PRINT ISSN 1119-8362
Electronic ISSN 1119-8362

Full-text Available Online at
https://www.ajol.info/index.php/jasem
http://www.bioline.org.br/ja

J. Appl. Sci. Environ. Manage.
Vol. 26 (5) 913-919 May 2022

COVID-19 Pandemic and Volatility Persistence of the Nigerian Crude Oil Price

[*1]SAMSON, TK; [2]RAHEEM, MA

*[*1]Statistics Programme, College of Agriculture, Engineering and Science, Bowen University, Iwo, Nigeria*
[2]Department of Statistics, University of Uyo, Uyo, Akwa Ibom State, Nigeria
**Corresponding Author Email: kayode.samson@bowen.edu.ng; Tel: +2348032794217*
Other Authors Email: rahemarsac@yahoo.com

ABSTRACT: Impacts of COVID-19 pandemic on the global economy cannot be overemphasized, especially with Nigeria, which largely depends on crude oil as a major source of her revenue. Thus, investigating COVID-19's impacts on the volatility persistence of Nigerian crude oil price forms the nucleus of this study. Our modelling framework was based on GARCH, EGARCH and GJR-GARCH with two asymmetric innovation distributions Daily price data on the Nigerian crude oil sales (in dollars per barrel), ranging from 4th Jan., 2010 to 27th May, 2021, were obtained from the Central Bank of Nigeria (CBN). To capture the impact of the pandemic, the data were divided into two periods, before Covid-19 was proscribed as a pandemic by World Health Organisation (01/04/2010 to 10/03/2020) and during COVID-19 pandemic (11/03/2020 to 27/05/2021). Result shows that the leverage effect were positive and significant in both periods which indicates that positive shocks increases volatility more than negative news of the same sign. Also, EGARCH-SSTD and GJR-GARCH (1,1)-SSTD were the best fitted models for before and during pandemic respectively. Result shows that volatility persistence was higher during COVID-19 period (1.012639) than before the COVID-19 pandemic (0.988749) .There was also an increase and over persistence in the volatility of Nigerian crude oil price during COVID-19 than before COVID-19 period.

DOI: https://dx.doi.org/10.4314/jasem.v26i5.19

Impact factor: http://sjifactor.com/passport.php?id=21082

Google Analytics: https://www.ajol.info/stats/bdf07303d34706088ffffbc8a92c9c1491b12470

Dates: Received: 27 May 2021; Revised: 13 April 2022; Accepted: 11 May 2022

Keywords: COVID-19 Pandemic, Volatility Modelling, Skewed Student-t Distribution, Crude oil price

Crude oil is the major source of revenue generation in Nigeria. This has made Nigeria to be described as a mono-economic nation. Crude oil contributes significantly to Nigeria revenue (Alhassan and Kilishi, 2016). For instance, oil receipts accounted for 82.1%, 83.0% and about 90% of Nigeria revenue in 1974, 2008 and 2010 respectively (Central Bank of Nigeria Statistical Bulletin, 2011). This means that whatever happens to crude oil price in the international market could have significant effect on Nigeria economy. Like any other financial time series, crude oil prices could show sudden spike thereby generating volatility in crude oil price. Like other financial time series, crude oil prices are heteroscedastic (Tsay, 2005; 2014). Thus modelling its volatility requires application of appropriate time-varying models such as GARCH-family models to underpin the behaviour of the inherent volatility. First among these models is the Engle (1982) Autoregressive Conditional Heteroscedasticity (ARCH) which expresses volatility as a function of the past squared errors. However, given its major limitation of requiring higher order ARCH candidate models before convergence; thus, to fulfill model parsimony the Generalized ARCH model was introduced by Bollerslev (1986). Meanwhile, for lack of ability to capture asymmetric effects of shocks due to news, leading to spikes in volatility of most assets, further extensions to GARCH were introduced. Among these are Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) of Nelson (1991), Glosten, Jagannathan and Runkle – Generalized Autoregressive Conditional Heteroscedasticity model (GJR-GARCH) of Glosten, Jagannathan and Runkle (1993), Asymmetric Power Autoregressive Conditional Heteroscedasticity (APARCH), etc. Several studies have applied different GARCH-family candidate models in modelling volatility of crude oil prices, but with slightly different objectives from our current study. For example, Olomola and Adejumo (2006) applied Vector Autoregressive (VAR) model to examine effects of the Nigerian crude oil price shocks on four economic variables (real exchange, money supply, output and inflation) using quarterly data for 34 years. Their findings revealed that besides output and inflation where no effect was identified, shocks to crude oil prices significantly influence money supply and exchange rate, suggesting possibilities of a future rise

