International Journal of Advanced Finance and Accounting | *ISSN 2765-8457*
Published by ACADEMIC INK REVIEW | *https://airjournal.org/ijafa*
12011 WestBrae Pkwy, Houston, TX 77031, United States
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Effect of Oil Price Fluctuation on the Trading Volume of the Nigerian Capital Market

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Publication Process	***Date***
Received	***June 4th, 2021***
Accepted	***June 23th, 2021***
Published	***June 30th, 2021***

ABSTRACT

This study examined the effect of oil price fluctuation on the trading volume of the Nigerian capital market using monthly frequency data that cover the period from January,1997 to August 2020. It employed the non-linear autoregressive distributed lag methodology for data analysis. The results of the empirical analysis suggest that oil price fluctuations have significant and positive effect on the market volume in the Nigerian capital market and that there is no asymmetric effect between the variables. The study recommends that Nigeria should devise strategies that can ensure stability in their capital markets. It can do this by vigorously pursuing pro-growth policies irrespective of the fluctuations in oil price and other macroeconomic variables.

Keywords: *Oil Price Fluctuation; Nigerian Capital market; Trading Volume; ARDL*

1. Introduction

Crude oil, is one of the most important production inputs. Quite often, It has been identified by many as a commodity which plays an essential role in the world economy (Heo, Yoo & Kwak, 2010; Difiglio, 2014; Le & Chang, 2015; cited in Yoshino, Rasoulinezhad & Chang, 2019). For Yoshino et al. (2019), one of the major causes of political tensions among nations is the economic advantage of crude oil as an important production input in the post-industrial era or its uses in transport and electricity generation sectors.

Namovsky (2018) asserts that as oil prices increase, international trade becomes more localized because countries begin to trade relatively more with their neighbors. On the other hand, when oil prices plummet, trade becomes more dispersed since the distance between countries becomes less relevant. Namovsky (2018) observes that these results are highly significant across specifications, and advises that the magnitude should not to be ignored. In spite of the observable attention being given to alternative renewable natural sources of energy like wind, water, nuclear, and solar power, the part played by crude oil in macroeconomic movements has continued to be significant. Oil prices have been highly variable—twice as variable as those of other goods.

There is ample evidence in literature that, since the 1970s, movements in the international oil prices have continued to attract a lot of attention. They have become a subject of debate and a considerable issue for several nations. This is more particularly the case with the oil-exporting countries where public authorities tie their budgets to oil revenues. Their economic growth can be hit by these changes directly and indirectly. The same applies to oil-importing countries where petroleum is the raw material for producing goods and transportation. Shortly after the tremendous oil price shocks of the 1970s, a large body of literature began to grow with the intention of identifying the effect of oil price movements on the real economic activity. Hamilton (1983), that was among the early studies which probed the oil price and aggregate economy relationship, witnessed that ten out of the eleven post-war recessions in the United States up to 1983 were preceded and caused by oil price shocks. This discovery motivated many scholars to carry out additional research on the causal relationship between the two variables. In the list of such studies are Bernanke, Getter and Watson (1997), Bohi (1989), Brown and Yucel (2001), Burbidge and Harrison (1984), and Gisser and Goodwin (1986). However, the studies concerning the connection between oil price and the stock market were relatively recent. Peter and De-Mello (2011) cited in Soyemi, Akingunola and Ogebe (2017) attribute this situation to the difficult nature of evaluating stock market activities which trended only from the late 1990s. Some of those past studies did not notice any relationship between them (Degiannakis, Filis & Arora, 2017) but a lot of them found reasonable evidence of relationship between the two variables. Concerning the effect of oil price shocks on stock market fluctuations, Malik and Ewing (2009) observed significant transmission of volatility between oil price and some sectors in the US stock market. For Arouri and Rault (2011), there is volatility transmission from oil to European stock markets. In addition, Degiannakis, Filis and Kizys (2014) observe that an upward movement in the price of oil related to increased aggregate demand significantly increases stock market volatility in Europe, and that supply-side shocks and oil specific demand shocks have no effect on volatility.

