OIL PRICE AND STOCK PRICES VOLATILITY TRANSMISSION IN NIGERIA

Sesan Oluseyi Adeniji
Kamaldeen Ajala
Musa Abdullahi Sakanko

ABSTRACT

The study investigates the relationship between oil price (OP), oil price volatility (OPV) and stock price volatility (SPV) in Nigeria, using an Autoregressive Distributed Lag (ARDL) model, Toda-Yamamoto-Dolado-Lutkepohl (TYDL) test, and Breitung-Candelon Frequency Domain Causality Test. The study shows that OP causes the SPV and OPV in a one-way direction in the long run. However, there was evidence of a bi-directional relationship with SPV in the medium run. It also shows that the OPV and SPV positively impact OP in the short and long run. Overall, the study found a greater tendency for oil prices to adjust back to their long-run equilibrium when affected by stock market prices. Therefore, it recommends that policymakers consider the movement in oil price and stock price in shaping the capital market's operation and ensuring the proceeds from increased oil prices are utilised maximally for economic revitalisation in Nigeria.

Keywords: *Oil Price, Oil Price Volatility, Stock Price Volatility, ARDL, Bound test, Toda-Yamamoto Causality test*
JEL: *E3, G17, C5*

[1] Department of Economics, University of Jos, Jos, Nigeria.
[2] West African Monetary Agency, Freetown-Sierra Leone.
[3] Department of Economics, University of Abuja, Abuja, Nigeria.

1.0 Introduction

Oil price volatility and its impact have long been a source of concern and discussion in academia and policy-making circles across the globe. The first dramatic fluctuation in oil prices could be traced back to 1974, and the volatility persisted over the years (ThankGod & Maxwell, 2013). Since 1974, the identified main determinants of the sharp movements in oil prices till the late 1990s were attributed to supply shocks. Therefore, it can be concluded that oil prices tended to drive the economic cycle during the period. Moreover, a slowdown in the non-OPEC production in the early 2000s led to the overall supply of oil not meeting the overall demand (ECB, 2012).

Incessant oil shocks have severely disrupted economic activities over the last three decades. Its attendant inimical macroeconomic implications create challenges for policy-making in the oil-importing and oil-exporting countries (Cashin and Mcdermoth, 2000; Daniel, 1997; Hamilton, 1996; Hooker and Oswald, 1996 and Hooker, 1996).

Interestingly enough, Nigeria is a monolithic economy, and her over dependence on crude oil revenue makes it highly vulnerable to the adverse effect of fluctuation in the oil price. As a result, the commodity market is highly affected by this irregular rise and fall in oil prices, which often destabilises all sectors of the economy's plans and activities.

More noticeably, structural changes in the crude oil market response to the global financial crisis in 2008 exposed and increased the depth of the stock market systems' vulnerability to shock. Due to the ugly influence, the 2008 global shock exerted on the entire market system; the oil market participants became more tactful in their trading strategies by increasing their sensitivity to external information (Lin, Liang & Tsai, 2019). Like the 2008 global financial crisis, in early 2020, a slump in the oil price coupled with the global affliction of the novel coronavirus gave birth to heightened global risk aversion, and it led to more significant disruption of the global financial cum stock markets system.

Considering its impact on corporate liquidity earnings, the significance of crude oil price to the global economy, particularly the stock market behaviour, is reflected by the increasing empirical inquiry into the nexus between crude oil prices and the stock market (Badeeb and Lean, 2018). Conventionally, an increase in oil price is believed to cause a rise in input costs for most businesses and an increase in consumers' spending on crude oil products most especially in emerging economies like Nigeria despite the global rise in the awareness and use of renewable energy, the multiplier effect of which reduces corporate earnings of other businesses. Furthermore, future corporate earnings reports form parts of the determinants of rising and falling stock prices. The crude oil price shocks also affect the stock market through the influence of the later on monetary policy instruments, interest rate, inflation rate, corporate income, and other economic activities in developed and less developed countries (Gourène and Mendy, 2018).

From the extant studies, Shaikh (2019) finds the predictability of various parameters based on the time using neural network and quantile regression methods and considered for 2007 to 2016. Based on Barone, Adesi, and Whaley's (BAW) neural networks model, several estimates have been shown. Estimation parameters include opening, closing, highest and lowest price of the commodity and volumes traded for a given commodity on each trading day. The neural network estimates explain that the West Texas Intermediate (WTI/USO's) future prices can be predicted with minimal error, and similar can be used to predict future volatility. The quantile regression results suggest that crude oil prices and crude oil price volatility index (OVX) are strongly associated. Bai and Perron least squares estimate evidence of the presence of a break in the time series. The main results uncover several exciting facts that implied volatility tends to remain calm during the global financial crises and higher throughout the post-crisis period. The empirical outcome on the OVX provides some practical implications for the trader and investor, in which oil futures can serve better to hedge the crude price volatility.

The application of the stock options volatility index (VIX) methodology to United States Oil Fund, LP(USO) options, which cover a wide range of stock prices, has shown that the market's expectation of 30-day fluctuation of crude oil prices can be measured by the OVX of the Chicago Board Options Exchange (Lin, Liang & Tsai, 2019). According to Huskaj and Larsson (2016), many researchers agreed that the inclusion of VIX is widely considered the world's premier barometer of investor sentiment, and market volatility significantly enhances the volatility model's performance. Nevertheless, the OVX has not drawn researchers' attention in predicting oil prices changes. However, in their submission, Maghyereh, Awartani and Bouriin (2016) view oil prices as forward-looking and a product of market consensus about the future uncertainties because volatility is a result of market option prices. Liu, Ji & Fan (2013) also posited that the level of uncertainty in the oil market and the market expectations for future thirty-day crude oil price volatility could be measured and predicted respectively by OVX. It is worth noting that OVX and the market's implied volatility are very similar, and the former is a market-determined forecast.

Conspicuously, the reviewed literature reveals a host of studies on the relationship between crude oil price and the implied volatilities. Cai, Lu, Ren & Qu (2019) explored the dynamic relationship between crude oil price and implied volatility indices in China using the MF-DCCA approach; Balccilar & Ozdemir (2018) examined the nexus between the oil price and its volatility risk in stochastic volatility in the mean model with time-varying parameters; Agbeyegbe (2015) explored the shape of the crude oil price return and the implied volatility relationship; Liu, Tseng, Wu & Ding (2020) examined the implied volatility relationships between crude oil and the US stock markets; hence, the birth of desire to domesticate this topic and contribute to the body of knowledge.

This research's uniqueness stems from the desire to combine OPV (crude oil price volatility) and SPV (stock price volatility) as the policy variables. Therefore, this work aims to explore the impact of OPV and SPV on the behaviour of crude oil prices as the target factor in the country of interest. Also, VAR-Based, and Breitung- Candelon Frequency Domain Causality tests are employed to examine the causal relationship among the variables of interest. To achieve this study's set objective, the linear econometric analysis technique is employed - ARDL (autoregressive distributed lag model) technique is used to measure the linear and dynamic relationship between oil prices and implied volatilities.

Structurally, this study is divided into the following sections: Introduction, literature review, methodology, empirical results and discussion, and conclusion.