**Corresponding Author Email: kayode.samson@bowen.edu.ng; Tel: +2348032794217*

in crude oil price triggering significant rise in real exchange rates. Similarly, Amaefula (2019) applies GARCH (1, 1) model to investigate effects of subsidy removal, volatility and crude oil price on economic growth in Nigeria. The study relied on yearly data covering periods between 1973 and 2017. The study findings besides establishing positive effects of volatility on economic growth, also shows effects of positive shocks of global oil price are greater than negative shocks. Meaning, effects of rise in crude oil prices on GDP growth rate is higher than effects of drop in price on GDP decline rate. Also identified is that fuel subsidy removal generates significant decline on the GDP growth rate. Study by Ito (2015) on the application of Vector Autoregressive (VAR) model to investigate effects of fluctuation in Russian' crude oil prices on the country's macroeconomic variables, using quarterly data ranging from the first-quarter of 1994 to the third-quarter of 2009, shows that a one-percent increase in crude oil prices, caused about seventeen percent depreciation in the country's exchange rate. According to Aigheyisi (2018)'s study where Exponential GARCH model is employed to investigate the effect of crude oil price volatility on business cycle in Nigeria controlling for the effects of some macroeconomic variables (money supply, exchange rate, inflation, trade openness and foreign direct investment). Finding showed that in the short-run, there was positive and significant effect of oil price volatility on real GDP volatility. However, at long run, no significant effect was identified. Further findings reveal that there was no statistically significant effect of other variables of other macroeconomic variables on business cycle in Nigeria at both the short-run and long run, which implies that crude oil price volatility was the only threat to short-run growth in the real GDP. Deebom, and Essi (2017)'study fitted appropriate GARCH family model to examine the price volatility and risk returns of the Nigerian crude oil export markets with data, obtained from covering between January, 1987 and June, 2017. While fitting the model three error distributional assumptions were considered as proposed in our current study, namely: Normal, student's-t and generalized error distributions. Their findings having selected first order symmetric GARCH model [GARCH, (1,1)] in student -t error assumption as the best fitted model, showed that there was evidence of positive risk; indicating either investments or investors' likelihood of higher returns for holding risky assets. Demachi (2012) examined the effects of oil price volatility and changes in the international oil price on the macro-economy of Nigeria. The study applied Structural Vector Auto Regression (SVAR) model on monthly data series obtained between January 1970 and May 2011. The finding showed that changes in the international oil price have significant effect on Nigeria's exchange rate while the effect of price volatility was not significant. Further finding revealed that money supply increases as crude oil price increases, which mean that as the global crude oil price increases, the money supply in the domestic market increases considerably. Alhassan and Kilishi (2016) study employed three volatility models namely: GARCH-M, EGARCH and TGARCH to daily, monthly and quarterly data to investigate impacts of crude oil price volatility on some selected macroeconomic variables in Nigeria. The study reveals that asymmetric models, namely TGARCH and EGARCH outperformed symmetric models: GARCH (1 1) and GARCH – M. The study also shows that all the macroeconomic variables considered were highly volatile in reaction to rise in volatility in crude oil prices. By implication, according to the study, the Nigerian economy is vulnerable to both internal and external shocks. The study also establishes a preference for asymmetric models when dealing with effects of the Nigerian crude oil price volatility on macroeconomic variables. Apparently, the motivation of this study is reinforced with the fact that none of the reviewed studies is focused on investigating impacts of COVID-19 on the Nigerian crude oil prices as proposed in this study; and as much as we are aware, studies with similar objectives as in the current study are very scanty. Thus, in this study, it aimed at identifying appropriate GARCH-family models-symmetric or asymmetric, based on the inherent stylized facts, that best fit the data. Consequently, we hope to determine to what extent the shock due to COVID-19 has affected the volatility of Nigerian crude oil price within the investigated periods.

