



## EFFECT OF OIL PRICE VOLATILITY ON AVERAGE MONTHLY SHARE PRICE OF SUB-SAHARA AFRICAN COUNTRIES

**Elias Igwebuike Agbo**

Department of Accounting and Finance, Faculty of Management and Social Sciences, Godfrey Okoye University, Ugwuomu-Nike, Emene, Enugu State, Nigeria.

**Abstract:** *This study investigated the effect of oil price volatility on the average monthly closing share price of sub-Saharan African countries using Nigeria as a case study. The EGARCH methodology was used to investigate this impact, while monthly frequency data for 1997:1 -2016:12 were employed. Average monthly exchange rates and inflation rates were introduced as control variables. The results of the empirical investigation suggest that an asymmetric behavior is present and that there is volatility persistence. They also show that oil price volatility has a positive and significant impact on the volatility of the average monthly closing share price in the Nigerian capital market. The implication is that a unit increase in oil price causes some increase in the average monthly closing share price. The study advises market participants to target oil price movements as an important instrument for predicting the volatility of share prices in sub-Saharan African nations*

**Keywords:** Nigeria, sub-Saharan Africa, crude oil price, volatility, average monthly closing price, capital market, EGARCH

### 1. Introduction

Crude oil price fluctuations have captured the attention of scholars as they regard such shocks as important determinants which affect macroeconomic activities and, eventually, stock market indices in different corners of the universe. The anxiety among researchers, economists, investors and governments concerning the frequent fluctuation in oil prices as highlighted above started to take serious dimension when the seminal work of Hamilton (1983) found that ten out of the eleven economic recessions that took place in the United States of America were caused by such movements. The degree of attention currently given to oil price volatility is justified also by the fact that oil prices play important roles in the modern economy. Cunado and Garcia (2003) and Kilian (2008) see oil price shocks as a variable that have significant effect on domestic price levels, gross domestic product, investment and savings. Consequently, irregular and unpredictable movements in the energy markets have

become an issue of serious concern (Eksi, Senturk & Vildirim, 2012).

The relationship between the volatility of stock market and macroeconomic variables has been widely examined in developed countries (Obi, Oluseyi & Olaniyi, 2018). This area has been extensively investigated by international journals including Ibrahim (1999), Xiufang Wang (2010), Zukamain and Shamsuddin (2012) and Kang and Ratti (2013). Jung and Park (2011), among others. Degiannakis, Filis and Kizys (2014), Kang, Ratti, and Yoon (2015) and Bastianin and Manera (2016) cited in Obi et al. (2018) regard the connection between crude oil price and stock market volatility as one of the most recently researched topics. The passion for investigating the nexus between the two variables arises from the belief that the price of oil is endogenous and is caused by changes in both demand and supply and that a hike in the world price of oil decreases economic activities through production and consumer goods (Masih, Peters and De Mello, 2010). Another reason for the recent shift of the attention

Economics and Social Sciences Academic Journal

An official Publication of Center for International Research Development

Double Blind Peer and Editorial Review International Referred Journal; Globally index

Available @CIRD.online/ESSAJ: E-mail: [essaj@cird.online](mailto:essaj@cird.online)



of several studies to the interaction between oil and stock returns is the assumption of the investing public that correlations have important implications for asset allocation and portfolio optimization.

The results of the study of Basher and Sadorsky (2006) have shown that the volatilities in oil price contribute significantly in determining the size of the returns of several developing stock markets. This observation of Basher and Sadorsky (2006) and the general impression on the importance of oil price volatility and its economic consequences notwithstanding, the studies carried out on the relationship between oil price volatilities and stock markets are relatively few, especially in sub-Sahara African countries. For instance, in Nigeria, Yaya and Shittu (2010) Oseni and Nwosa (2011), Emenike and Adeniji (2015) are among the very few that have conducted such studies. After carrying out a related study,

In the face of the many alternative explanations of the relationship between the two items that have taken place in the recent past, it is obvious that past researchers have not succeeded in finding a solution, a situation which has left much gap in literature. In addition, to the best of this researcher's knowledge, not much research has been carried out in developing countries to establish the correlation between oil price volatility and the major stock market performance indicators. Consequently, this study is motivated to contribute in filling this vacuum by finding out the effect of oil price volatility on the average monthly share price of sub-Sahara African countries. Nigeria is used as a case study.

The importance of this venture is underscored by its anticipated ability to come up with results that will improve stock returns forecasting accuracy, generate relevant information for investors and policy makers, provide reference materials for researchers and the academia as well as help business enterprises in constructing diversified portfolios and improving their risk management strategies (see Youssef & Mokni, 2019).

The period covered by this study spans from January 1st 1997 to December 31st 2016. The starting date of the

sample period is determined by the availability of data on the dependent variable (average monthly closing price). We use December 31st 2016 as the end date as the latest date for which all the relevant time series data were available when this project started. The reason for extending the study period to December 2016 is to incorporate some of the months when Nigeria entered and had the full impact of a five-quarter economic recession that ended in the beginning of the first quarter of 2017..

The remaining part of this study is structured as follows: Section 2 provides a review of the related theories and related empirical studies. Section 3 contains the methodology adopted in this study. Section 4 provides the estimation results, while section 5 presents the conclusion.

## **2.0 Review of the Related Literature**

### **2.1 Theoretical and Conceptual Framework**

According to Arnold, Gourène & Mendy, (2018), crude oil is one of the commodities that are most widely used. It is employed in various manners in all sectors and almost at all the levels of the world economy. The level of world crude oil consumption has not altered, in spite of the recent advent of renewable and alternative energies sources. Instead, the rate of consumption of petroleum continues to be on the increase, especially among the developed and industrialized nations (Arnold et al., 2018). Petroleum is one of the most essential commodities. It has a significant impact on a country's economic activity, whether the country is an oil-importer or an oil-exporter. The prices of this commodity is a function of market demand, the quantity produced, the reserves available, the geopolitical situation, as well as a number of other factors (Arnold et al., 2018).

Many researchers consider oil price as a proxy for information flow. Oil price increase leads to causes an increase in production costs. Also, fluctuations in oil price affect stock markets because of the uncertainty they create for the financial sector but this depends on the forces that are responsible for the increase in oil prices. Bittlingmayer (2005) documents that oil price fluctuations arising from



war risks and those related to other causes display asymmetric effects on stock price dynamics.

Volatility measures unpredictability, or the spread about a central tendency (Adeniji 2015). Adeniji (2014) defines it as a constant fluctuation in price. Volatility refers to upward and downward drifts of the prices of crude oil universally. It is the conditional standard deviation of the underlying assets return and denoted by  $\sigma$ . Volatility refers to a characterization of price changes over time and has to do with consecutive positive and negative price shocks. According to Obi et al. (2018), volatility is mostly related to asset price and shows to what extent and how often the price of an asset fluctuates. A stock is considered as volatile when its price will differ significantly over time. Volatility describes the level of price oscillation in a stock, futures contract or any other market with dispersion around the mean or average return of a security and asset price (see Abken and Nandi 1996).

Obi et al. (2018) consider volatility as having a link with the variance of an asset price in the stock market and as being likely to harm the smooth functioning of the financial system and adversely affect economic performance (Rajni & Mahendra 2007; Mollah, 2009).