The importance of trading volume as one of the fundamental building blocks of the theories of stock market interventions and in modeling asset markets is highly recognized in literature. However, even though several models of asset market have focused their attention on the way that returns behave, such as how they can be predicted as well as how they can change and their information content, their implications for trading volume do not seem to have received significant attention (Lo & Wang,2000). In Nigeria particularly, the studies that have examined the relationship between oil price shocks and stock return are relatively few. That notwithstanding, the findings of those studies hardly agree. For instance, while Omisakin, Adeniji and Omojolabi (2009), Mordi, Michael and Adebiyi (2010), Abbas and Terfa (2010), Adebiyi, Adenuga, Abeng and Omanukwue (2010), Akomolafe and Danladi (2014), Akinlo (2014), Iheanacho (2016), Lawal, Somoye and Babajide (2016), Soyemi et al. (2017), Ojikutu, Onolemhemhen and Isehunwa (2017) and Obi, Oluseyi and Olaniyi (2018) find negative effect of oil price fluctuations on stock return others find contend that the effect is positive. The following examples illustrate the nature of disagreement in the results of earlier works on this subject – matter. Both Adaramola (2012) and Effiong (2014) report a negative relationship between oil price shock and stock return. For Okany (2014) observes no cointegration between the two variables. Effiong (2014) reports that the effect of oil price shock on stock price in Nigeria is insignificant.

The disagreement among results has left much gap in literature. The present study intends to contribute to this debate by examining the nexus between oil price fluctuations and of one of the stock market performance indicators in Nigeria. Precisely, the main objective of this paper is to ascertain the effect of oil price volatility on the volatility of the trading volume in the Nigerian capital market. The choice of Nigeria in this study is motivated by the fact that

Nigeria is qualified among all the West African countries to be used as proxy. Nigeria is an emerging economy which is not only acclaimed to be the sixth largest member of OPEC and the largest net-exporter of oil in Africa but is also a highly promising economy for international portfolio diversification (Akinlo, 2012). The importance of this study lies on its envisaged ability to generate results that will improve stock returns forecasting accuracy, provide relevant information for investors and policy makers, make available reference materials for researchers and the academia and also assist firms in constructing diversified portfolios and determining risk management strategies. This study extends the existing literature in two distinct ways. Firstly, the study provides, to the best of our knowledge, the first empirical inquiry on the impact of Brent oil price fluctuations on stock market activities in Nigeria, with emphases on the trading volume in the Nigerian capital market. Secondly, it is one of the few recent studies on the oil/stock relationship in Nigeria using monthly data. Thirdly, this research has its scope extended to August, 2020.

The remaining part of this paper is arranged as follows. In section 2, a brief literature review is highlighted. Section 3 describes the empirical model, while section 4 presents the estimation results and discussion. Section 5 concludes the study.

2 Literature Review

2.1 Theoretical and conceptual review

Several researchers consider crude oil as representing information flow. For an oil-importing country, an increase in oil price is expected to have a positive impact (Hooker,1999), Ceteris paribus, oil price increase will bring about an increase in production costs, as oil is regarded as the most important production input (Arouri & Nguyen, 2010). According to Hamilton (1988a, 1988b), and Barro (1984) cited in Youssef and Mokni (2019), the increasing cost of crude oil will affect consumer's behavior, which will, in turn, decrease their demand and spending on them as a result of higher consumer prices. When the consumption of crude oil is reduced, there will be a cut down in production and, in return, an increase unemployment (Brown & Yücel, 2001; Davis & Haltiwanger, 2001 in Youssef & Mokni, 2019). In addition, oil price movements affect stock markets as a result of the uncertainty they create for the financial sector. However, this depends on the forces that push up oil prices (demand-side or supply). Some transmission channels exist between oil and stock market return, namely, stock valuation channel, monetary channel, output channel, fiscal channel and uncertainty channel (Degiannakis, Filis & Arora, 2017).

The impact of crude oil price on stock markets has continued to attract attention from researchers and investors from theoretical and empirical angles through sectoral, country-specific, regional and global analyses (see Dutta, Nikkinen & Rothovius, 2017; Ftiti, Guesmi & Abid, 2016; Hamdi, Aloui, Alqahtani, & Tiwari, 2019; Huang, An, Gao & Sun; 2017; Ji, Liu, Zhao & Fan, 2018; Kang, de Gracia & Ratti, 2017; Luo & Qin, 2017;Tursoy & Faisal, 2018; Wong & El-Massah, 2018; Xiao, Zhou, Wen, & Wen, 2018; Zhu, Guo, You & Xu, 2016).