2.0 Literature Review

2.1 Empirical Review

The literature on the connection between oil price, oil price volatility, and stock price volatilities is broad and continues to expand. Several studies have been carried out to examine the short-run and long-run relationship between oil price and implied volatility (OVX) worldwide and in Nigeria. The review covers several regions globally, while earlier studies include (Masih, Peters, De

Mello 2011; Arouri, Jouini, & Nguyen 2012; Gomes, Clermont & Chaibi 2014; Kang, Ratti, Yoon 2015). They all reveal the existence of a significant volatility spillover between oil price and its implied volatility.

Masih, Peters, & De Mello (2011) examines the connection between Oil price volatility and stock price fluctuations in an emerging market; a case study of South Korea. The study employs a VAR model, and the results reveal significant volatility spill-overs between oil price and sectoral stock returns. Its further suggests that a far better understanding of these links is crucial for portfolio management within the presence of oil price risk. Similarly, Arouri, Jouini, & Nguyen (2012) use the VAR–GARCH approach to investigate the volatility spillovers between oil and stock markets in Europe from 1998 to 2009. The study reveals that investors increasingly require boundary markets to increase returns and low correlation with traditional assets. As such, financial market participants understood the volatility mechanism across these markets to form a better portfolio in investment decisions. Gomes, Clermont & Chaibi (2014) employs a bivariate BEKK-GARCH (1, 1) model to simultaneously estimate the mean and conditional variance between equity stock markets and oil prices. The research covers a period of 2008 to 2013, and findings show a significant transmission of shocks and volatility between oil prices and a few of the examined markets.

However, recent studies by (Liang and Tsai 2019; Hamdi, Aloui, Alqahtani and Tiwari 2019; Tiwari, and Kang 2019; Alamgir, Saki, Bin Amin 2020; Essa and Giouvris 2020; Ahmed, Huo 2020; Abdulkarim, Akinlaso, Hamid and Ali 2020) investigates the changes and dynamics in the relationship between oil prices, oil price volatility, and stock price volatilities. Lin, Liang, and Tsai (2019) analyse the linear and non-linear long-run and short-run dynamic relationship between oil prices and two implied volatilities: oil price volatility index (OVX) and stock index. The study employs linear autoregressive distributed lag (ARDL) and non-linear autoregressive distributed lag (NARDL) on data collected from 2007 to 2018. The results of the linear model show that there exists a long-run equilibrium relationship between oil prices and OVX(VIX). While using the non-linear model, the outcome not only favours the long-run equilibrium but also an increasing OVX(VIX) has a higher negative impact on oil prices than a decreasing OVX(VIX), thus indicating that in the long run, an asymmetric cointegration exists between the variables. The study's findings further show that once there are major international political and economic events, structural changes in oil prices affect the behaviour of OVX(VIX).

Moreover, Hamdi, Aloui, Alqahtani, and Tiwari (2019) examine the relationship between oil price and sectoral indices in the Gulf Cooperation Council (GCC) countries using quantile regression analysis (QRA) from 2006–2017. The QRA results for non-linear wavelet denoising using a soft-thresholding series indicate that all the sectors are interdependent of oil price volatility. In contrast, the interdependence between the oil price and stock returns sectors are rated by frequency domain causality. Furthermore, Kumar, Pradhan, Tiwari, and Kang (2019) investigate the extent of time-varying volatility and correlations between crude oil, natural gas, and stock prices in India using various multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) techniques with and without asymmetry. The study results reveal no long-run cointegration between crude oil, natural gas, and stock prices in India.

In contrast, Balcilar & Ozdemir (2019) observe the nexus between the oil price and its stochastic volatility (SV) within the mean model with time-varying parameters (TVP) from 1980 to 2017. The results show that high price volatility in oil markets creates uncertainty and risk, while an increased risk premium may give feedback into the oil prices. However, the combination of the TVP and SV approaches in analysing the oil price and oil price volatility relationship has a flexible model that robustly allows structural breaks and stochastic volatility shocks.

Similarly, Alamgir, Saki, Bin Amin (2020) examine the nexus between oil prices and stock market: Evidence from 4 selected South Asian countries. The study utilised a Non-linear Autoregressive Distributed Lag (NARDL) model from 1997–2018. Findings from the study show a positive relationship between the world oil price and stock market index, and the response of the stock market index to positive and negative oil price shocks is asymmetric. The study concludes that higher oil prices in the world market affect the stock price. Furthermore, Essa and Giouvris (2020) analyse the long and short-run elasticities of oil price and oil price volatility on US illiquidity premiums (return on illiquid-minus-liquid stocks), with the US Oil Fund options implied volatility OVX index. Data collected for this study covers a period from 2007 to 2018. The study utilises the autoregressive distributed lag model (ARDL) and an error correction model (ECM), and the findings show that oil price significantly impacts premium payments.

In contrast, OVX significantly negatively impacts premium payments for the full sample and post-crisis period. However, while the oil price has a significantly positive impact on payments both in the long- and short-run, for the full sample and post-crisis period, OVX only has a significantly negative impact in the short-run for the full sample. Ahmed and Huo (2020) uses a tri-variate VAR-BEKK-GARCH model to investigate Volatility transmissions' dynamic relationship across the international oil market, commodity futures, and stock markets using China as a case study from July 2, 2012, to June 30, 2017. The study's findings show a significant unidirectional return interaction among the Chinese stock market, the global oil market, and the key commodities indicators in China. Additionally, there is the non- existence of return spill-overs between gold, stock, and oil commodities, while regarding the volatility spill-overs, findings show bi-directional shocks spill-overs between oil and stock markets.

Aside from the international studies carried out, Abdulkarim, Akinlaso, Hamid, and Ali (2020) address the relationship between crude oil price changes in some selected African Islamic stock markets using data from 2011 to 2018. The study employs three main techniques: maximal overlap discrete wavelet transform (MODWT), continuous wavelet transform (CWT), and the multivariate-GARCH-DCC to analyse whether these markets have any diversification opportunities. Findings from the study based on MODWT results show that the Egyptian Islamic index leads all indices, CWT results show that investors would gain diversification benefits in almost all markets (except South Africa) and enjoy the benefit that comes with long- term investments, while the results from the multivariate-GARCH-DCC show low correlations between the Egyptian and Tunisian Islamic indices, with oil-price returns suggesting diversification benefits in these markets. It was concluded that Tunisia's has the lowest volatility with the crude oil index of all the Islamic stock markets. In the same vein, Enwereuzoh, Odei-Mensah, and Junior (2021) investigate the impact of crude oil shocks on selected African stock markets classified into oil- exporting (Nigeria, Tunisia, and Egypt) and oil-importing (Botswana, South Africa, Kenya, and Mauritius). Using a Structural Vector Autoregressive model and a two- state regime smooth transition regression framework on monthly data from January 2000 to July 2018, the key findings from the study show that global demand shock does not matter in oil-importing countries, and there is little evidence that oil supply shock affects the real stock return for oil-exporting and oil-importing countries. The oil-specific shock is significant for most countries, and negative price shocks have more impact than positive price shocks.

Not many studies have examined the dynamic relationship between oil prices, oil price volatility, and stock price volatility in Nigeria. Instead, most of the studies focused on the impact of these variables either individually or collectively on the economic growth of the country (Adebiyi, Adenuga, Abeng & Omanukwue, 2009; Olayeni, Tiwari, and Wohar, 2020; Tule, Ndako and Onipede, 2017; Adaramola, 2012).