The three major volatility estimates include conditional-volatility, realized-volatility, and implied-volatility (Degiannakis, Filis and Kizys, 2014). Conditional volatility refers to the conditional standard deviation of the asset returns given the most recently available information. The conditional variance process of  $Y_t$  can be defined as  $V(Y_t/I_{t-1})$  which is equivalent to  $\sigma_t^2$ , for  $I_{t-1}$ . This represents the information set that investors know when they make their investment decisions at time  $t$ . The daily conditional-volatility is the conditional variance of daily returns which is generated by the GARCH (1,1) model. It is generally used and based on the assumption that investors know the most recently available information when they make their decisions to invest in securities. The implied-volatility is a volatility index which is considered as an essential instrument for measuring the sentiments of investors which are inferred from option prices. Realized volatility is based

on the idea of employing high frequency data to compute measures of volatility at a lower frequency. Both the conditional-volatility and realized-volatility measures the volatility of the moment as both of them estimate the stock market volatility at the current time. This study adopts the conditional volatility framework.

Stock markets are considered by many as the yardstick for measuring the performance of the economy of a nation. They play an important role in capital accumulation, the productivity of capital, financing of innovations in technology and economic development (Levine, 1997). Oil prices are considered in theory as having a strong link with stock markets the movements in oil price affect stock markets through their influence on economic activity, corporate income, inflation, and monetary policy (Huang, Musulis and Stoll, 1996).

The most prominent indicators of capital market performance, particularly in Nigeria, include gross capital formation, market capitalization, all share index, total value of shares traded, trading volume, number of deals, total new issues, listed domestic companies, total listed equities, government stock (bonds), market size, market concentration, closing price, efficiency of the assets pricing process in the securities market and liquidity of the stock exchange (Odo, Anioke, Onyeisi & Chukwu, 2017). This paper is concerned with the average monthly closing price of shares in the Nigerian capital market.

According to Wang (2015), technical traders employ different types of stock trading rules to forecast the prices of stocks, namely moving average rules, support and resistance rules, trend line rules, big buyer, big seller and manipulator rules, band and stop rules as well as volume and strength rules (see also Bouchaud, Farmer & Lillo, 2008; Aldridge, 2013; Bollinger, 2002 cited in Wang, 2015).

The closing price of a stock is the final price at which the stock trades during regular market hours on any given day. Even at the time of 24-hour trading, there is a closing price for any stock or other security (Kenton, 2019). Investors employ closing stock price for making investment



decisions(Saint-Leger,2019). According to Kenton(2019), the closing price is usually considered the most accurate valuation of a share or other security until trading takes off on the next trading day. A share's closing price is the standard benchmark which investors use to track its performance over time.Majority of shares and other financial instruments are traded after-hours, but the trading activity takes place in much smaller volumes. This explains why the closing price of any security is often different from its after-hours price.Closing prices are useful performance indicators used by investors to assess fluctuations in stock prices over time.Investors can use the closing price on one day to compare the closing price on the previous day, or 30 days earlier or a year earlier,in order to measure the changes in market sentiment towards that stock. Every stock news sites permits investors to chart closing prices for a period of years,usually since the day the company went public.A significant pitfall of closing price is that the closing price of any company's stock will usually be unable to reflect any news released by the company that day.We uses the monthly averages of daily closing prices of shares for this study.

## **2.2 Empirical Review**

The inquiry on the correlation between oil price and stock market activities is not a new research area.area of research. However, the impact of oil price shocks from the poit of view of the causes has been receiving more attention from researchers due to its importance. For example, Sadorsky (1999) cited in Obi et al. (2018) explored the impact of oil price shocks on stock market activities. He used a generalized autoregressive conditional heteroskedastic (GARCH) model to model oil price volatility and vector autoregression (VAR) model for empirical analysis. His results show that oil prices and oil price volatility both affect the stock market activities and real stock returns significantly. He found that oil price dynamics have actually changed and that, after 1986, oil price movements explain a greater part of the forecast error variance in real stock returns than do interest rates. In

addition,Sardorsky found that oil price volatility shocks have asymmetric effects on the economy of a nation.

In the same vein, Park and Ratti (2007) investigated the impact of oil price shocks on the stock markets in the United States and 13 European countries during the period from 1986:1 to 2005:12. They used variance decomposition for analysis. The results of their study reveal that Norway real stock return as an exporter of oil responded positively and significantly to oil price increase. They also show that oil price shocks account for a statistically significant percentage of the volatility in real stock returns..

For Andreas and Constantinos (2009), they sought to identify the impact of oil price returns on oil price volatility of countries such as Greek, the United States, the United Kingdom and the German stock markets. The EGARCH models and structural equation models (SEM) were used for statistical anlysis. At the end of the empirical analysis, the authors found that Greek stock market index returns and the United States stock market index returns are both sensitive to the oil price returns fluctuations while the German and the United Kingdom's stock market returns are not affected by oil price shocks.

While investigating emerging markets such as South Korean economy, Masih et al (2010), sought to ascertain the impact of oil price volatility on stock price shocks.The authors created a model that included variables such as interest rates, economic activity, real stock returns, real oil prices and oil price volatility.They employed cointegration test, a Vector Error Correction (VEC) model, variance decomposition and impulse response as tools for statistical analysis. The result of the cointegration test shows that there is a long run relationship among the variables while the VEC model result reveals the supremacy of oil price volatility on real stock returns and demonstrates how this has increased with time. Their conclusion is that oil price volatility can have significant impact on the time horizon of investment and firms should adjust their risk management procedures accordingly.



In a related study, Ono (2011) investigated the impact of oil prices on real stock returns in Brazil, China, India and Russia. The study covered the period from 1999:1 to 2009:9. The author employed Vector Auto Regressive models and emerged with results that show that oil price volatility has positive and significant effect on real stock returns of China, India and Russia, while the reverse is the case for Brazil. He equally found that for India, statistically significant asymmetric effects of oil price increases and decreases exist. The analysis of variance decomposition result indicates that the contribution of oil price shocks to volatility in real stock returns is comparatively large and statistically significant with regard to China and Russia.

Also Oskooe (2011) examined the relationship between stock market and oil price in Iran and international oil market. The author used mean and variance models for analysis. The results of the study show that the variance of oil price fluctuations does not bring about the variance of Iran stock returns and that there is no volatility spillover effect between Iran stock market and international oil market.

Hasan and Ratti (2012) carried out a study to ascertain the effect of oil price return and oil return volatility on the return and volatility of the sectors of Australian stock market respectively. They studied the risk-return trade off of those sectors. The study employed daily data indices for 10 Global Industry Classification Standard (GICS) sectors in Australian stock market and oil price during the period from 31 March 2000 to 31 December 2010. The GARCH-in-mean (GARCH-M) methodology was employed. The results of the study show that for the overall market index, an increase in oil price return significantly decreases return, and an increase in oil price return volatility significantly decreases volatility. However, for the energy and materials sectors, increased oil price return brings about some increase in sector returns.

Also, Walid, Saudm, Tarek and Axel (2013) investigated the current state of oil market volatility knowledge, highlighted the properties and characteristics of the oil

price volatility models and discussed the different modelling approaches to oil price volatility. They used generalised autoregressive conditional heteroskedasticity-models usually applied in the oil price volatility as well as West Texas Intermediate futures price data. While the researchers noticed the prevalence of GARCH models, they found that none of the models emerged as a paramount reference for the forecasting of crude oil price volatility. Consequently, they concluded that comparative studies, which examined the effect of differing factors that influence oil price volatility generally result in a lack of consensus on which of those models has the superiority of the forecasting capabilities. Based on this finding they envisaged an inherent need to study alternative approaches.