MATERIALS AND METHODS

Data Presentation and Computation of Returns from Crude Oil Prices: The data used in this study are the daily crude oil prices (in Dollars/ barrel), covering period encompassing pre- and during Covid-19 pandemic, from 4th Jan. 2010 to 27th May 2021; and were obtained from Central Bank of Nigeria (CBN) official website www.cbn.gov.ng. The two covered periods are: (1.) "before the incidence of COVID-19 pandemic was announced globally as a pandemic by the World Health Organisation (WHO) (1/04/2010 and 10/03/2020)"; and (2.) "Periods of COVID-19 pandemic (11/03/2020 and 27/05/2021). The daily crude oil price returns were computed from daily crude oil price using the formula:

$$r_{t(cop)} = \log\left(\frac{p_{t(cop)}}{p_{t-1(cop)}}\right);\ t = 2,3,\ldots n. \qquad (1)$$

Where, $P_{t(cop)}$ is the present day crude oil price, $P_{t-1(cop)}$ is the daily crude oil price at the previous day and n is the number of observation.

Stationary of the Crude Oil Price Returns and Test of ARCH Effect: Stationary testing is critical to model building in time series analysis. The stationary of the daily crude oil prices reruns series was tested using Augmented Dickey Fuller Test, which was implemented using the E-View version 9.0. Additionally, to guarantee the use of volatility models, the presence of heteroscedasticity (ARCH effect) was tested using the Lagragian Multiplier test (LM) also carried out in E-View 9.0.

Volatility Models Specification: The following volatility models were considered in this study EGARCH (p,q) and GJR- GARCH (p,q) but for model parsimony both the order of autoregression (p) and moving average (q) were restricted to 1 (p=1, q=1). These models were specified as follows:

Generalized Autoregressive Conditional Heteroscedasticity [GARCH) (p, q)] model

$$r_{t(cop)} = \mu + \varepsilon_t \qquad (2)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2,\ \varepsilon_t = \sigma_t z_t \qquad (3)$$

Where, $\sigma_t^{\ 2}$ is the conditional variance, ω represents the constant tern while α_i and β_j are the ARCH and GARCH terms respectively, p and q are the orders of ARCH and GARCH respectively, The following are the stationary conditions associated with the model parameters: $\omega > 0,\ \alpha_i \geq 0\ \ \beta_j \geq 0$ and the general persistence measure is: $\alpha_i + \beta_j < 1$. If p=1, and q =1, we have GARCH (1, 1) given as:

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2,\ \varepsilon_t = \sigma_t z_t \qquad (4)$$

Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model

$$\ln\left(\sigma_t^2\right) = \omega + \sum_{i=1}^{n} \alpha_i \left[\lambda \varepsilon_{t-i} + \gamma \left\{ \left|\varepsilon_{t-i}\right| - \sqrt{\frac{2}{\pi}} \right] + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right),\ \varepsilon_t = \sigma_t z_t \qquad (5)$$

Where, ω is constant term (long-run volatility), α_i is ARCH term while β_j is the GARCH term and, γ is the leverage term and σ_t is the volatility.

If p=1, and q =1, we have EGARCH (1, 1) given as:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha_1 \left[\lambda \varepsilon_{t-1} + \gamma \left\{ \left\{ \left|\varepsilon_{t-1}\right| - \sqrt{\frac{2}{\pi}} \right\} \right] + \beta_1 \ln\left(\sigma_{t-1}^2\right),\ \varepsilon_t = \sigma_t z_t \qquad (6)$$

Glosten, Jagannathan and Runkle – GARCH (GJR-GARCH) model

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{v} \gamma_i \varepsilon_{t-k}^2 d_{t-k}^-\ ,\ \varepsilon_t = \sigma_t z_t \qquad (7)$$

Where, $\begin{cases} d_t^- = 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases}$, if $\varepsilon_{t-1} > 0$, it is good news while $\varepsilon_{t-1} < 0$ means bad news

Error distributions used in estimating volatility models: The estimation of the parameters of the volatility models were estimated at two skewed innovation distributions namely: skewed student t- distribution and skewed generalized error distributions defined as follows:

Skewed student t-distribution

$$f(z_t, \mu, \sigma, \psi, d) = \begin{cases} bc\left[1 + \frac{1}{\psi - 2}\left(\frac{b\left(\frac{\sigma_t - \mu}{\sigma}\right) + a}{1 - d}\right)^2\right]^{-\frac{\psi+1}{2}}, \varepsilon_t < -\frac{a}{b} \\ bc\left[1 + \frac{1}{\psi - 2}\left(\frac{b\left(\frac{\sigma_t - \mu}{\sigma}\right) + a}{1 + d}\right)^2\right]^{-\frac{\psi+1}{2}}, \varepsilon_t \geq -\frac{a}{b} \end{cases} \qquad (8)$$