Adebiyi, Adenuga, Abeng & Omanukwue (2009) examines the effects of oil price shocks and exchange rate on Nigeria's real stock returns from 1985:1-2008:4. The study employs a multivariate VAR analysis and shows real immediate and significant negative real stock returns to oil price shock in Nigeria. Also, the Granger causality test results show that causation runs from oil price shocks to stock returns, which means that variation in the stock market is explained by oil price volatility. Furthermore, there is unidirectional causation from stock returns to the real exchange rate, indicating the authorities need to concentrate on domestic economic policies to stabilise the stock market. Also, Olayeni, Tiwari, Wohar (2020) investigate the dynamic relationship among global economic activity, crude oil price and production, stock market behaviour, and the Nigeria-US exchange rate. Employing a single-equation error correction model, the results show that the exchange rate solely bears the burden of short-run adjustments with causal effects from the other variables involved in the model.

Similarly, it confirms the presence of asymmetry equilibrium-pathh adjustment. It suggests that the positive and negative variations must be accounted for in the policy-making process to ensure stable exchange rate movement. Tule, Ndako, and Onipede (2017) investigate volatility spillover in the Nigerian sovereign bond market arising from oil price shocks, using Vector Autoregressive Moving Average - Asymmetric Generalized Autoregressive Conditional Heteroscedasticity (VARMA-AGARCH) model. The study covers the period March 22, 2011, to April 14, 2016. While the study endogenously and consecutively detects structural breakpoints using the Bai and Perron (2003) framework test, the model was modified using the breakpoints in the VARMA-AGARCH model. The results demonstrate a significant cross-market volatility transmission between the oil and sovereign bond markets with great sensitivity to structural breaks. Adaramola (2012) assesses the long-run and short-run dynamic outcomes of oil price on stock returns in Nigeria over 1985–2009 using a bivariate model, and the empirical results show that stock return has a significant positive impact on oil price shock in the short-run and a significantly negative impact in the long-run. The Granger causality test indicates strong causation from oil price shock to stock returns, implying that oil price volatility variations in the Nigerian stock prices are explained.

In the same vain the relationship between stock market price volatility and macroeconomic volatilities was examined by Adeniji (2015). The study used monthly data from January 1990 to December 2014 and employed the GARCH (1,1) model. The results reveal that three out of the five macroeconomic variables studied have a relationship with stock prices volatility, the volatility in GDP, inflation, and money supply do not Granger-cause stock market prices volatility. In contrast, only interest rate volatility and exchange rate are significantly related to stock market prices volatility from the regression analysis. Also, Obi, Adeniji, & Evans (2018) examine the impact of oil price shocks on stock market price volatility in Nigeria using a non-linear autoregressive distributed lag (NARDL) model with quarterly time series data from 1986 to 2016. The oil price shocks impact was disaggregated into oil supply shocks, oil demand shocks, and oil specific demand shocks, while these were also separated into their positive and negative effects. The results from the empirical analysis reveal that there is a long-run relationship among the variables, and positive oil price shocks in their various forms exert a positive and significant impact on the volatility of stock prices in the long and short-run except for the oil supply shock that has a negative impact in the long run, while adverse oil price shocks exert a negative impact on the volatility of stock prices in the short and long run. Hence, the findings from the study affirmed the presence of a non-linear relationship between oil price shocks and stock price volatility in Nigeria.

Osaze and Oriakhi (2013) examine the consequences of oil price volatility on the Nigerian economy's growth from 1970 to 2010. Using quarterly data and employing the VAR methodology, the study finds that of the six variables employed, oil price volatility directly impacted real government expenditure, real exchange rate, and actual import, while real GDP, real money supply, and inflation impact relate to other variables. This finding suggests that the oil price fluctuations determine government expenditure levels, which could determine the growth of the Nigerian economy. Pan, Wang, Chongfeng Wu, & Yin (2017) introduce a regime-switching GARCH-MIDAS model to investigate the relationships between oil price volatility and macroeconomic fundamentals. This model was used to account for the effects of long-term macroeconomic factors and short-term structural breaks in oil volatility. The in-sample and out-of-sample outcomes show that macroeconomic fundamentals can contribute valuable information regarding future oil volatility beyond historical volatility. They also find evidence that the structural breaks cause a higher degree of GARCH-implied volatility persistence. Two-regime GARCH-MIDAS models can reasonably beat the single-regime similarities in forecasting oil volatility out-of- sample.

From the review above, several studies examine the oil price, oil price volatility, and stock price volatilities across the globe; while very few have been carried out in the African and Nigeria context, most of the studies covered the relationship between oil price volatility and macroeconomic variables, stock market, or economic growth (Okoro 2014; Adeniji, 2015; Osaze and Oriakhi, 2013; Aregbeyen & Fasanya 2017; Chuku, EÆ ong, Sam, & Ndifreke 2010; Chongfeng Wu, & Yin 2017). Hence, this study examines the relationship between the oil price, oil price volatility, and stock price volatility in Nigeria.

2.2 Theoretical Review and Framework

Scientific research requires a background on which empirical analysis can leverage on. As postulated by Fama (1970), capital market activities concerning stock prices are efficient. According to Fama, the capital market is efficient when all the market activities reflect all available public or general information. There are different levels at which the market efficiency hypothesis could be obtained, namely, weak level form, semi-strong level form, and strong level form. The first level occurs when stock prices are determined based on the previous year's prices, while the second level form predicts stock prices using previous prices and considers the availability of clear and publicly made corporate announcements. The third level form assumes that all information made available to the public are incorporated in the stock prices. Fama concluded that stock prices are determined according to the investors' rational behaviour and not necessarily based on the technical analysis through extrapolation of past prices for the future stock prices or fundamental approach, which enables the identification of mispriced stocks. However, the theory has been criticised because stock prices can at least be predicted partially. This submission has been supported by the results of studies conducted within the behavioural finance field, which proposed that investors do not always behave rationally and their decisions are often influenced by some behavioural biases such as overconfidence, loss aversion, overreaction, and not only availability of public information. Grossman and Stiglitz (1995) gave the most controversial critique of the theory. He believed that markets could not be perfectly efficient since this would lead to market collapse due to the absence of profit to collect information.

To examine the existence of the proposed research problem, the study adopts as its theoretical framework the linear/symmetric theory of Hamilton (1983). Different studies have adopted other approaches on the relationship between oil price volatility and the stock market. For example, An, Sun, Gao, Han, & Li (2018) employed the Shannon Entropy Information theory in analysing the oil-stock space of China, while Arouri, Jouini, & Nguyen (2012) hinged their studies on the value of equity theory, the Hamilton theory is apt and suitable for this research. The theory was an outcome of the US economy's observation after experiencing oil prices hikes in the post-world war II era showed a strong correlation between oil prices and dire macroeconomic variables. The conclusion of this theory has been supported by different empirical pieces of evidence (Burbidge and Harrison, 1984 & Gisser and Goodwin, 1986), while most empirical studies use multivariate models which include crude oil prices and other macroeconomic variables like price level, employment, output, investment, exchange rate, among others, as postulated by the Hamilton theory, this study only relates oil prices to stock market prices.