Hammaa, Jarbouib and Ghorbelc (2014) initially investigated the connection and interaction between oil and stock markets in Tunisia in terms of volatility at the sector-level. Later, they estimated the best hedging strategy for oil stock portfolio vis-a-vis the risk of negative change in stock market prices. While the authors used a bivariate GARCH model to determine the impact in terms of volatility in the variation of the oil price on the different sector index, they employed the conditional variances and conditional correlation to estimate the hedging ratio and discover the best hedging strategy. Their result shows that the majority of correlations are unidirectional from the oil market to Tunisian stock market. The results equally show that the conditional variance of a stock sector returns is affected both by the volatility surprises of the stock market and by those of oil market. They concluded that the GARCH-BEKK is more effective than the others versions in minimizing the risk of oil-stock portfolio.

Degiannakis et al (2014) also investigated the effects of oil price shocks on stock market volatility. That they did in Europe by concentrating on three measures of volatility, i.e. the conditional, the realized and the implied volatility and putting into consideration the sources of oil price shocks and employing the Structural VAR statistical model. They found that supply-side shocks and oil specific



demand shocks do not have effect on stock market volatility. However, they observed that oil price shocks arising from aggregate demand shocks have a negative link and impact on stock market volatility.

According to Obi et al. (2018), for the Nigerian economy, Effiong (2014) was the first to conduct the study that examined the effect of the origin of oil price shocks on Nigeria's stock market. The period covered by that work was from 1995:1 to 2011:12. The author decomposed oil price shocks into oil supply shocks, aggregate demand shocks and oil-specific demand shocks, using a structural vector auto-regression model, impulse response and variance decomposition. The result from the impulse response shows that, stock market's response to oil supply shocks is insignificantly negative but significantly positive to aggregate demand and oil-specific demand shocks. The collective effects of the oil price shocks was seen to be accounting for about 47 per cent of the changes in stock prices in the long term.

In the same dimension, Adeniji (2015) examined the link between stock market prices volatility and macroeconomic variables' volatility in Nigeria. Adeniji employed monthly time series data for the period of January 1990 – December 2014. The bi-variate and multivariate VAR Granger causality tests and GARCH (1,1) model were employed for empirical analysis. The results of the study show that only volatility in interest rate and exchange rate Granger -cause stock market prices volatility. Based on this result, the author concluded that, the supremacy of non-institutional investors and the existence of information asymmetry problem among investors could have been responsible for the weak relationship between stock market prices volatility and macroeconomic variables' volatility in developing countries like Nigeria.

Also, Ekong and Effiong (2015) studied the impacts of demand and supply shocks in the crude oil-market on Nigeria's macroeconomy in respect of the period 1986 - 2011. They used a structural vector autoregressive (SVAR) model, after were disentangling oil price shocks into three components: oil supply shocks, aggregate demand shocks

and oil-specific demand shocks. The result from the impulse response shows that the macroeconomic aggregates have a different response pattern to each of the types of oil price sh

Cotemporarily, Babajide, Lawal and Somoye (2015) examined the impact of both the exchange rate volatility and oil price volatility on stock market volatility in Nigeria. While doing so, they took into consideration the combined effect of exchange rate volatility and oil price shocks, The authors used EGARCH estimation techniques to find out if either the volatility in exchange rate, oil price volatility or both impact stock market volatility in Nigeria. Their results of their study show that that share price volatility is caused by both the exchange rate volatility and oil price volatility. Consequently, the authors recommend that policymakers should pursue policies which tend to stabilize the exchange rate regime on the one hand, and guarantee the net oil exporting position for the economy. They also advise the market practitioners to formulate portfolio strategies in such a manner that volatility in both exchange rates and oil price will be taken into consideration when taking investment decisions.

Obi et al. (2018) examined the impact of oil price shocks on stock market price volatility in Nigeria using Non-linear Autoregressive Distributed Lag (NARDL) to carry out statistical analysis and quarterly data for the period of 1986 to 2016. The oil price shocks were decomposed into oil supply shocks, oil demand shocks and oil specific demand shocks. The results of the study show that there is long-run relationship between oil price and stock price. They also reveal that positive oil price shocks, in their various forms, exert positive and significant impact on the volatility of stock prices both in the long-run and short run; an exception is the case of oil supply shocks that have negative impact in the long-run. In addition, negative oil price shocks were found to be exerting negative impact on the volatility of stock prices both in the short and long-run. However, after employing Wald test, the authors realized that due to asymmetry, the positive impact of these shocks on volatility of stock prices differs in both short run



and long run. In summary, the findings from the study affirm the presence of nonlinear relationship between oil price shocks and stock prices volatility in Nigeria and indicate that positive and negative oil price shocks affect stock prices volatility in different ways.

Most recently, some studies have explored the potential asymmetric *nexus* between the crude oil market and other asset prices. For instance, while the study by Balcilar, Gupta and Miller (2014) reveal that using a linear framework would result in mixed results. Cheikh, Naceur, Kanaan and Rault (2018) warn that ignoring non-linearity can lead to problematic results.

### **3.0 Methodology**

#### **3.1 Data**

This study examines the asymmetrical effects of oil price volatility on average closing price of the shares in the Nigerian capital market. It relies on monthly frequency data as was the case in Sadorsky (1999), Park and Ratti (2008), Driesprong, Jacobsan and Maat (2008) and Cunado and Perez de Gracia (2013) and Dhaoui and Kraief (2014), among others. We are motivated to use monthly frequency data as many empirical studies have shown preference for high-frequency data when investigating oil-stock-prices correlation (see Cheikh, Naceur, Kanaan and Rault, 2018). In order to ensure the robustness of the estimation, we used an alternative crude oil benchmark (West Texas Intermediate) in comparison with the Brent crude price and discover that using that alternative price type has not significantly affected the results of our benchmark specifications. The oil prices are denominated in US dollars and obtained from the Energy Information Administration (EIA) database. In alignment with Alikhanov and Nguyen (2011), out of the several types of crude oil, we select Europe Brent for the oil-exporting country that we intend to study.

Oil price volatility is computed using the historical method. The data for the average monthly closing price are obtained in daily frequencies from the Nigerian Stock Exchange (NSE) database of the relevant period and converted to monthly averages. The average monthly data

on Nigeria's official exchange rate and inflation rate are retrieved from the Central Bank of Nigeria (CBN) publications of the relevant years. The variables of the study include the historical prices of Brent spot crude oil (OP) used as independent variable. The UK Brent nominal price is used as proxy for the nominal oil price as was used in earlier studies such as Cunado and Perez de Gracia (2003, 2005, 2013) and Engemann, Owyang and Wall (2011), while investigating the kind of correlations between oil shocks and macroeconomic variables. Average monthly closing price (AMCP) is used as the dependent variable. The inflation rate (INF), measured as the first logarithmic difference of the consumer price index, is introduced in this study as a control variable; it stands as a proxy for the real stock return. This is done in alignment with Park and Ratti (2008) and Cunado et Perez De Gracia (2013). The official exchange rate (OER) is the number of units of local currency per one USD. The data for that have also been employed by this study as a control variable. The motivation for using of this variable together with the oil price is hinges on the desire to benefit from the spread between oil supply and oil demand shocks. Exchange rate was used by earlier works like Kilian (2009) and Kilian and Park (2009). This apart, literature identifies inflation rates and exchange rates as part of those macroeconomic variables that affect stock market significantly (see Fama, 1963). In addition, exchange rate has a significant effect on stock return for exporting country just as industrial production has significant effect on a country engaged in production (Ahkhanov and Nguyen, 2011; Chen, Roll and Ross, 1986).