Or

Where, ψ and d represent the shape and skewness parameters respectively and a and b are constants given by

$$a = 4dc\left(\frac{\psi - 2}{\psi - 1}\right),\ b = 1 + 3d^2 - a^2,\ c = \frac{\Gamma\left(\frac{\psi + 1}{2}\right)}{\sqrt{\pi(\psi - 2)\Gamma\left(\frac{\psi}{2}\right)}} \quad (9)$$

Skewed Generalized Error Distribution

$$f(z_t / \rho, d, \theta, \delta) = \frac{\rho}{2\theta\Gamma\left(\frac{1}{\rho}\right)} \exp\left[-\frac{|z_t - \delta|^{\rho}}{[1 + sign(z_t - \delta)d]^{\rho}\theta^{\rho}}\right] \quad (10)$$

$$\theta > 0,\ -\infty < \varepsilon_t < \infty,\ \rho > 0,\ -1 < d < 1,\ -\infty < z_t < \infty$$

where,

$$\theta = \Gamma\left(\frac{1}{\rho}\right)^{0.5} \Gamma\left(\frac{3}{v}\right)^{-0.5} S(d)^{-1}, \quad (11)$$

$$\delta = 2dS(d)^{-1} \quad (12)$$

$$S(\varepsilon) = \sqrt{1 + 3\psi^2 - 4A^2\psi^2} \quad (13)$$

$$A = \Gamma\left(\frac{2}{\rho}\right)\Gamma\left(\frac{1}{\rho}\right)^{-0.5} \Gamma\left(\frac{3}{\rho}\right)^{-0.5} \quad (14)$$

Where, $\rho > 0$ is the shape parameter, d is a skewness parameter with $-1 < d < 1$.

Estimation of the parameters: The parameters of these volatility models were estimated at the two skewed innovation distributions using R package (Rugarch function in R).

Model selecting Criteria: The performance of these volatility models at these two skewed innovation distributions was compared using the Log likelihood and Akaike Information Criteria (AIC) defined as:

$$AIC = \frac{-2LL + 2k}{n} \quad (15)$$

Where, LL is the log likelihood, n and k are the number of observations and number of parameters respectively. Model with the highest Log likelihood and least values of Akaike Information Criteria was considered as the best fitting model among the competing models. The persistent in volatility of the different volatility model were computed using the formulae:

For GARCH (1,1) model: $\alpha_1 + \beta_1$ (16)

For EGARCH (1,1): $|\beta_1|$ (17)

GJR GARCH (,1): $\alpha_1 + \beta_1 + \frac{\gamma_1}{2}$ (18)

RESULTS AND DISCUSSION

The mean crude oil price during the pandemic was positive while that after the pandemic was negative but the minimum returns during the pandemic was less than that obtained before the pandemic with higher standard deviation during the Covid-19 (0.036736) than before Covid-19 (0.010298). This implies that although the mean returns were positive during Covid-19; returns were more consistent before than during the Covid-19 pandemic. This indicates more risk during than before Covid-19 pandemic. The kurtosis of 43.67310 and 32.44041 were obtained before and during the pandemic which implies that the returns in these periods were leptokurtic indicating the presence of fat tail in the series and this is also corroborated by the result obtained from Jarque bera statistic which reveals that the returns do not follow normal distribution (P<0.05). There was also presence of ARCH effect (P<0.05); evidence that the return series is time-varying (heteroscedastic). Thus, an essential requirement for the application of GARCH-family models is confirmed. The fat tail of the distribution returns justify the use of skewed Student –t and skewed- generalized error distribution which have fat tail than the normal distribution. The ADF test for stationarity result shows p-value less than 0.05 indicating that the returns series for both periods were stationarity. The estimates of the parameters of both the mean equation and the volatility models were presented in Table 3. Result in Table 3 shows that in all the estimated models, the ARCH was significant which implies that the Nigerian crude oil market news about past volatility has significant impact on the current volatility. The GARCH terms were also significant which shows an evidence of volatility clustering of the Nigerian crude oil price returns. In all the volatility models estimated, the leverage effect was positive and significant indicating that positive shocks increases volatility more than negative shock of the same sign. Result of the best fitting model for both period show positive and significant leverage effect meaning that positive shocks increases volatility more than negative shock of the same sign (P<0.05). Before COVID-19, the leverage effect was 0.091619 while during COVID-19 was 0.436740 meaning that positive shocks increases volatility more than negative shock of the same sign during COVID-19 than before COVID-19 pandemic. Volatility persistence during COVID-19 was greater than 1 (1.012639) which implies that indicates over persistence of shocks which may eventually explode into infinity whereas this was not the case before COVID-19 (volatility persistence =0.988749). This indicates high level of risks in the Nigerian crude oil price returns during Covid-19. This finding is corroborated by that of Sharma (2020) which established stronger market volatility during Covid-19 period than pre-Covid-19 period in Asia. This finding is also corroborated by the finding by Deupura and Narayan (2020) which found that COVID-19 increased daily oil price volatility. This finding was not is agreement with that of Yong, Ziaei and Szulczyk (2021) in Malaysia and Singapore stocks where decreased volatility persistent was obtained during Covid-19 period.