3.0 Methodology

3.1 Model Specification

To empirically investigate the relationship between oil price and implied volatilities in Nigeria, this study adopts the model of Lin, Liang & Tsai (2019), which is stated as follows:

OP = f (OVX or VIX, μ) ………………(1)

Where OP = Oil price, OVX = Oil price volatility, VIX = Stock index options volatility and μ = White noise.

For this study, the model in equation 1 is modified by combining OVX and VIX as the independent variables, i.e., examining the impact of OVX and VIX on oil price in Nigeria. Therefore, the model is re-specified as follows:

OP = f (OPV, SPV, μ) ……………… (2)

The econometric form of equation 2 is, therefore, stated as:

$$OP_t = \beta_0 + \beta_1 OPV_t + \beta_2 SPVt + \varepsilon_t \qquad (3)$$

Where:
OP = Oil Price
OPV = crude oil price volatility
SPV = Stock index option of volatility
β_0 = Intercept term
β_1, $+\beta_2$, = Slopes (that is, the
ε = Error Term
t= Time

3.2 Technique of Analysis

(A) ARDL Technique

Following the objective of this study, exploring the linear relationship between oil price and implied volatilities, the Autoregressive distributed lag (ARDL) model is employed as an econometric estimation technique for this study. Autoregressive Distributed Lag (ARDL) model as a distributed lag model is used in this study because it allows examining how past behaviours of the target variable and other independent variables impact the contemporaneous value of the dependent variable.

For the ARDL model, it is statistically required that the stationarity properties of the variables of interest are a mixture of I(0) and I(1) to avoid a misleading regression result. It is also essential to choose an efficient and appropriate lag structure for the specified model. In this study, the Akaike Information Criterion (AIC) is selected to determine the optimal lag structure for this study.

The ARDL (p, q, r) specification for our model is as follows:

$$\Delta OP_t = c_0 + c_1 t + \pi_1 OP_{t-1} + \pi_2 OPV_{t-1} + \pi_3 SPV_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta OP_{t-i} + \sum_{j=1}^{q} \delta_j \Delta OPV_{t-j} - \sum_{r=1}^{r} \theta_r \Delta SPV_{t-i} + \varepsilon_t \ldots\ldots\ldots\ldots (4)$$

Where; c_0 is the intercept, c_0 is the slope of the time trend, π_1 is the slope of one lag period of OP, π_1 is the slope of OPV, π_1 = slpoe of SPV, Op is the Oil price, OPV is the oil price volatility index, SPV is Stock index options of volatility, p, q and r are the lag values of the explained (dependent) variable and the regressors (independent) variables, respectively, while ε_t is the error term.

Also, in line with the position of Pesaran and Shin (1995) and Pesaran *et al.* (1996b), it is imperative to explore the presence of cointegration, i.e., the long-run relationship among the variables of interest using the ARDL F-Bounds cointegration test approach, given that the series are a mixture of I(0) and I(1). To do this, a test of the hypothesis was conducted. Thus, the $H_0: = \pi_1 = \pi_2 = \pi_3 = 0$ was tested against the $H_1: \neq \pi_1 \neq \pi_2 \neq \pi_3 \neq 0$.

The t- statistics were also used to examine the regressors' significance, and the null hypothesis is $H_0: = \pi_1$. According to Pesaran, Shin, and Smith (2001), the $H_0: = \pi_1 = \pi_2 = \pi_3 = 0$ is rejected when long-run co-movement or cointegration is established among OP_t, OPV_t and SPV_t, which implies the presence of a long-run relationship among the underlying variables.

Linear Causality tests were also conducted. Shin, Yu, and Greenwood-Nimmo (2014) came up with a causality test built on the premise that future events will not have a causal effect on the past and present events, but past events can exert influence on the present and future events. We examined whether the target variable and the policy variables exhibit mutual predictability strength. The following multivariate vector autoregressive model based on the error correction method was estimated:

$$\Delta OPV_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1,i} \Delta OP_{t-i} + \sum_{j=1}^{p} \alpha_{2,i} \Delta OPV_{t-j} + \sum_{k=1}^{p} \alpha_{3,i} \Delta SPV_{t-k} + \alpha_4 ect_{t-1} + \varepsilon_{1t}; \ldots\ldots (5)$$

$$\Delta SPV_t = \beta_0 + \sum_{i=1}^{p} \beta_{1,i} \Delta OP_{t-i} + \sum_{j=1}^{p} \beta_{2,i} \Delta OPV_{t-j} + \sum_{k=1}^{p} \beta_{3,i} \Delta SPV_{t-k} + \beta_4 ect_{t-1} + \varepsilon_{2t}; \ldots\ldots (6)$$

$$\Delta y_t = \gamma_0 + \sum_{i=1}^{p} \gamma_{1,i} \Delta y_{t-i} + \sum_{j=1}^{p} \gamma_{2,i} \Delta x_{t-j} + \sum_{k=1}^{p} \gamma_{3,i} \Delta z_{t-k} + \gamma_4 ect_{t-1} + \varepsilon_{3t}; \ldots\ldots (7)$$

The ect_{t-1} is a one-period lag of error correction term.
In equation 5, if H_0: $\alpha_1 = \alpha_3 = 0$ *is accepted, then* OP_t and SPV_t do not granger cause OPV_t, individually. Similarly, in equation 6, if H_0: $\beta_1 = \beta_2 = 0$ *is accepted then* OP and SPV_t do not granger cause SPV_t individually, and lastly, in equation 6, if H_0: ? = ? = 0 *is accepted, then* OPV_t and SPV_t do not granger cause OP_t individually.

(B) Causality Test Techniques
TYDL and Breitung-Candelon Frequency Domain Causality Tests are adopted to examine the causal relationship among the variables of interest in this study.

TYDL Causality Test
TYDL (Toda-Yamamoto and Doado-Lutkepohl) is a causality test technique developed to mitigate the Granger causality challenges. The Granger causality proposed by Granger (1969) is characterised by the shortcomings of specification

bias which often leads to a misleading result. Engle and Granger (1987) defined variables X and Y as being co-integrated if the linear combination of the variables is stationary, whereas the variables are not stationary at level. Hence, if these variables are not stationary and co-integrated, the inference from the standard Granger- causality test will be considered invalid.

TYDL is considered superior to the Granger causality approach because it is developed on augmented VAR modelling and includes a modified Wald test statistic (MWALD). Besides, the TYDL approach does not require pretesting for the co- integrating properties of the model. It thereby avoids the potential bias as it can be applied regardless of the stationarity properties of the series, whether a series is I(0), I(1) and even I(2), co-integrated or non-co-integrated of arbitrary order.

Causality Tests in Time and Frequency Domain
Over a specified period, the Granger causality test reveals whether the previous changes in x(y). influence the current changes in y(x). On the other hand, the linear measure of feedback from one variable to another at a given frequency established in Gweke (1982) can provide detailed information about feedback relationships between x and y over different frequency bands.

This attempt would enable us to quantify what fraction of total power at frequency ù of variable x is attributed to variable y Also, evidence from extant studies, for example, Yýldýrým and Taþtan (2009), reveals that the application of causality test in the time and frequency domain can lead to change in the direction and change in the significance of the Granger causality.