According to IEA (2016), crude oil is a common source of fuel and accounts for 39.9 percent of the world fuel consumption. In spite of the rising efforts at renewable and alternative energies, crude oil consumption remains unaffected (Gourène & Mendy, 2018). Badeeb and Lean (2018) contend that the increasing theoretical and empirical inquiry into the relationship between crude oil prices and stock markets shows the importance of crude oil to the world economy through its effect on corporate liquidity and earnings. Theoretically, the equity valuation theory proposes that stock price is the sum of the discounted values of expected future cash flows at different investment horizons that depend on macroeconomic economic conditions such as interest rate, inflation, production cost, aggregate demand and investors' confidence (see Arouri, Jouini & Nguyen, 2012; Badeeb & Lean, 2018). Crude oil price shocks affect the stock markets through their influences on monetary policy instruments, inflation, corporate income and other economic activities (Gourène and Mendy, 2018) in both developed and emerging economies.

Trading volume, also called volume of trade, is the total number of shares or contracts traded in a stock market for a given security. It is measured on share options, contracts, futures contract and other types of commodities. It is normal for every stock exchange to take stock of its trading volume and provide the data. This is reported almost on hourly basis throughout a given trading day. Trade [or trading] volume informs investors about the stock market's activity as well as liquidity. When the trading volume is high for a specified security, the implication is that it has high liquidity; it means that there is better order execution and an active market for bringing buyers and sellers together. Trading volume is usually higher when the price of a security is changing. Whether positive or negative, the news concerning a company's financial status, products, or plans will ordinarily cause a temporary movement in the trade volume of its share. There is a link between trading activity in individual stocks and market – wide volume.

According to Wang (2015), technical traders employ different types of stock trading rules to forecast the prices of stocks, viz: -

a) *Moving average rules:* These are the trading rules most commonly employed by technical traders. They are based on price moving averages of different lengths based on the understanding that the share price will be on a trend if a shorter moving average is crossing a longer moving average.
b) *Support and resistance rules:* These rules refer to the important reference points of past prices which the technical traders look at when they make their buy or sell decisions.
c) *Trend line rules:* Trend lines are the lines which connect the peaks or troughs and extend into the future. These include uptrend line and downtrend line.
d) *Big buyer, big seller and manipulator rules:* There are institutional traders who manage huge sums of money and usually desire to purchase or sell a large amount of stocks. Since the amount of stocks offered or asked around the trading price is usually not big, the large buy or sell order has to be sliced into small pieces and executed incrementally over a long period (Bouchaud, Farmer & Lillo, 2008; Aldridge, 2013 cited in Wang, 2015).
e) *Band and stop rules:* The bands are envelopes around a moving average which have variable sizes. The most widely used band is the Bollinger Band which adds and subtracts the moving estimate of two standard deviations of returns to a moving average (see Bollinger, 2002 cited in Wang, 2015).
f) *Volume and strength rules:* These refer to the trading rules that employ not only their own past prices but also other information such as volume and the prices of other stocks in the market.

Several studies have used varying measures for trading volume. A group of studies use aggregate turnover minus the total number of shares traded divided by the total number of shares outstanding (*see* Campell, Grossman & Wang, 1999; LeBaon, 1992; Smidt, 1990; the 1996 NYSC Fact Book cited in Lo and Wang, 2000). Yet another group of authors use individual share volume in analyzing price/volatility and volatility/volume link (see Andersen, 1996; Epps and Epps, 1976 as well as Lamoureux & Lastrapes, 1990,1994 in Lo and Wang, 2000). Other measures of trading volume include individual turnover, individual dolar volume normalized by aggregate market dollar volume, and number of trading days per year (Lo & Wang,2000). This study is anchored on the model that measures trading volume as the total number of shares traded. We anchored our paper on this measure of trading volume for the purpose of simplicity.

2.2 Empirical Review

The studies concerning the crude oil price-macroeconomy nexus started from the developed economies and gradually trickled down to emerging markets. However, only a few of them were on the African continent (Kelikume & Muritala, 2019). The pioneering studies included Burbidge and Harrison (1984) and Gisser and Goodwin (1986).

Burbidge and Harrison (1984) carried out an investigation similar to Hamilton (1983). The authors obtained data for five OECD countries. They found a significant impact of rising oil price on real outputs at varying degrees for the countries investigated,

namely the US, UK, Canada, Japan, and Germany. The study by Gisser and Goodwin (1986) was a further investigation on the relationship between crude oil price and macroeconomy in the US. They found strong evidence for a significant impact of oil prices on the US macroeconomy.