#### **3.1.1 Descriptive statistics**

Table 1 summarizes the statistics of the data series. The average monthly series for all the variables are positive. OER has the highest average monthly data (131.3484), while INF has the lowest average monthly data (11.47804). The size of the standard deviation indicates the risk of the data series. OER has the highest standard deviation (52.08417), while INF has the lowest standard



deviation( 4.202081). AMCP has the highest positive skewness ( 5.107047) and positive kurtosis(43.06137). AMCP has a positive skewness (5.107) and a positive kurtosis (43.061). OP possesses a normal skewness (0.4584). It is platykurtic (1.9113).OER mirrors a normal skewness (0.285226) . It has a positive kurtosis (5.911730). INF equally mirrors a normal skewness (0.248519) . It also has a positive kurtosis (3.143751)..

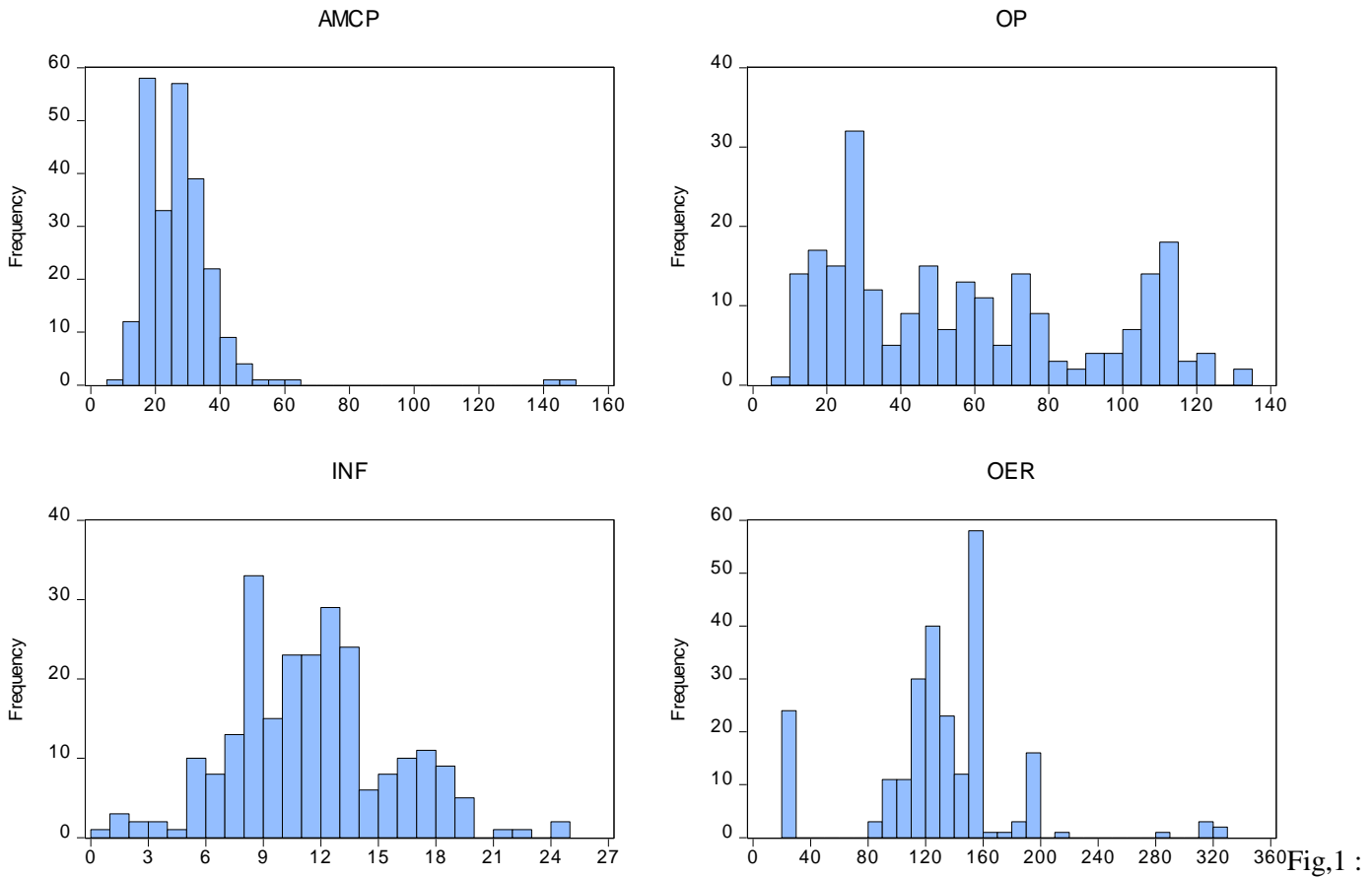
We use the Jarque Bera statistic to determine the normality of the data series. The statistic measures the Jarque Bera statistic measures the difference between the skewness and kurtosis of the series with those of the normal distribution. The null hypotheses of the Jarque Bera test is that the

distribution is Normal – So a probability-value greater than 0.05 indicates that the distribution is normally distributed. The Jarque Bera statistics AMCP is 17092.41 and a p-value of 0.000; This means that AMCP is not normally distributed since the p-value is less than 0.05 (0.0000). The Jarque Bera statistics for INF is 2.677119.It has a p-value of 0.262223; This means that INF is not normally distributed since the P-value which is less than 0.05 .Also,the Jarque Bera statistics for OER is 88.03586. Its p-value is 0.00000, implyiny that OER is not normally distributed. The Jarque Bera statistics for OP is 20.25920 . It has a p-value of 0.000040;This means that OP is not normally distributed since the p-value is less than 0.05( see fig.1).

Table 1 : Descriptive Statisticsa

	AMCP	OP	INF	OER
Mean	27.46450	57.48429	11.47804	131.3484
Median	27.20000	50.31000	11.38500	130.3400
Maximum	147.3100	133.9000	24.10000	321.5451
Minimum	9.810000	9.800000	0.900000	21.88610
Std. Dev.	13.97091	34.55795	4.202081	52.08417
Skewness	5.107047	0.458444	0.248519	0.285226
Kurtosis	43.06137	1.911314	3.143751	5.911730
Jarque-Bera	17092.41	20.25920	2.677119	88.03586
Probability	0.000000	0.000040	0.262223	0.000000
Sum	6591.480	13796.23	2754.730	31523.63
Sum Sq. Dev.	46649.55	285426.2	4220.139	648349.7
Observations	240	240	240	240





Histograms showing the normality of OP,AMCP,OER andINF.

### 3.1.2 Unit Root Tests

By conducting unit root tests, we examine the properties of our variables, particularly their stationarity. We test for the presence of unit roots in their levels (I,0) and first differences of oil prices (DOP) and trading volume (DAMCP). Since our study's scope covers periods of high fluctuations in oil and stock markets, especially between 2007 and 2016, it is expected that structural changes would occur in the oil price and market value series. The summary results of these statistical tests (Tables 2 & 3) for both oil price and trading volume series show that the null hypothesis of a unit root cannot be rejected for some of the variables across levels. The non-stationarity of some of the series at their levels [I,0] implies that the application

of Ordinary Least Squares technique will invariably produce a spurious regression whose estimates will be both unreliable and misleading. According to Asaolu and Ilo (2012), modern econometric techniques have shown that a linear combination of two variables that are each I(1) and which contain stochastic trends can be achieved through appropriate methods such that their residuals become I(0) or stationary. As long as they are not cointegrated if a and b are I(1), then the residuals from the regression of those series would be I(0) (see Adam, 1992 in Asaolu & Ilo, 2012). Hence, we difference the series in order to find out if the series are stationary at first differences. The differenced forms of OP, AMCP, OER and INF now become DOP, DAMCP, DOER and DINF respectively. We observe



that for the variables in first log differences, all unit root tests suggest that we should reject the null hypothesis of non-stationarity.