The measure of linear feedback from variable x to y at frequency ù as established in Gweke (1982), is stated as follow:

$$M_{y \to x}(\omega) - \log\left|\frac{2\pi f_x(\omega)}{|\psi_{11}(e^{-i\omega})|^2}\right| - \log\left|1 + \frac{|\psi_{12}(e^{-i\omega})|^2}{|\psi_{11}(e^{-i\omega})|^2}\right| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Given that $|\psi_{12}(e^{-i\omega})|^2$ 0, the measure of linear feedback becomes zero, and in terms of frequency, variable y would not Granger cause variable x.

As such, in Breitung and Candelon (2006), a VAR equation that re-specified the relationship between variables *x* and *y* are established as follows:

$$x_t = a_1 x_{t-1} + \cdots a_p x_{t-p} + \beta_1 y_{t-1} + \beta_p y_{t-p} + \varepsilon_{1t} \quad \text{.............................(9)}$$

Gweke's tested null hypothesis $M_{y \to x}(\omega) = 0$ is similar to the null hypothesis of *H0: R ω β = 0* where *β* denotes the vector of the coefficient of variable *y* and R *ω* =

cos *ω* cos *2ω* .... *cos pω*

sin *ω* sin *2ω* .... *cos pω*

Breitung and Candelon (2006) version of causality in time and frequency domain is adopted in this study. It simplifies the Geweke (1982) null hypothesis so that a usual F-statistics can be used to test causality in the frequency domain.

3.3 Data Source and Definitions

The oil and stock prices data are sourced from the CBN online statistical database. The oil and stock prices spanned from 1991m1-2019m12. The returns are calculated using the change in the log of the series multiplied by a hundred, and this is tantamount to the loss of the initial observation making the returns series spanned from 1991m2- 2019m12. The volatilities are extracted from the AR-EGARCH models. The conditional mean equation for the oil price EGARCH follows the autoregressive of order one while stock price follows the autoregressive of order two. The graphics of the oil price, stock, and oil price volatilities help reveal the integration or stationarity nature of the variables before adopting a formal unit root test. It is evident from Figure

1 that oil price shows a visible pattern of trend, and this implies that it is not stationary over the sample periods, but its returns show that it is stationary after the first difference. By convention, volatilities are to be stationary, and the graphics for the two volatilities show this. However, no statistics can be derived from the graphical inspection. Based on this, we employed the Augmented Dickey-Fuller unit root tests to investigate the stationarity properties of these variables statistically and are discussed in the unit root section below.

4.0 Empirical Results and Discussion

4.1 Variables' Trend Inspection

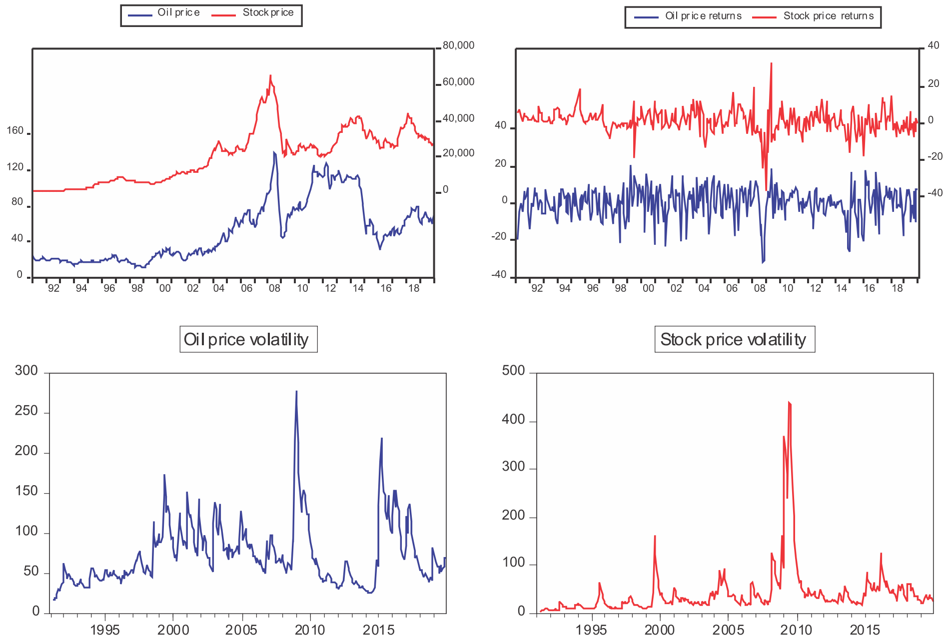

Figure 1: Graphical illustration of prices, returns, and volatilities for oil and stock

The oil price, stock price, oil price returns, stock price returns, oil price volatility, and stock price volatility are examined, using graphical illustration, presented in Figure

1. The first graph shows the behaviour of the oil price and stock price over the period under study. The red colour plot denoted the stock price while the stock price is denoted by blue colour. The trends in both cases reached a peak in 2009, which can be attributed to the effect of the global financial crises of 2008. The oil price and stock price graph are the oil price return and stock price returns chart. The two appear to be mean-reverting variables revealing shocks in the pattern in 2008 and 2009. Also, the oil price volatility and stock price volatility charts show a similar pattern and the same evidence of shock was revealed in 2008 and 2009.

4.2 Data Descriptive and Statistics

Table 1
Descriptive statistics

Variable	N	Mean	SD	CV	Normality	Pairwise correlation					
Oil price	348	51.10	33.87	0.66	36.30***	1					
Stock price(SP)	348	19951	14784	0.74	16.54***	**0.78*****	1				
Oil price returns(OPR)	347	0.30	8.59	28.63	40.32***	0.05	0.01	1			
Stock price returns(SPR)	347	1.13	6.30	5.58	482.02***	-0.11**	-0.10*	**0.16*****	1		
Oil price volatility(OPV)	346	73.52	39.56	0.54	356.12***	-0.18***	0.07	0.03	-0.15***	1	
Stock price volatility(SPV)	345	41.74	54.56	1.31	10655.61***	0.18***	0.23***	0.10*	-0.15***	**0.50*****	1

Source: Authors computation

****** p < 0.01; ** p < 0.05; * p < 0.1***

Table 1 shows the descriptive statistics for the oil price, stock price proxied with the all-share index, oil price returns used in computing the volatility, stock price returns used in computing the volatility, oil price volatility, and stock price volatility, respectively. The first column shows the means values for the variables and is all positive. The second column shows the standard deviations, while the third column shows the coefficient of variation, which shows the relative dispersion of the variables. In a pairwise sense, it can be deduced from the coefficient of variation that oil price has slight variation than the stock price index, whereas oil price returns have much variation than the stock price index returns.

It is also interesting to note that oil price is less volatile than the stock price, as suggested by the coefficient of variation (0.54 is far less than 1.31). The Jarque-Bera probability values in the fourth column are significant, which signifies that none of the variables follows a normal distribution. The last segment of the table shows the pairwise correlation between the variables. It can be deduced that there is a strong and significant positive correlation between oil price and stock price, whereas the correlation between their returns is very weak though positive and significant. Likewise, it is revealed that the correlation between oil price volatility and stock price volatility is positive and relatively strong at 50% and significant. It can also be deduced that a significant negative correlation exists between oil price and its volatility, whereas it significantly correlates positively with stock price volatility; the degree of the correlations is of the same absolute magnitude but weak.