The studies conducted by Sadorsky (1999) show that oil prices and stock markets are negatively correlated. Using monthly data for the US economy, Sadorsky (1999) examined the impact of oil price shocks on market returns and two other key macroeconomic measures-industrial production and interest rate. The findings indicate that positive oil price shocks affect real stock returns and that a more significant fraction of the forecast error variance in stock returns is explained by movements in oil prices instead of interest rate.

Karpoff (1986) developed a theory of trading volume based on assumptions that market agents frequently revise their demand prices and meet potential trading partners randomly. The author created a model that describes two distinct ways that informational events affect trading volume, namely, (a) investor disagreement leads to increased trading and (b) volume can increase even if investors interpret the information identically. Papapetrou (2001)'s study on the Greek economy disclosed interdependence between oil and stock data and a significant impact of oil price.

Bittlingmayer (2005) observed that oil price fluctuations arising from war risks, and those related to other causes, display asymmetric effects on stock price dynamics.

Rafailidis and Katrakilidis (2014) also found that oil prices and stock returns are negatively correlated.

Wang (2015) employed the fuzzy systems theory to convert the technical trading rules commonly used by stock practitioners into excess demand functions that were subsequently used to drive the price dynamics. The technical trading rules were recorded in natural languages where fuzzy words and vague expressions abound. The author demonstrated the details of how to transform the technical trading heuristics into nonlinear dynamic equations.

Diaz, Molero and de Gracia (2016) explored the co-movement between oil price volatility and stock returns in the G7 economies using monthly data for the period from 1970 to 2014. The result of the study showed that there exists an inverse relationship between oil price volatility and stock market performance. The study also found that the world oil price volatility has a more significant negative impact on stock markets than the national oil price volatility.

Odupitan (2017) studied the impacts of dwindling crude oil prices on oil producing countries, using Nigeria as a case study. The study observed that in 2015, Nigeria emerged as having the largest economy in Africa, with an estimate of about $1.1 trillion. It had moved significantly away from agriculture, which used to be the main sector of the economy, to oil exploration since oil discovery in the late 1950s. Also, as a result of the overreliance on oil, several other sectors of the economy such as manufacturing, energy, transportation, banking and telecommunications were directly influenced and relied on the activities within the oil sector. In 2008, at the height of the global boom when crude oil price reached its record highest price, the other sectors of the economy experienced a positive turnaround. However, shortly after the global prices of crude oil crashed in 2014, the Nigeria witnessed around 3% fall in GDP just as the government revenues declined and the other non-oil sectors of the economy contracted.

Ding, Liu, Zhang & Long (2017). investigated the contagion effect of global oil price volatility on the investor's sentiment in China using the structural vector autoregression approach. The result showed that world crude oil price fluctuations significantly Granger caused Chinese stock market investor sentiment in both the short-run and long-run.

Tursoy andFaisal (2018). investigated the long-run and short-run interaction between stock prices, gold prices and crude oil prices by applying monthly data from Turkey for the period between January 1986 and November 2016. The study used the autoregressive distributed lag (ARDL) model to estimate the cointegration and short-run relationship. Additionally, it employed FMOLS, DOLS and CCR cointegrating equations to examine the long-run coefficients between the variables. The results showed that both short-run and long-run results confirm negative relationship between the gold price and stock prices, and a positive relationship between crude oil and stock prices.

Wong and El-Massah (2018) examined the effects of oil price changes on Gulf Cooperation Council stock markets between 2005 and 2015. Using the Granger causality and impulse response techniques, the result of the study exhibited a significant negative impact from oil price fluctuations on the GCC stock markets.

An, Sun, Gao, Han & Li (2018) explored the influence of Brent oil price fluctuations on the stock prices of the petrochemical block and the electric equipment and new energy block for China using the Shannon entropy of information theory. The results revealed that both networks have different fluctuations characteristics in different periods.

Gourène and Mendy (2018) sought to find the relationship between oil prices and the six largest African stock markets using the wavelet coherence analysis. The study reported a low co-movement between oil prices and African stock markets except for South Africa and Egypt.