Since the Augmented Dickey Fuller test in table 2 shows a significant result ( p-value is 0.0000),we reject the null

hypothesis. This means that DOP does not have a unit root [ it is stationary]. Also, since the Augmented Dickey Fuller test in table 3 shows a significant result ( p-value is 0.0000),we reject the null hypothesis. This means that DAMCP is stationary.

**Table 2 : Unit Root test for DOP**

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=14)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-8.620566	0.0000
Test critical values: 1% level	-3.457865	
5% level	-2.873543	
10% level	-2.573242	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(DOP)

Method: Least Squares

Date: 06/04/19 Time: 14:35

Sample (adjusted): 4 240

Included observations: 237 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DOP(-1)	-0.742573	0.086140	-8.620566	0.0000
D(DOP(-1))	-0.166106	0.064700	-2.567305	0.0109
C	0.118816	0.397821	0.298666	0.7655
R-squared	0.458697	Mean dependent var		0.039030
Adjusted R-squared	0.454070	S.D. dependent var		8.286513
S.E. of regression	6.122662	Akaike info criterion		6.474448
Sum squared resid	8771.955	Schwarz criterion		6.518348
Log likelihood	-764.2221	Hannan-Quinn criter.		6.492143
F-statistic	99.14494	Durbin-Watson stat		2.001256
Prob(F-statistic)	0.000000			



Table 3 : Unit Root Test for DAMCP

Null Hypothesis: DAMCP has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on SIC, maxlag=14)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-19.25599	0.0000
Test critical values: 1% level	-3.457984	
5% level	-2.873596	
10% level	-2.573270	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(DAMCP)

Method: Least Squares

Date: 06/04/19 Time: 16:02

Sample (adjusted): 5 240

Included observations: 236 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DAMCP(-1)	-2.826851	0.146804	-19.25599	0.0000
D(DAMCP(-1))	1.054496	0.109827	9.601445	0.0000
D(DAMCP(-2))	0.471450	0.057801	8.156486	0.0000
C	0.185124	0.703366	0.263197	0.7926
R-squared	0.821339	Mean dependent var	-0.031186	
Adjusted R-squared	0.819029	S.D. dependent var	25.39614	
S.E. of regression	10.80370	Akaike info criterion	7.614458	
Sum squared resid	27079.02	Schwarz criterion	7.673167	
Log likelihood	-894.5061	Hannan-Quinn criter.	7.638124	
F-statistic	355.5162	Durbin-Watson stat	1.983664	
Prob(F-statistic)	0.000000			

### 3.1.3 Johansen Cointegration Test for AMCP, OP, INF and OER

From the trace test output in table 4a the null hypothesis is that there is no co-integration among the variables; that is that the variables are not co-integrated. This hypothesis is rejected at 5% since the p-value is 0.0267. The second hypothesis is

**Economics and Social Sciences Academic Journal**

**An official Publication of Center for International Research Development**

Double Blind Peer and Editorial Review International Referred Journal; Globally index

Available @CIRD.online/ESSAJ: E-mail: [essaj@cird.online](mailto:essaj@cird.online)



that there is at "most 1" cointegrating equation. This is accepted as the p-value in table 4b is 0.2812. The implication is that in the long run, the variables will be cointegrated or there is long run association between the variables. Trace test indicates 1 cointegrating equation at the 0.05 level.

**Tabl 4a : Trace Test**

Date: 06/23/19 Time: 17:21

Sample (adjusted): 6 240

Included observations: 235 after adjustments

Trend assumption: Linear deterministic trend

Series: AMCP OP OER INF

Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.111073	50.65417	47.85613	0.0267
At most 1	0.062277	22.98527	29.79707	0.2468
At most 2	0.032938	7.874542	15.49471	0.4789
At most 3	1.57E-05	0.003685	3.841466	0.9504

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

**Tabl 4a :  
Trace  
Maximum  
Eigen  
Value Test**

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.111073	27.66890	27.58434	0.0488
At most 1	0.062277	15.11073	21.13162	0.2812
At most 2	0.032938	7.870857	14.26460	0.3919
At most 3	1.57E-05	0.003685	3.841466	0.9504



Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

### 3.1.4 Stability Test for the model for DAMCP as the dependent variable (DAMCP, DOP, DOER, DINF)

From the CUSUM test (fig.2) it is evident that the dependent variable (DAMCP) represented by the blue line did not digress out of the 5% significance boundary. There is no deviation from the 5% boundary. This implies that the model is stable.

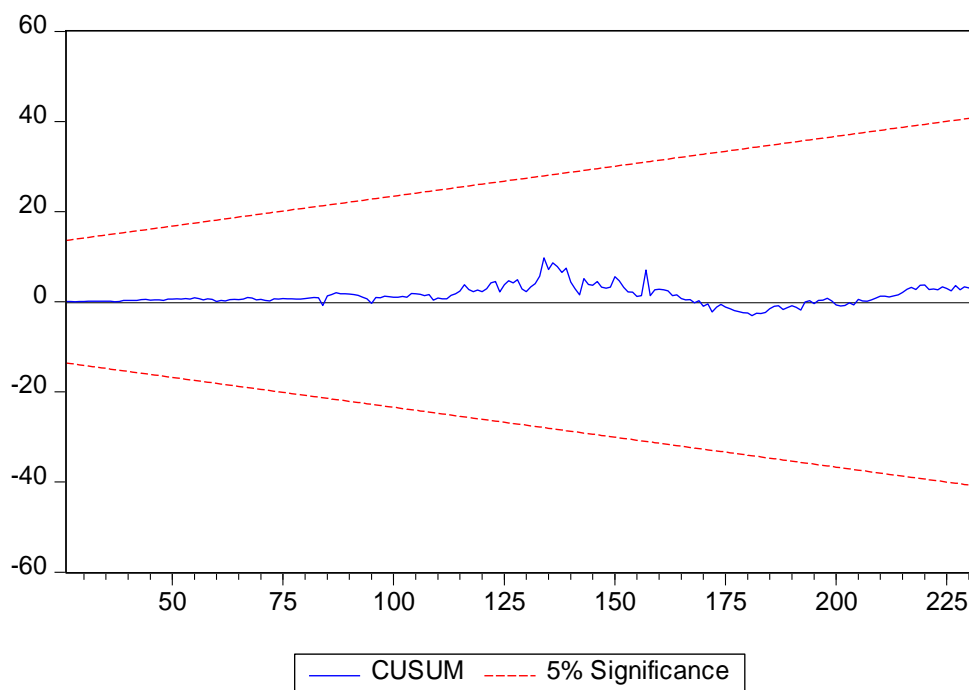


Fig. 2 : CUSUM Test

### 3.1.5 Test for Serial Correlation

The absence of serial correlation in the residuals is a pre-requisite for forecasting with EGARCH. We employ a version of the Lagrange Multiplier for testing for the existence of serial correlation in the residuals. The results in table 5 show that there is no serial correlation.

**Table 5 Result of the test for serial correlation**

Residual Serial Correlation LM Tests  
 Null Hypothesis: no serial correlation at lag order h  
 Date: 06/05/18 Time: 10:09  
 Sample: 1997M01 2016M12  
 Included observations: 238

Lags	LM-Stat	Prob
1	116.0284	0.1078
2	214.2274	0.0700
3	114.00524	0.0760
4	19.60522	0.0222
5	16.52016	0.6212
6	29.00062	0.5712
7	106.1186	0.5202
8	25.20578	0.2011
9	06.87860	0.0127
10	29.00162	0.0107
11	120.0452	0.2116
12	75.05110	0.0525

Probs from chi-square with 49 df.