Unit Root Test Results

Table 2 shows the ADF unit root test results for oil price, oil price volatility, and stock price volatility. The result shows that oil price is not stationary, but a variable that contains a unit root; the probabilities of the t-stat at first difference are all significant. As expected, both oil price and stock price volatilities are stationary as the probabilities of the t-stat at the level are all significant.

Table 2

ADF tests for variables

Variable	Deterministic term	level	Diff.	Remark
Oil price (OP)	Constant	-1.92	-13.42***	*I*(1)
	Constant and Trend	-2.58	-13.41***	*I*(1)
	None	-0.70	-13.43***	*I*(1)
Oil price volatility (OPV)	Constant	-4.87***	-16.50***	*I*(0)
	Constant and Trend	-4.91***	-16.48***	*I*(0)
	None	-1.83*	-16.52***	*I*(0)
Stock volatility (SPV)	Constant	-4.51***	-16.33***	*I*(0)
	Constant and Trend	-4.66***	-16.31***	*I*(0)
	None	-3.39***	-16.35***	*I*(0)

Source: Authors computation

****** p < 0.01; ** p < 0.05; * p < 0.1***

4.3 Results of the ARDL Models

Table 3 presents the results of the ARDL Models. Since oil price, OPV, and SPV are different integrated orders, an ARDL regression is employed to study OPV and SPV's impact on the oil price. Akaike information criterion is used for selecting the optimal lag for the ARDL model, and the optimal ARDL (2, 0) is selected. The F-statistic values (5.123 and 5.098) are higher than the upper bound asymptotic values (4.37, 3.49 and 3.09) at 1%, 5% and 10%, respectively. The result mirrors evidence that the variables of interest exhibit a long-run relationship or they are co-integrated. It implies long-run joint reversion of the variables to the position of equilibrium. Also, this result approves the applicability of the ARDL model specified for this study. The significant value of 0.009 and 0.014, which corresponds to the short-run or immediate impacts, reveals that OPV and SPV simultaneously impacted oil prices positively. This suggests that the oil market has begun to accumulate leverage, rapidly changing oil markets for a significant event that could happen soon, leading to an increase (decrease) in OPV and SPV that causes (decrease) oil prices to increase. However, on the day of the real major event, short-term speculators sold (bought) the oil spot in the opposite direction, allowing the oil price to drop (rise). This phenomenon is somewhat similar to short-term selling in the stock market.

The lower portion of Table 3 shows the estimated long-run equilibrium impact of OPV and SPV on oil price, and the results suggest that OPV and SPV significantly impacted oil price positively, just as in the short run. The estimated long-run coefficient of 0.965 implies that a 1% rise (decline) in the OPV leads to a 0.965% unit increase (decrease) on average in oil prices in the long run, while the estimated long- run coefficient of 0.807 implies that a 1% rise (decline) in the SPV leads to 0.807% units increase (decrease) on average in oil prices in the long-run respectively. The immediate effect of SPV on oil price has more weight than that of OPV; however, the long-run effect is more than that of SPV. The error correction coefficient of SPV representing the adjustment toward long-run equilibrium is much larger than that of OPV, which is -0.009 (0.9%) and -0.017 (1.7%), respectively.

Table 3
Results of linear ARDL model and ARDL bound test

OPV OP			SPV OP		
Variable	**Coefficient**	**t-stat**	**Variable**	**Coefficient**	**t-stat**
OP_{t-1}	1.164***	14.109	OP_{t-1}	1.152***	13.513
OP_{t-2}	-0.173**	-2.076	OP_{t-2}	-0.169*	-2.08
OPV_t	0.009**	2.178	SPV_t	0.014**	2.311
L_{OPV}	0.965***	7.248	L_{SPV}	0.807*	1.917
$CointEq_{t-1}$	-0.009**	-2.028	$CointEq_{t-1}$	-0.017**	-2.547
$B.T_{Trend}$	5.123***	-	BT_{Trend}	5.098***	-
$Adj.R^2$	0.986	-	$Adj.R^2$	0.986	-
$X^2_{auto.}$	1.301	0.367	$X^2_{auto.}$	0.301	0.743
X^2_{Reset}	3.671	0.113	X^2_{Reset}	0.542	0.792
$X^2_{Norm.}$	3.024	0.220	$X^2_{Norm.}$	0.977	0.112
$X^2_{Het.}$	0.463	0.590	$X^2_{Het.}$	2.482	0.288

Source: Authors computation
****** p < 0.01; ** p < 0.05; * p < 0.1***

4.4 VAR Based Causality Tests

To test for the short-run linear causal relationship between the oil price, OPV, and SPV, the Toda-Yamamoto-Dolado-Lutkepohl (TYDL) test is employed. In Table 4, the test result shows that the null hypothesis that the OP does granger cause OPV is accepted. However, oil price does granger cause OPV, as the test statistics are significant at 1% level. The result also reveals that the null hypothesis that the SPV does granger could not be rejected. Nevertheless, oil price does granger cause SPV as the test statistics are significant at the 10% level. Therefore, under the linear VAR framework, we can conclude that oil prices can predict the volatilities of the stock and oil prices in a one-way direction under the linear VAR framework.

Table 4
Results of TYDL and Granger causality tests

Causality Direction		TYDL
OPV	**OP**	0.133
OP	**OPV**	65.04***
SPV	**OP**	0.133
OP	**SPV**	5.796*

Source: Authors computation

****** p < 0.01; ** p < 0.05; * p < 0.1***

4.5 Breitung-Candelon Frequency Domain Causality Test

In the frequency domain causality framework, a shorter frequency corresponds to a more extended period. In other words, there is an inverse relationship between the time-frequency and the spectral frequency, and this can be converted using T= 2 ? /þ, where T is the periods (yearly, daily, monthly, etc.) and þ is the spectral frequency which ranges from zero to ? . Since the graphs are plotted on the 10 units scale, the conversion to get the frequency þ is ? X/100, where X is any given point on the chart. Substituting this for þ gives T= 200/X. Conventionally, the null hypothesis states that causality does not occur at any frequency, i.e. neither in the short-run, medium-run or the long run. For example, figure 2A reveals that OPV does not granger caused oil price at any frequency as its test line is below the critical values. On the contrary, figure 2B depicts that the oil price granger caused OPV at all frequencies (in the short, medium, and long runs) as its test line is above the critical values.