Table 1: Descriptive statistics for Nigeria daily crude oil returns from crude oil prices before, during Covid-19 pandemic and full period

Periods	Variable	Mean	Median	Minimum	Maximum	Std. Dev	Skewness	Kurtosis	Jarque-Bera	p-value
Before COVID-19 pandemic	Crude oil returns	-0.000160	0.000000	-0.125627	0.113879	0.010298	-1.576066	43.67310	160321.	0.00
During COVID-19 pandemic	Crude oil returns	0.001124	0.001646	-0.286830	0.255768	0.036736	-1.305162	32.44041	10883.00	0.00
Full period	Crude oil returns	-0.000026	0.000107	-0.286830	0.255768	0.015766	-2.149008	115.3401	1375520	0.00

Source: *Authors' computations.*

Table 2: ADF test for stationarity of daily crude oil returns and test of heteroscedasticity

Variable	ADF Test for COPR before COVID-19 Pandemic		ADF Test for COPR during COVID-19 Pandemic		ADF Test for COPR for the Full period		ARCH effect before COVID-19 pandemic		ARCH effect during COVID-19 pandemic		ARCH effect for the Full period	
	ADF statistics	p-value	ADF statistics	p-value	ADF statistics	p-value	F-statistic	p-value	F-statistic	p-value	F-statistic	p-value
At level	-53.55329	0.0001	-15.14077	0.000	-20.40460	0.0000	507.799	0.00	36.112	0.00	370.18	0.00

Source: Authors' computations. *COPR- Crude oil price returns, p<0.05 for ADF means that the series is stationarity and p-value less than 0.05 for test of heteroscedasticity implies that there is presence of ARCH effect. ADF- Augmented Dickey Fuller*

Table 3: Parameter estimates of the mean equation and the volatility models for daily crude oil price returns before, during COVID-19 pandemic in Nigeria and the full period