**3.2 Model**

An appropriate choice of model and its appropriate specification is an important part of any academic research.

**3.2.1 Model Specification**

Many studies find the presence of nonlinear connections between oil and economic activity (see Mork, 1989; Hamilton,1996). The latter studies suggest that oil price increases exert more influence on other macroeconomic variables than oil price decreases. This implies an asymmetric behaviour of oil price shocks and their effects on output level.

In this study, we perform estimation with Exponential GARCH (EGARCH). EGARCH is a model that Soyemi et al. (2017) report has been used frequently in recent studies to measure volatility (Lawal et al.2016; Eagle, 2017). This approach is considered as a better means for accounting for the size effect of oil price fluctuations on the dependent variable and allowing for movements in the conditional variance (see Manasseh & Omeje, 2016; Lawal et al., 2016). The EGARCH model was proposed by Nelson (1991). It is important in capturing asymmetry, which is the different impacts on conditional volatility of positive and negative shocks of equal magnitude, and possibly also leverage, which is the negative correlation between returns shocks and subsequent shocks to volatility. One advantage of the EGARCH model over the basic GARCH (1,1) specification is that it is an asymmetric model that specifies the logarithm of conditional volatility and avoids the need for any parametric constraints EGARCH has some form of leverage effects in its equation. According to Sadorsky (1999), many authors have suggested that oil price volatility shocks may have an essential role in explaining economic activity. Some authors regard volatility of price shocks as an accurate measure of the rate of information flow in financial markets. Mokni and Mansouri (2017) report that such models are capable of capturing different volatility stylized facts which are often noticed in financial time series, namely volatility clustering, heteroskedasticity and long memory, contemporaneously.

The EGARCH[p,q] model is specified as follows: -

$$\log(h_t) = \alpha_0 + \sum_{j=1}^q \beta_j \log(h_{t-j}) + \sum_{i=1}^p \alpha_i \left| \frac{u_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^r \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}}$$

**(conditional variance equation).....(1.1)**

Source : Brooks (2014).

For this study, the conditional mean and variance equations for testing the hypothesis is presented as follows:-

$$\text{LOG(GARCH)} = \text{C(1)} + \text{C(2)*DOP} \dots\dots\dots(1.2)$$

$$\text{LOG(GARCH)} = \text{C(3)} + \text{C(4)*ABS[RESID(-1)]/@SQRT\{GARCH(-1)\}} + \text{C(5)*RESID(-1)/@SQRT(GARCH(-1))} + \text{C(6)*LOG\{GARCH(-1)\}} + \text{C(7)*DOP} \dots\dots\dots(1.3)$$

LOG (GARCH) is a conditional variance of the residual; it is the dependent variable. C (3) stands for the constant which shows the last period (t-1) volatility. C(4) is the constant that stands proxy for the impact of a magnitude of a shock (size) /arch effect / spillover effect . It shows the impact of long term volatility. At five percent level of significance, if C(4) has a p-value not above 0.05, the implication is that it is significant and there is likely an impact of long term volatility..C (5) is the gamma (γ) - the leverage term. The gamma parameter measures the asymmetry or the leverage effect. If gamma is equal to 0, then the model is symmetric. When gamma is less than 0, then positive shocks ( good news) generate less volatility than negative shocks ( bad news) do. When gamma greater than 0, the implication is that positive innovations are more destabilizing than negative changes..C (6) represents the GARCH effect – the alpha. Its parameter represents a magnitude effect or the symmetric effect of the model. Beta ( the GARCH term) estimates the persistence in conditional volatility notwithstanding anything happening in the market. When beta is relatively large, the implication is that volatility takes a long time to die out



following a crisis in the market. C (7) is DOP ( (the explanatory variable),The statistics for the hypotheses are shown in tables 11 – 16. The decision is base on 5% level of significance. According to Brooks (2014), the model above, which is based on the assumption of normal Gaussian distribution, captures the asymmetric volatility through the variable gamma( $\gamma$ ). The sign of the gamma determines the size of the asymmetric volatility and whether the latter is positive or negative.

The null hypothesis is that oil price volatility had no positive and significant impact on average monthly closing price. The model for testing this hypothesis is presented respectively :as follows:-

$$DAMCP = C(1) + C(2)*DOP$$

$$\dots\dots(2.4)$$

$$LOG(GARCH) = C(3) + C(4)*ABS[RESID(-1)/@SQRT\{GARCH(-1)\}] + C(5)*RESID(-1)/@SQRT\{GARCH(-1)\} + C(6)*LOG\{GARCH(-1)\} + C(7)*DOP\dots\dots(2.5)$$

Where DAMCP represents the first differnce of the average monthly closing price in the Nigeriancapital market and DOP represents the first difference of the Brent spot oil price both in their first difference forms.

#### 4.0 Empirical results

We see from figure 3 that there is a prolonged period of high volatility (big shock) from day 1 to day 50 and and that there exists a prolonged period of low volatility (small shock) from day 55 to day 200. In other words, periods of high volatility are followed by periods of high volatility and periods of low volatility tend to be followed by periods of low volatility. This suggests that residual or error term is conditionally heteroskedastic.

As estimation equations (1.1 and 1.2) represent, we model the volatility of crude oil returns with an AR(1)-EGARCH(1,1) specification. Table 6 shows the test results . We observe that all the parameter estimates of the EGARCH(1,1) model are highly statistically significant. We employ the sum of  $\beta_1$  to measure the persistence in

volatility and observe that  $\alpha_1$  in the GARCH model is closer to unity for each period.

In equation 1.2 , the LOG (GARCH) which is the conditional variance of the residual and the dependent variable stands for the volatility of the average monthly closing price. The constant(C(3)) indicates the last period (t-1) volatility. It is an arch (alpha) term which explains volatility clustering. C(4), which stands for the impact of a magnitude of a shock (size), arch effect or spillover effect, indicates an impact of long term volatility.It has a p-value of 0.0011, implying that it is significant and that there seems to be an impact of long term volatility. In addition, C5, the leverage coefficient or gamma is negative at -0.058876 and non-significant with a p-value of 0.6714 .This shows that there is leverage effect and that: positive shocks ( good news) generate less volatility than negative shocks ( bad news) Further,C(6), the beta or GARCH term has a value of 0.117653 and a p-value of 0.0281.This implies that the GARCH effect is significant and that there is volatility persistence. Oil price volatility ( DOP) is an exogenous variable or variance regressor as it can also contribute in the volatility of average monthly closing price in equation 1.2. Oil price volatility (DOP) has a p-value of 0.0000. This means that the impact of oil price volatility on the volatility of avearge monthly closing price ( DAMCP) is significant. DOP has a positive coefficient at 0.157141 which means that its impact of on DAMCP is in the positive direction. Based onthe findings of this study using the EGARCH [1,1] esimation technique, oil price volatility has a positive and significant impact on the volatility of the average monthly closing price in the Nigerian capital market.

sss

**Fig. 3 :EGARCH Estimation graph**

**Table 6 : EGARCH Estimation statistics**

Dependent Variable: DAMCP  
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)  
Date: 06/15/19 Time: 22:12  
Sample (adjusted): 2 231  
Included observations: 230 after adjustments



Convergence achieved after 43 iterations

Coefficient covariance computed using outer product of gradients

Presample variance: backcast (parameter = 0.7)