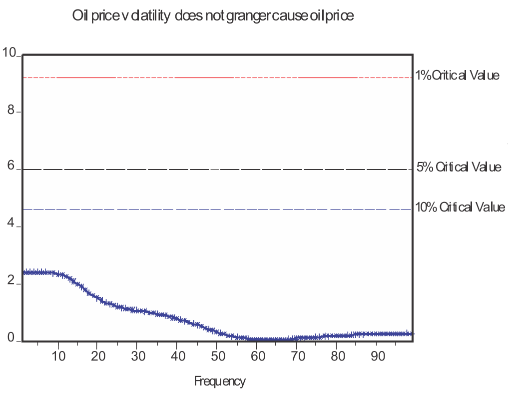

Figure 2A

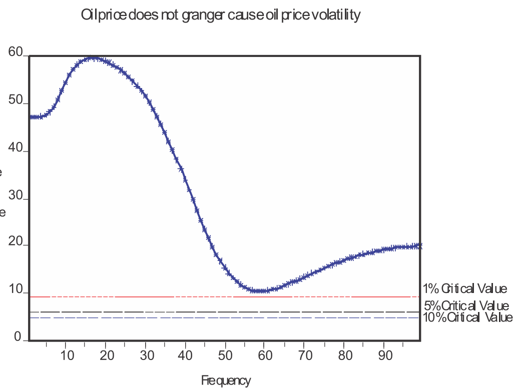

Figure 2B

Figure 3A reveals that SPV does not granger caused oil price at any frequency at a 1% level. However, the story is different for the 5% level of significance. Figure 3A also shows that SPV granger causes oil price in the medium run only; at frequencies less than 1.13(greater than 5months2weeks) but greater than 0.41(less than 15months1week). Also, for the 10% level, the figure shows that SPV granger causes oil price in the medium run only; at frequencies less than 1.57(greater than 4months) but greater than 0.31(less than 20months). On the other hand of the hypothesis, Figure 3B reveals that oil price granger causes SPV in the medium-run to the very long run. For instance, at the 1% level, oil price granger causes SPV in the medium-run to a very long run at frequencies less than 1.19(about 5months1week to a very long run). Also, at the 5% level, oil price granger causes SPV in the medium-run to a very long run at frequencies less than 1.38(about 4 months 2 weeks to a very long run); whereas, oil price granger causes SPV in the medium-run to a very long run at frequencies less than 1.48 (about 4months1week to a very long run) at 10% level.

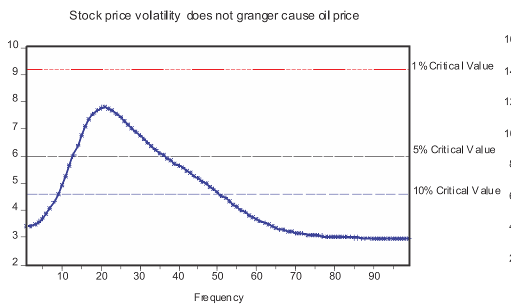

Figure 3A

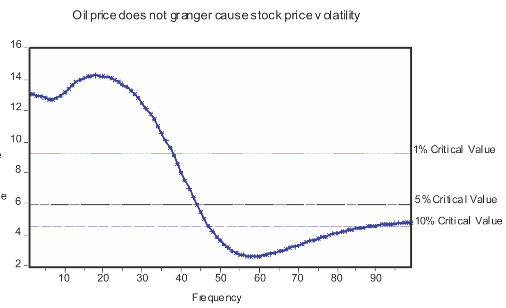

Figure 3B

Causality	Direction	Short-run	Medium-run	Long-run
OPV	**OP**	No	No	No
OP	**OPV**	Yes	Yes	Yes
SPV	**OP**	No	Yes	No
OP	**SPV**	No	Yes	Yes

Source: Authors computation

4.6 Discussion

This study empirically investigated the dynamic relationships between oil price, oil volatility, and stock price volatility using ARDL methodology and their causal relationship using the VAR based and the frequency domain tests. The study found that oil price and stock price volatilities positively impacted oil prices both in the short and long run. This is contrary to the result found in the study of Jeng-Bau et al. (2019). This study found that the short-run effect of stock price volatility on the oil price is more than that of oil itself; whereas, the versa is the case in the long run. Thus, there is a greater tendency that the oil price adjusts back to its long-run equilibrium when affected by stock market price instabilities than the oil market irregularities.

The VAR-based granger causality test results reveal that stock and oil price volatilities could not predict (cause) the next oil price, whereas past oil prices could foretell the stock price and oil price volatilities. However, these findings are weak by not suggesting the horizon of the causality, and the Breitung-Candelon frequency causality test is adopted to circumvent the shortcomings. The Breitung-Candelon reveals that oil price volatility does not granger cause oil price in the short-run, medium-run, or the long-run, whereas the oil price granger causes oil price volatility in the short-run medium-run, and the long-run, respectively. This agrees with the VAR based result. The result shows that stock price volatility only granger causes oil price in the medium-run, whereas the oil price granger causes stock price volatility in the medium and long runs.

5.0 Conclusion

Conclusively, the empirical analysis disagrees with Lin, Liang, & Tsai (2019) and suggests that stock price volatility influences oil prices in the short run and long run. More explicitly, in the short run, the stock price volatility exerts more influence on oil price than the magnitude of effect oil price volatilities have on oil price, while the reverse is the case in the long run. Thus, this study gives a better understanding of the effect of irregularities or fluctuations in stock prices on oil prices, and it exposes the workings of the market to the policymakers, investors, buyers, and sellers that oil price may quickly revert to equilibrium position for an extended period if affected by the irregularities in the stock prices, unlike when the target variable; oil price is affected by its volatility. It recommends that policymakers consider the movement in oil price and stock price in shaping the capital market's operation and ensuring the proceeds from increased oil prices are utilised maximally for economic revitalisation in Nigeria.

REFERENCES

Abdulkarim, F. M., Akinlaso, M. I., Hamid, B. A., & Ali, H. S. (2020). The nexus between oil price and Islamic stock markets in Africa: A wavelet and Multivariate-GARCH approach. Borsa Istanbul Review, 20(2), 108-120.

Adaramola, A. O. (2012). Oil price shocks and stock market behaviour: The Nigerian Experience. Journal of Economics, 3(1), 19-24.

Adebiyi, M. A., Adenuga, A. O., Abeng, M. O., & Omanukwue, P. N. (2009, June). Oil price shocks, exchange rate and stock market behaviour: Empirical evidence from Nigeria. In *Proceedings of the 14th Annual Conference of the African Econometric Society*.

Adeniji, S. O. (2015). An empirical investigation of the relationship between stock market prices volatility and macroeconomic variables' volatility in Nigeria. European Journal of Academic Essays, 2(11), 1-12.

Ahmed, A. D., & Huo, R. (2020). Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from China. Energy Economics, 93, 104741.

Alamgir, F., & Amin, S. B. (2020). The nexus between oil price and stock market: Evidence from South Asia. *Energy Reports*, *7*, 693-703.

An, Y., Sun, M., Gao, C., Han, D. & Li, X. (2018). Analysis of the impact of crude oil price fluctuations on China's stock market in different periods—Based on time series network model. Physica A: Statistical Mechanics and its Applications, 492, 1016-1031.

Aregbeyen, O., & Fasanyan, I. O. (2017). Oil price volatility and fiscal behaviour of the government in Nigeria. *Asian Journal of Economic Modelling*, *5*(2), 118-134.

Arouri, M. E. H., Jouini, J. & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. Energy Economics, 34(2): 611-617.

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of applied econometrics*, *18*(1), 1-22.

Balcilar, M., & Ozdemir, Z. A. (2019). The nexus between the oil price and its volatility risk in a stochastic volatility in the mean model with time-varying parameters. Resources Policy, 61, 572-584.

Breitung, J., & Candelon, B. (2006). Testing for short-and long-run causality: A frequency-domain approach. *Journal of econometrics*, *132*(2), 363-378.

Burbidge, J. & Harrison, A. (1984). Testing for the effects of oil-price raises using vector Autoregressions. International Economic Review, 25(2): 459-484.