While examining the Chinese oil-stock relationship, Hu, Liu, Pan, Chen and Xia (2018) combined the Structural VAR model and the non-linear Autoregressive Distributed Lag (NARDL) model to ascertain the long run and short-run asymmetric effects of structural oil price shocks on the Chinese stock market. The empirical results showed that the demand-side shocks of oil price have a significant impact on the Chinese stock market in the short-run and long-run, while the supply shock does not.

Al-hajj, Al-Mulali and Solarin (2018) studied how fluctuations in oil price, interest rate, exchange rate, industrial production, and inflation impact on the stock market returns for Malaysia. The study employs the non-linear autoregressive distributed lag (NARDL) to analyze monthly data covering the period between January 1990 to November 2016 and from May 2000 to November 2016 for the aggregate market and the nine sectors, respectively. The ARDL bounds test result indicates the existence of a long-run cointegrating relationship.

Pal and Mitra (2019) investigate the interdependency between oil price and automobile stock return from August 01, 1996 to June 20, 2017, using the wavelet time-frequency domain analysis. The results of the study showed that the co-movement between oil price and automobile stock return was strong during November 2000 - December 2002 and March 2006 - December 2009.

Kelikume and Muritala (2019) examined the impact of oil price on African stock markets, using quarterly data from five selected oil producing countries with stock market presence, from Q1:2010 to Q4: 2018. It deployed dynamic panel analysis technique for a model comprising stock returns, real gross domestic product growth rate, exchange rate and OPEC basket price. The results of the study show that an adverse effect of oil prices existed on stock markets in Africa, attributable to fragmented and underdeveloped capital markets. The relationship exhibited by stock markets and the oil price has an immediate implication of shifting foreign direct investments in and away from stock markets in African oil dependent economies.

According to Kelikume and Muritala (2019), among the studies on developing economies, Africa has not been a focal point (see Al-hajj et al., 2018; Wong & El-Massah, 2018; Zhu et al., 2016), According to the authors, the few studies on Africa such as Asaolu and Ilo (2012), Aye (2014), Gil-Alana and Yaya (2014), Gupta and Modise (2013), Lin, Wesseh and Appiah (2014) and Gourène and Mendy (2018) are deficient in scope and methodology.

The past studies have adopted different theories to underpin their analysis of the impact of oil price volatility on stock markets. For instance, An et al. (2018) adopted the Shannon Entropy Information Theory to analyze the oil-stock space for China, while Arouri et al. (2012) anchored their studies on the value of equity theory. This study is anchored on the nonlinearity theory was agreement with Cheikh, Naceur, Kanaan and Rault (2018) that contend that ignoring non-linearity can lead to problematic results and Balcilar, Gupta and Wohar (2016) that argue that using a linear framework would result in mixed results. Consequently, the non-linear autoregressive distributed lag approach was employed for estimation.

3. Methodology

3.1 Data

This work employed monthly historical data spanning the period from January 1997 to August 2020 to explore the effect of oil price(OP) fluctuations on market volume(MVOL) in the Nigerian capital market. Oil prices per barrel were extracted from the US Energy Information Administration (EIA) short-term outlook. The Europe Brent spot price was selected as the explanatory variable. Monthly data series covering the period from January 1997 to August 2020 were employed for estimation in line with the general preference of empirical studies for such data-frequencies especially when investigating oil-stock-prices correlation This study covers the periods of economic recession in Nigeria as well as the Covid-19 pandemic.Concerning the oil price data, monthly Brent spot prices were used .They were denominated in US dollars and obtained from the US Energy Information Administration (EIA) short-term outlook. In order to check for robustness, pre-tests were conducted with other crude oil benchmarks such as West Texas Intermediate (WTI) and the OPEC spot prices. It was confirmed that using those oil prices instead of the Brent spot prices would not significantly change the results of our benchmark specifications. The monthly data on Nigeria's market volume were retrieved from the Nigeria Stock Exchange (NSE), Stock Exchange House, 2-4 Customs Street, Lagos, Nigeria through contactcentre@nigerianstockexchange.com and www.nse.com.org.. Each of the two data series used for the work comprised 284 observations. The data sets were fed into the computer as Excel files with two columns - the date and the corresponding information for the particular date. From the Excel, the data sets were trasferred to the Eviews 10 software for regression analysis.