$\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1))) + \text{C}(5)$

$+ \text{C}(6) * \text{LOG}(\text{GARCH}(-1)) + \text{C}(7) * \text{DOP} + \text{C}(8) * \text{DINF} + \text{C}(9) * \text{DOER}$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.437148	0.537999	0.812545	0.4165
DOP	0.157141	0.036166	4.344990	0.0000

Variance Equation

C(3)	3.379152	0.284097	11.89437	0.0000
C(4)	0.641187	0.196371	3.265182	0.0011
C(5)	-0.058876	0.138782	-0.424233	0.6714
C(6)	0.117653	0.053588	2.195487	0.0281
C(7)	-0.195244	0.017051	-11.45026	0.0000
C(8)	-0.058587	0.014743	-3.973785	0.0001
C(9)	0.001345	0.012206	0.110160	0.9123

R-squared	0.002365	Mean dependent var	0.055043
Adjusted R-squared	-0.002011	S.D. dependent var	14.83549
S.E. of regression	14.85040	Akaike info criterion	7.119512
Sum squared resid	50281.84	Schwarz criterion	7.254046
Log likelihood	-809.7439	Hannan-Quinn criter.	7.173781
Durbin-Watson stat	2.997342		

Estimation Equation:

$$\text{DAMCP} = \text{C}(1) + \text{C}(2) * \text{DOP} - - - 1.1$$

$$\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1))) + \text{C}(5) * \text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(6) * \text{LOG}(\text{GARCH}(-1)) + \text{C}(7) * \text{DOP} + \text{C}(8) * \text{DINF} + \text{C}(9) * \text{DOER} - - 1.2$$

#### 4.0 Conclusion and policy implications

This study has investigated the effect of oil price volatility on the average monthly closing share price of sub-Sahara African countries using Nigeria as case study. We used the EGARCH methodology to investigate this impact and monthly frequency data for 1997:1 -2016:12 . The results of the empirical investigation show that an asymmetric behavior is present and that there is volatility persistence. They also show that oil price volatility has a positive and significant impact on the volatility of the average monthly closing share price in the Nigerian capital market. The implication is that a unit increase in oil price causes some increase in the average monthly closing share price. The positive link between oil price and the average monthly closing share price in Nigeria is explained by the fact that Nigeria is an oil-exporting country. . The study advises market participants to target oil price movements as an important instrument for predicting the volatility of share prices in sub-Sahara African nations

#### References.

- Abken, P. A. & Nandi, S. (1996). "Options & Volatility". *Economic Review*; December, pg.21-35.
- Abraham, T.W. (2014) Stock market reaction to selected macroeconomic variables in the Nigerian economy. *CBN Journal of Applied statistics*, 61-71
- Adeniji, S. O. (2014). An Appraisal of Stock Prices Volatility in the Nigerian Stock Market in an Era of Democracy. *Unpublished MSc. Thesis*, Department of Economics, University of Lagos
- Adeniji, S. O. (2015). An Empirical Investigation of the Relationship between Stock Market
- Alikhanov, A. & Nguyen, T. (2011). The impact of oil price on stock returns in oil-exporting economies: The case of Russia and Norway. *Master Thesis in Finance*. School of Economics and Management. Lund University.

Andreas, E. L. & Constantinou, K. (2009). The Effects of the increasing oil price returns and its volatility





- on four emerged stock markets. *European Research Studies*, Volume XII, Issue (1).
- Arnold, G.; Gourène, Z. & Mendy, P. (2018). Oil prices and African stock markets co-movement: A time and frequency analysis. *Journal of African Trade*
- Babajide, A. A., Lawal, A. I. & Somoye, R. O. (2015). Monetary policy dynamics and the stock market movements: Empirical Evidence from Nigeria. *Journal of Applied Economic Science*, X (8) 38, 1179 – 1189.
- Balcilar, M., Gupta, R. and Miller, S. (2014). Regime switching model of US crude oil and stock market prices: 1859-2013. Department of Economics. *Working Paper*. University of Connecticut. September.
- Basher, S. A. and Sadorsky, P. (2006). Oil price risk and emerging stock market. *Global Finance Journal*, Vol. 17, pp. 224–251.
- Bittlingmayer, G. (2005). Oil and stocks: Is it war risk? University of Kansas manuscript, December 29, 2005.
- Cheikh, N.B.; Naceur, S. B.; Kanaan, C. & Rault, C. (2018). Oil prices and GCC stock markets: New evidence from smooth transition models. *IMF Working paper WP /18/98*.
- Chen, N., Roll, R., & Ross, S.A. (1986), Economic forces and the stock market. *The Journal of Business*, 59, 383-403.
- Cunado, J. & Perez de Gracia, F. (2003). Do oil price shocks matter? Evidence from some European countries, *Energy economics*, 25, 137 – 154.
- Degiannakis, S. George Filis, G. and Renatas Kizys, R. (2014). The effects of oil price shocks on stock market volatility: Evidence from European data. Department of Economics Richmond Building, Portland Street, PO1 3DE Portsmouth, UK.
- Degiannakis, S., Filis, G. & Arora, V. (2017). Oil prices and stock markets. Working Paper Series. Independent Statistics and Analysis. U.S. Energy Information and Administration. June.
- Dhaoui, A and Bacha, S. (2017). Investor emotional biases and trading volume's asymmetric response: A non-linear ARDL approach tested in S&P500 stock market. *Cogent Economics & Finance* (2017), 5: 1274225.
- Driesprong, G. Jacobsen, B & Maat, B. (2003) Drilling oil: another puzzle. Research paper ERS – 2003 - 082 – F & A, *Erasmus Research Institute of Management (ERM)*
- Eagle, B. (2017). Oil price volatility and macroeconomy: Tales from top two oil producing economies in Africa. *Journal of Economics and Financial studies*, 05(05), 45-55.
- Effiong, E. L. (2014). *Oil shocks and Nigeria stock market: what have we learned from crude oil market shocks?* OPEC, Oxford: John Wiley and Sons Ltd, 9600. Garsingloro, 36 – 38
- Ekong, C. N. & Effiong, E. L. (2015). Oil price shocks and Nigeria's macroeconomy: Disentangling the dynamics of crude oil market shocks. *Global Business Review*, 16(6), 920-935.
- Eksi, I. H.; Senturk, M. & Vildirim, H. S. (2012). Sensitivity of stock market indices to oil price: Evidence from manufacturing sub-sectors in Turkey. *Panoeconomics*, 4, 463 – 474.
- Emenike, K. O. and Okwuchukwu, O. (2014). Stock Market Return Volatility and Macroeconomic Variables in Nigeria. *International Journal of Empirical Finance*, Vol.2, No. 2, Pg. 75-82 ISSN (Print Version) 0975-3931 ISSN (On Line Version) 2278-1277 *Journal of Global Economy*, Volume 14 No 3, September, 2018
- Fama, E. (1963), Mandelbrot and the stable paretian distribution. *Journal of Business*, 36, 420-429.