Volatility models	Periods	Id	μ (p-value)	ω (p-value)	α (p-value)	β (p-value)	γ (p-value)	Skewness (p-value)	Shape (p-value)	Volatility persistence
GARCH (1,1)	Before COVID-19	SSTD	0.000041 (0.821533)	0.000002 (0.804529)	0.112943 (0.420921)	0.869709 (0.000000)	-	0.971039 (0.000000)	4.554771 (0.000007)	0.982652
		SGED	-0.000040 (0.54692)	0.000003 (0.25238)	0.136868 (0.00000)	0.837368 (0.00000)	-	0.973276 (0.00000)	1.054532 (0.00000)	0.974236
	During COVID-19	SSTD	0.00084 (0.171326)	0.000030 (0.029067)	0.404872 (0.008312)	0.594127 (0.000000)	-	0.909099 (0.000000)	3.052415 (0.000000)	0.998999
		SGED	0.00178 (0.00000)	0.000030 (0.00000)	0.395877 (0.00000)	0.603122 (0.00000)	-	0.964788 (0.00000)	0.727249 (0.00000)	0.998999
	Overall period	SSTD	0.000123 (0.396384)	0.000006 (0.000117)	0.201166 (0.000000)	0.757979 (0.00000)	-	0.966042 (0.00000)	4.112262 (0.00000)	0.959145
		SGED	-0.000024 (0.90897)	0.000007 (0.00000)	0.221562 (0.00000)	0.742302 (0.00000)	-	0.965028 (0.00000)	1.004411 (0.00000)	0.963864
EGARCH (1,1)	Before COVID-19	SSTD	-0.000103 (0.444267)	-0.109086 (0.000000)	-0.045130 (0.000009)	0.988749 (0.000000)	0.091619 (0.000000)	0.958163 (0.000000)	4.513388 (0.000000)	0.988749
		SGED	-0.000199 (0.014975)	-0.173426 (0.000000)	-0.042236 (0.004718)	0.981835 (0.000000)	0.126746 (0.000119)	0.953101 (0.000000)	1.057171 (0.000000)	0.981835
	During COVID-19	SSTD	0.000857 (0.214636)	-0.600043 (0.004782)	0.014130 (0.813361)	0.928063 (0.000000)	0.381074 (0.003076)	0.916918 (0.000000)	2.880051 (0.000000)	0.928063
		SGED	0.001773 (0.00000)	-0.530875 (0.00000)	0.064664 (0.00000)	0.935451 (0.00000)	0.392165 (0.00000)	0.962481 (0.00000)	0.715147 (0.00000)	0.935451
	Overall period	SSTD	-0.000048 (0.741660)	-0.224794 (0.000000)	-0.041186 (0.000891)	0.976478 (0.000000)	0.148941 (0.000000)	0.948712 (0.000000)	4.149330 (0.000000)	0.976478
		SGED	-0.000179 (0.001564)	-0.259000 (0.000000)	-0.027477 (0.025664)	0.972508 (0.000000)	0.190086 (0.000000)	0.946506 (0.000000)	1.002892 (0.000000)	0.972508
GJR-GARCH (1,1)	Before COVID-19	SSTD	0.000016 (0.91425)	0.000002 (0.392061)	0.082054 (0.015026)	0.865599 (0.000000)	0.065904 (0.056093)	0.973026 (0.000000)	4.605119 (0.000000)	0.980605
		SGED	-0.000081 (0.21346)	0.000003 (0.52119)	0.092614 (0.00000)	0.834452 (0.00000)	0.089301 (0.00000)	0.969825 (0.00000)	1.058450 (0.00000)	0.971717
	During COVID-19	SSTD	0.000554 (0.398798)	0.000031 (0.042529)	0.161881 (0.189907)	0.632388 (0.000000)	0.436740 (0.009965)	0.904089 (0.000000)	2.914497 (0.000000)	0.997639
		SGED	0.001318 (0.00000)	0.000028 (0.00000)	0.263412 (0.00000)	0.633028 (0.00000)	0.206052 (0.00000)	0.930510 (0.00000)	0.733995 (0.000000)	0.999466
	Overall period	SSTD	0.000067 (0.639566)	0.000006 (0.000003)	0.128301 (0.000000)	0.762266 (0.000000)	0.135566 (0.000692)	0.965211 (0.000000)	4.149825 (0.000000)	0.95835
		SGED	-0.000078 (0.346662)	0.000007 (0.000000)	0.163536 (0.000000)	0.745154 (0.000000)	0.112851 (0.007787)	0.959270 (0.000000)	1.001582 (0.000000)	0.965116

Source: Authors' computations, id- error innovation, SSTD- Skewed Student-t- distribution, SGED- Skewed generalized error distribution.

Table 4: Fitness and forecasting performance of GJR- GARCH estimated at Skewed Student –t Distribution (SSTD) and Skewed Generalized Error Distribution for Nigerian crude oil price

Periods	Volatility models	Id	LL	AIC	ARCH effect after model fitting
Before COVID-19	GARCH (1,1)	SSTD	7989.505	-6.9061	0.08661
		SGED	7943.100	-6.8660	0.06737
During COVID-19	GARCH (1,1)	SSTD	841.5514	-5.5890	0.47940
		SGED	837.731	-5.5634	0.42660
Overall period	GARCH (1,1)	SSTD	8818.417	-6.7476	0.31570
		SGED	8762.672	-6.7050	0.28630
Before COVID-19	EGARCH(1,1)	SSTD	8017.408	-6.9294	0.85860
		SGED	7961.591	-6.8811	0.36710
During COVID-19	EGARCH(1,1)	SSTD	840.5909	-5.5759	0.91310
		SGED	837.1659	-5.5529	0.39280
Overall Period	EGARCH(1,1)	SSTD	8842.652	-6.7654	0.64730
		SGED	8777.705	-6.7157	0.92140
Before COVID-19	GJRGARCH(1,1)	SSTD	7992.537	-6.9079	0.10750
		SGED	7946.645	-6.8682	0.082700
During COVID-19	GJR-GARCH(1,1)	SSTD	843.9761	-5.598	0.52910
		SGED	837.868	-5.5576	0.96940
Overall Period	GJR-GARCH(1,1)	SSTD	8824.526	-6.7516	0.37310
		SGED	8765.929	-6.7067	0.3101

id- innovation distribution, LL- log likelihood, AIC- Aikaike Information Criteria, bolded values are the least LL, highest AIC.