3.2. Model specification

Several studies in the past were based on the conventional cointegration approach which examines relationships between changes in oil and stock prices.Many of them also used a multivariate vector autoregression just to determine if and how volatility transmits from one market to another and the possible feedback effect in lead-lag scenarios. Some other studies employed the least square regression technique for the same purpose.

Generally, the co-integration approach which some studies employed tends to support the long-run relationship between oil price and stock market indicator.However, it fails to consider short-run relationship and is required only when the variables are differently integrated or have different orders.Some studies like Gourène and Mendy (2018) employed the wavelet analysis technique. This method has several limitations that affect the robustness of the study's results.Also, a number of previous studies applied the frequency domain causality technique to wide areas of economic research.. Yet other empirical works like Tursoy and Faisal (2018) had used a combination of the ARDL bounds cointegration, fully modified ordinary least square, and the dynamic ordinary least square techniques to examine whether a long-run and short-run relationship exist amongst stock prices and crude oil price.Authors such as Hu et al. (2018) combined the Structural VAR model and the non-linear Autoregressive Distributed Lag (NARDL) model to determine the longrun and short-run asymmetric effects of structural oil price shocks.The results generated after using those different analytical techniques have tended to conflict with one another. Such divergence in result arose partly because some methods considered only a short-run relationship as against the others which capture long-run associations (Kelikume and Muritala, 2019).

Rather than align with the symmetric or linear theory which Hamilton (1983) developed, this study employed the Nonlinear Autoregressive Distributed Lag (NARDL) model as adopted by Jungo and Kim (2019) based on the assumption of nonlinearity. To investigate the subject thoroughly, and unlike what many previous studies did, specific account was taken of the asymmetric effects of oil price changes in the modeling process.

The attraction of NARDL, which is an improvement on ARDL and introduced by Shin,Yu and Greenwood-Nimmo (2014), lies in the fact that it is said the simplest method available for modeling combined short- and long-run asymmetries (Allen & McAleer, 2020).It employs the bounds testing framework and can be applied to both stationary and non-stationary time series vectors, or combinations of both so long as none of the data series is of the I(2) integration order (Paseran, Shin & Smith, 2001). Accounting for asymmetry in stock data analysis yields robust inferences (Zhu et al., 2011; Ghosh & Kanjilal, 2016). It is very construction allows one to incorporate the possibility of asymmetric effects of positive and negative changes in explanatory variables on the dependent variable. Further, NARDL method provides graphs of cumulative dynamic multipliers used to trace out the adjustment patterns following the positive and negative shocks to explanatory variables. NARDL model captures the nonlinear and asymmetric co-integration between variables. In addition, it distinguishes between the short-term and long-term effects of the independent variables on the dependent variable. Further, just like is the case with ARDL.

Apart from theNARDL's flexibility of allowing both I(0) and I(1)in the model, its approach to cointegration provides several more advantages over other methods (Phong, Bao & Van, 2017; Phong, Bao & Van, 2018). Firstly, it can generate statistically significant result even with small sample size, while Johansen cointegration method requires a larger sample size to attain significance (Pesaran, Shin & Smith, 2001). Secondly, while other cointegration techniques require the same lag orders of variables, it allows various ones.Thirdly, NARDL technique estimates only one equation by OLS method rather than a set of equations like other techniques (Srinivasana and Kalaivanib, 2013). Finally, NARDL approach outputs unbiased long-run estimations, provided that some of the variables in the model are endogenous (see Pesaran & Pesaran, 1997; Harris & Sollis, 2003).

In order to capture non-linear and asymmetric relationship among the variables, the NARDL model developed by Shin et al. (2014) was applied in this study.

According to Phong, Van and Bao (2019), variables are deemed to be cointegrated if there exists a stationary linear combination or long-term relationship among them. For testing cointegration, such as Engle and Granger(1987). Johansen (1988) are frequently employed. Nevertheless, when variables are integrated at I(0) or I(1), the 2-period-residual-based Engle-Granger and the maximum-likelihood-based Johansen methods may produce biased results regarding long-run interactions among variables (Engle & Granger,1987; Johansen, 1988). Relating to this issue,the Autoregressive Distributed Lag (ARDL) method proposed by Pesaran and Shin (1998) provides unbiased estimations regardless of whether I(0) and I(1) variables exist in the model.