- Hamilton, J. D. (1983). Oil and the macro economy since World War II. *Journal of Political Economy*. 91 , 228 – 248
- Hammaa, W. Jarbouib, A. and Ghorbelc, A. (2014). Effect of oil price volatility on Tunisian stock market at sector-level and effectiveness of hedging strategy. 1st TSFS Finance Conference, TSFS 2013, 12-14 December 2013, Sousse, Tunisia.
- Hasan, M. Z., & Ratti, R. A. (2012). Oil price shocks and volatility in Australian stock returns. Global Accounting, Finance and Economics Conference. University of Notre Dame Australia Business Conference Papers.
- Huang, R., Musulis, R. & Stoll, H. (1996). Energy shocks and financial markets. *Journal of futures markets*, 16(1), 1 – 27.
- Ibrahim, M. H., (1999). Macroeconomic Variables and Stock Prices in Malaysia: An Empirical Analysis. *Asian Economic Journal*, Vol. 13, No. 2, pp. 219-231.
- Jones, C. M. & Kaul, G. (1996). Oil and the stock markets. *Journal of Finance*, 51, 463 – 491. *Journal of International Financial Markets, Institutions and Money*, 23,
- Jung, H. and Park, C. (2011). Stock market reaction to oil price shocks: a comparison between an oil-exporting economy and an oil-importing economy. *Journal of Economic Theory and Econometrics*, 22(3):1–29.
- Kang, W. and Ratti, R. A. (2013). ‘Structural oil price shocks and policy uncertainty’, *Economic Modelling*, 35, pp. 314–319.
- Kang, W., Ratti, R. A., & Yoon, K. H. (2015). The impact of oil price shocks on the stock market return and volatility relationship. *Journal of International Financial Markets*,
- Kenton, W.(2019). What Is the Closing Price? <https://www.investopedia.com/terms/c/closingprice.asp>. August 22.
- Kilian, L. (2008). Exogenous oil supply shocks: how big are they and how much do they matter for the us economy? *The Review of Economics and Statistics*, 90(2):216{240.
- Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99, 1053-1069.
- Kilian, L. and Park, C. (2009). The Impact of Oil Price Shocks on the US Stock Market. *International Economic Review*, 50(4):1267{1287.
- Lawal, A.I., Somoye, R.O.C., & Babajide, A.A. (2016). Impact of Oil Price Shocks and Exchange Rate Volatility on Stock Market Behavior in Nigeria. *Binus Business Review*,7(2), 171-177. <http://dx.doi.org/10.21512/bbr.v7i2.1453>
- Levine, R.(1997).Financial development and economic growth: views and agenda
- Manasseh ,C.O. & Omeje, A. N. (2016). Application of generalized autoregressive conditional heteroskedasticity model on inflation and share price movement in Nigeria. *International Journal of Economics and Financial Issues*, 6(4), 1491 - 1501. . .
- Masih, R. Peters, S. and De Mello L. (2010). Oil price volatility and stock price performance in an emerging market: evidence from South Korea.
- Mokni, K. & Mansouri, F. (2017). Conditional dependence between international stock markets: A long memory GARCH – copula model approach. *Journal of motivational financial management*, 42-43;116-31.



- Mollah, S. A. (2009). "Stock Return & Volatility in the Emerging Stock Market of Bangladesh". *Journal of the Academy of Business & Economics*, 43 (2),29-78.
- Mork, K., (1989) Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results, *Journal of Political Economy*, Vol. 97, No. 3, pp. 740-744.
- Nelson, B. D. (1991). Conditional heteroskedasticity in asset returns: a new approach. *Econometrica*, 59: 347–70. [Crossref], [Web of Science ®] [Google Scholar]
- Obi, B., Oluseyi, A.S. & Olaniyi, E. (2018). Impact of Oil Price Shocks on Stock Market Prices Volatility in Nigeria: New Evidence from a Non-linear ARDL Cointegration, *Journal of Global Economy*, 14(3);173-189.
- Odo, S. I., Anioke, C. I., Onyeisi, O.S. & Chukwu, B. C. (2017). Capital market indicators and economic growth in Nigeria: An autoregressive distributed lag (ARDL) model. *Asian Journal of Economics, Business and Accounting*. 2(3), 1-16.
- Ogiri, L. H.; Amadi, S. N; Uddin, M. M. & Dubon, P. (2013). Oil price and stock market performance in Nigeria: An empirical analysis. *American Journal of Social and Management Sciences*, 4(1). 20 – 41. Retrieved from <http://www.seihub.org/Ajsms>
- Ono, S. (2011). Oil Price Shocks and Stock Markets in BRICs. *The European Journal of Comparative Economics* Vol. 8, n. 1, pp. 29-45.
- Onodugo, I. C. (2012). Oil price shock and the Nigeria's stock market: An empirical analysis. *Doctoral Thesis*. Department of Public Administration and Local Government. University of Nigeria Nsukka
- Oseni, I. O. and Nwosa, P. I. (2011), "Stock Market Volatility and Macroeconomic Variables Volatility in Nigeria: An Exponential GARCH Approach", *Journal of Economics and Sustainable Development*, Vol.2 (10), Pp. 28-42. ISSN (Print Version) 0975-3931 ISSN (On Line Version) 2278-1277189 *Journal of Global Economy*, Volume 14 No 3, September, 2018
- Oskooe, P. S. A. (2011). Oil price shock and stock market in an oil exporting country: Evidence from causality in mean and variance test». *International Conference On Applied Economics*, 443-451.
- Park, J. W. and Ratti, R. A. (2007). Oil price shocks and Stock markets in the U.S. and 13 European Countries. Department of Economics, University of Missouri-Columbia, MO65211, U.S.A.
- Park, J., Ratti, R.A. (2008), Oil price shocks and stock markets in the US and 13 European countries. *Energy Economics*, 30, 2587-2608.
- Rajni, M. & Mahendra, R. (2007). Measuring Stock Market Volatility in an Emerging Economy. *International Research Journal of Finance & Economics* 8,126-133 *The Journal of political Economy*, Vol. 81, No. 3, pp. 637 – 654.
- Sadorsky, P. (1999), Oil price shocks and stock market activity. *Energy Economics*, 21;.449-69..
- Saint-Leger, R. (2019). What Is the Significance of a Closing Price on a Stock? *CISI Capital Markets and Corporate Finance*. <https://finance.zacks.com/significance-closing-price-stock-3007.html> February 10
- Soyemi, K. A., Akingunola, R. O. & Ogebe, J. (2017). Effects of oil price shock on stock returns of energy firms in Nigeria. *Kasetsart Journal of Social Sciences*. XXX, pp 1-8. Retrieved from <http://dx.doi.org/10.1016/j.jkss2017.09.004>.
- Walid M., Saud M. A., Tarek, A. & Axel, P. (2013). An introduction to oil market volatility analysis. *OPEC Energy Review* © 2013 Organization of the Petroleum Exporting Countries. Published by



John Wiley & Sons Ltd, 9600 Garsington Road,  
Oxford OX4 2DQ, UK and 350 Main Street,  
Malden, MA 02148, USA..

Market Volatility: A Reassessment”, American  
Journal of Scientific and Industrial Research, 1 (2),  
115-117.

Wang, Y., Wu, C. & Yang, L., (2013), Oil price shocks and  
stock market activities: Evidence from Wavelet  
*Anal. Appl.*, 4 ;. 151-166

. Youssef, M. & Mokni, K. (2019). Do crude oil prices  
drive the relationship between stock markets of  
oil-importing and exporting countries?  
*Economies*, MDPI, Base, Switzerland, [http://  
creativecommons.org/licenses/by/4.0/1-22](http://creativecommons.org/licenses/by/4.0/1-22).

Xiufang Wang (2010) “The Relationship between Stock  
Market Volatility and Macroeconomic Volatility:  
Evidence from China” International Research  
Journal of Finance and Economics, ISSN 1450-  
2887 Issue 49, Euro Journals Publishing, Inc.

Zukarnain Z. & Shamsuddin, S. (2012). Empirical  
Evidence on the Relationship between Stock  
Market Volatility and Macroeconomics Volatility  
in Malaysia. *Journal of Business Studies Quarterly*  
2012, Vol. 4, No. 2, pp. 61-71.

Yaya, O. S. and Shittu, O. I. (2010), “On the Impact of  
Inflation and Exchange Rate on Conditional Stock