Table 5: Summary of volatility persistence based on the best fitting model

Periods	Best fitting model	Volatility persistence
Before COVID-19	EGARCH (1,1)-SSTD	0.988749
During COVID-19	GJR-GARCH(1,1)-SSTD	1.012639
Overall Period	GJR-GARCH(1,1)-SSTD	0.95835

The distribution parameters for both skewness and shape were significant (P<0.05) justifying the use of skewed Student-t and skewed generalized error distributions. Result reveals that the skewed- Student –t distribution outperformed skewed generalized error distribution. For Covid-19 period, EGARCH (1,1)-SSTD outperformed other volatility models while during Covid-19, GJR-GARCH(1,1)-SSTD gave the best results in terms of fitness. The finding has also revealed the superiority of the asymmetric volatility models over symmetric models.

This finding agreed with that of the finding by Alhassan and Kilishi (2016) on modeling macroeconomic and oil price volatility in Nigeria which also established that asymmetric volatility models outperformed the symmetric models. This finding is not corroborated by that of the finding by Deebom and Essi (2017) which found that the symmetric models outperformed asymmetric volatility models when modeling the volatility in crude oil price. This disparity in finding could as a result of the differences in the periods in which these studies were carried out. The recent Covid-19 pandemic can also be responsible for the differences in the finding of this study and that of the previous study by Deebom and Essi (2017).

*Conclusion***:** This study examined the impact of Covid-19 pandemic on the volatility of the Nigeria crude oil prices. Finding revealed higher leverage of Nigerian crude oil price during Covid-19 period than before Covid-19 period and that volatility persistence was higher during Covid-19 period than before the Covid-19 pandemic.

REFERENCES

Alhassan, A; Kilishi, AA (2016). Analysing Oil Price-Macroeconomic Volatility in Nigeria. *CBN. J. of Appl. Stat.* 7(1), 1-22

Aigheyisi, OS (2018). Oil Price Volatility and Business Cycles in Nigeria. *Stud. Bus. Econ.* 13(2), 31-40

Amaefula, CG (2019). The effects of Crude Oil Price, its Volatility and Subsidy Removal on Economic Growth: Experience from Nigeria. *Int. J. Res. Innovate. Appl. Sci.* 4, (12), 86-93

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *J. of Econometrics,* 31(3), 307-327

Central Bank of Nigeria (2011). Statistical Bulletin. Abuja, December.

Deebom, ZD; Essi, ID (2017). Modeling Price Volatility of Nigerian Crude Oil Markets Using GARCH Model. *Int. J. Appl. Sci. Math. Theo.* 3(4), 23-49

Demachi, K (2012). The Effect of Crude Oil Price Change and Volatility on Nigerian Economy. MPRA Paper No. 41413.

Devpura, N; Narayan, PK (2020). Hourly Oil Price Volatility: The Role of COVID-19. *Energy Res. Let.* 1(2), 1-5.

Engle, RF (1982). Autoregressive cCnditional heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometric*a, 987-1007

Glosten, LR, Jagannathan, R; Runkle, DE (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The J. Fin.* 48(5), 1779-1801.

Ito, K (2010).The Impact of Oil Price Volatility on Macroeconomic Activity in Russia (No. 2010, 5). Economic Analysis Working Papers

Nelson, DB (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 347-370

Olomola, P; Adejumo, AV (2006). Oil Price Shock and Macroeconomic Activities in Nigeria. *Int. Res. J. of Fin. Eco*. 3(1), 28-34

Olowe, RA (2009). Oil Price Volatility and the Global Financial Crisis. In 9th Global Conference on Business & Economics, Cambridge University, United Kingdom.

Sharma, SS (2020). A Note on the Asian Market Volatility during the COVID-19 Pandemic. *Asian Eco. Let.* (2), 191-204

Yong, JN; Ziaei, SM; Szulczyk, KR (2021). The impact of Covid - 19 Pandemic on Stock Market Return Volatility: Evidence from Malaysia and Singapore. *Asian Eco. Fin. Rev*., 11(3), 191-204