Cai, Y., Lu, X., Ren, Y., & Qu, L. (2019). *Exploring the dynamic relationship between crude oil price and implied volatility indices: A MF-DCCA approach. Physica A: Statistical Mechanics and Its Applications.* DOI: 10.1016/j.physa.2019.04.209

Cashin, P., H. Liang, and C.J. Mcdermoth. (2000). "How persistent are shocks to world Commodity prices? IMF Staff Papers, vol.47 (2).

Chuku, C., Effiong, E., & Sam, N. (2010). Oil price distortions and their short-and long-run impacts on the Nigerian economy.

Daniel N.C. (1997). "International Interdependence of National Growth Rates: A structural Trends Analysis", Journal of Monetary Economics 40:73-96.

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. Econometrica, 55(2), 251. doi:10.2307/1913236

Enwereuzoh, P. A., Odei-Mensah, J., & Junior, P. O. (2021). Crude oil shocks and African stock markets. Research in International Business and Finance, 55, 101346.

Essa, M. S., & Giouvris, E. (2020). Oil Price, Oil Price Implied Volatility (OVX) and Illiquidity Premiums in the US :(A) symmetry and the Impact of Macroeconomic Factors. Journal of Risk and Financial Management, 13(4), 70.

European Central Bank (2012). Annual Report.

Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work, Illinois, Chicago, Univ., Center for Mathematical Studies in Business and Economics.

Geweke, J. (1982). Measurement of Linear Dependence and Feedback between Multiple Time Series. *Journal of American Statistical Association, 77*, 304-324

Gisser, M. & Goodwin, T. H. (1986). Crude oil and the Macroeconomy: Tests of some popular notions: Note. Journal of Money, Credit and Banking, 18(1): 95-103.

Gomes, M., & Chaibi, A. (2014). Volatility spillovers between oil prices and stock returns: A focus on frontier markets.

Gourène, G. A. Z., & Mendy, P. (2018). Oil prices and African stock markets co-movement: A time and frequency analysis. Journal of African Trade. doi:10.1016/j.joat.2018.03.002.

Grossman, S. J. & Stiglitz, J. E. (1995). On the impossibility of informationally efficient markets. *The economics of information / edited by David K. Levine and Steven A. Lippman*.

Hamdi, B., Aloui, M., Alqahtani, F., & Tiwari, A. (2019). Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: Evidence from wavelet non-linear denoised based quantile and Granger-causality analysis. Energy Economics, 80, 536-552

Hamdi, B., Aloui, M., Alqahtani, F., & Tiwari, A. (2019). Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: Evidence from wavelet non-linear denoised based quantile and Granger-causality analysis. Energy Economics, 80, 536-552

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of political economy.* -912**,** 228-248.

Hamilton, J. D. (1996). *This is what happened to the oil price-macroeconomy relationship. Journal of Monetary Economics, 38(2), 215–220.* doi:10.1016/s0304-3932(96)01282-2.

Hooker, Mark A. (1996), "What Happened to the Oil Price-Macroeconomy Relationship?" Journal of Monetary Economics 38 (195-213).

Hooker MA & A.J Oswald. (1996). "Unemployment Equilibria and Input Prices: Theory and Evidence for the United States", Review of Economics and Statistics.

Huskaj, B., & Larsson, K. (2016). An empirical study of the dynamics of implied volatility indices: international evidence. Quantitative Finance Letters, 4(1), 77–85. doi:10.1080/21649502.2017.1292041.

Kang, W., Ratti, R. A., & Yoon, K. H. (2015). Time-varying effect of oil market shocks on the stock market—Journal of Banking & Finance, 61, S150-S163.

Kumar, S., Pradhan, A. K., Tiwari, A. K., & Kang, S. H. (2019). Correlations and volatility spillovers between oil, natural gas, and stock prices in India. Resources Policy, 62, 282-291.

Lin, J. B., & Tsai, W. (2019). The Relations of Oil Price Change with Fear Gauges in Global Political and Economic Environment. *Energies*, *12*(15), 2982.

Lin, J. B., Liang, C. C., & Tsai, W. (2019). Non-linear relationships between oil prices and implied volatilities: Providing more valuable information. Sustainability, 11(14), 3906.

Liu, Ming-Lei, Ji, Qiang & Fan, Ying, (2013). ***How does oil market uncertainty interact with other markets? An empirical analysis of implied volatility index***. ***Energy***, Elsevier, vol. 55(C), pages 860-868.

Liu, Z., Tseng, H.-K., Wu, J. S., & Ding, Z. (2020). *Implied volatility relationships between crude oil and the US stock markets: Dynamic correlation and spillover effects. Resources Policy, 66, 101637.* DOI: 10.1016/j.resourpol.2020.101637

Maghyereh, A. I., Awartani, B., & Bouri., E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. Energy Economics, 57, 78–93. ***https://doi.org/10.10 16/j.eneco.2016.04.010***

Masih, R., Peters, S., & De Mello, L. (2011). Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea. Energy Economics, 33(5), 975-986.

Obi, B., Adeniji, S. O., & Evans, O. (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), 173-190.

Okoro, E. G. (2014). Oil price volatility and economic growth in Nigeria: A Vector Auto-Regression (VAR) approach. Acta Universitatis Danubius. Economica, 10(1), 70-82.

Olayeni, O. R., Tiwari, A. K., & Wohar, M. E. (2020). Global economic activity, crude oil price and production, stock market behaviour and the Nigeria-US exchange rate. Energy Economics, 92, 104938.

Osaze, I. D., & Oriakhi, D. E. (2013). Oil price volatility and its consequences on the growth of the Nigerian economy: An examination (1970-2010). *Asian economic and financial review*, *3*(5), 683.

Pan, Z., Wang, Y., Wu, C., & Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime-switching GARCH-MIDAS model. *Journal of Empirical Finance*, *43*, 130-142.

Pesaran, H., Smith, R., & Im, K. S. (1996). Dynamic linear models for heterogeneous panels. In *The econometrics of panel data* (pp. 145-195). Springer, Dordrecht.

Pesaran, M. H., & Shin, Y. (1995). An autoregressive distributed lag modelling approach to cointegration analysis.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326. doi:10.1002/jae.616.

Shaikh, I. (2019). The Relation between Implied Volatility Index and Crude Oil Prices. Engineering Economics, 30(5), 556-566.

Shin, Y. & Yu, B. & Greenwood-Nimmo, M. (2014). Modelling Asymmetric Cointegration and Dynamic Multipliers in a Non-linear ARDL Framework. 10.2139/ssrn.1807745.

ThankGod, Apere & Ijomah, Maxwell. (2013). Macroeconomic Impact of Oil Price Levels and Volatility in Nigeria. International Journal of Academic Research in Economics and Management Sciences. 2. 10.6007/IJAREMS/v2-i4/48.

Tule, M. K., Ndako, U. B., & Onipede, S. F. (2017). Oil price shocks and volatility spill-overs in the Nigerian sovereign bond market. Review of Financial Economics, 35, 57-65.

Yıldırım, N. and H. Taştan, (2009), "Capital Flows and Economic Growth across Spectral Frequencies: Evidence from Turkey", Turkish Economic Association Discussion Paper 2009/2.