nigeria, the legislators must acknowledge past rather than current return on volatility of crude oil, in line with political and financial crises (bad news).

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