When cointegration is identified, the calculation procedure of NARDL is similar to that of the traditional ARDL (Phong et al., 2019). The general ARDL model for one dependent variable Y and a set of independent variable $X_1,X_2,X_3,...,X_n$ is denoted asARDL(p_0 $p_1,p_2,p_3,...,p_n$), in which p_0 is the lag order of Y and the rest are respectively the lag orders of X_1, X_2, $X_3,...,X_n$.

ARDL(p_0, p_1, p_2, $p_3,...,p_n$)is written as follows: $Y_t=\alpha+p_0\sum i=1(\beta_0,i\cdot Y_{t-1})+p_1\sum j=0(\beta_1,j\cdot X_{1,tj})+ p_2\sum k= 0(\beta_2,k\cdot X_{2,t-k})+p_3\sum l=0(\beta_{3,1}\cdot X_{3,t-1})+...+p_n\sum m=0 (\beta_{n,m}\cdot X_{n,t-m}) +\varepsilon t$.(1)

As is the case with ARDL, the NARDL methods begin with bound test procedure to identify the cointegration among the variables; in other words, the long-run relationship among the variables (Pesaran and B. Pesaran,1997). The Unrestricted Error Correction Model (UECM) form of ARDL is shown as: $\Delta Y_t=\alpha+p_0\sum i=1(\beta_{0,i}\cdot\Delta Y_{t-1})+ p_1\sum j=0(\beta_{1,j}\cdot\Delta X_{1,t-j})+p_2\sum k=0(\beta_{2,k}\cdot\Delta X_{2,t-k})+ p_3\sum l=0(\beta_{3,1}\cdot\Delta X_{3,t-1})+...+p_n\sum m=0(\beta_{n,m}\cdot\Delta X_{n,t-m}) +\lambda_0\cdot Y_{t-1}+\lambda_1\cdot X_{1,t-1}+\lambda_2\cdot X_2,t-1+\lambda_3\cdot X_{3,t-1}+...+\lambda_n\cdot X_{n,t-1}+\varepsilon t$.(2)

These hypotheses are tested to find the cointegration among the variables:

The null hypothesis $H_0:\lambda_0=\lambda_1=\lambda_2=\lambda_3=...=\lambda_n=0$: (no cointegration) against the alternative hypothesis $H_1:\lambda_{06}=\lambda_{16}=\lambda_{26}=\lambda_{36}=..._6=\lambda_{n6}=0$. (there exists cointegration among variables). The null hypothesis is rejected if the F statistic is greater than the upper bound critical value at standard significance level. However, if the F statistic is smaller than the lower bound critical value, H_0 cannot be rejected. Assuming that the F statistic lies between the upper and lower bound critical values, there would be no conclusion about the null hypothesis.

After the cointegration among variables has been identified, it is neceesary to ensure that the NARDL model is stable and trustworthy by conducting relevant tests,such as Wald test, Ramsey's RESET test using the square of the fitted values, Larange multiplier (LM) test, CUSUM (Cumulative Sum of Recursive Residuals) and CUSUMSQ (CumulativeSum of Square of Recursive Residuals), which allow some other essential examinations such as serial correlation, heteroscedasticity and the stability of residuals. After the NARDL model's stability and reliability have been confirmed,the short-run and long-run estimations can be implemented.

Based on the benefits of ARDL model, in order to evaluate the asymmetric impact of independent variables (oil price) on market volume, we employed NARDL (Non-linear Autoregressive DistributedLag) model proposed by Shin, Yu & Greenwood-Nimmo,2014), under the conditional error correction version displayed as follows:; The "+" and "−" notations of the independent variable respectively denote the partial sum of positive and negative changes. Specifically: $OP_t^+=t\sum i=1\Delta OP^+i=t\sum i=1\max(\Delta OPi,0)OP_t^-=t\sum i=1\Delta OP_i^-i=t \sum i=1 \min (\Delta OPi,0)$ (3)

Similar to the linear ARDL method, Shin et al. (2014) introduced the bound test for identifying asymmetrical cointegration in the long-run. The null hypothesis states that the effect is symmetrical in the longrun($H_0:\lambda_0=\lambda+1=\lambda-1=\lambda+2=\lambda-2=\lambda+3=\lambda-3=\lambda+4=\lambda-4=0$). On the contrary, the alternative hypothesis states that the effect is asymmetrical in the long-run ($H_1:\lambda06=\lambda+16=\lambda-16=\lambda+26=\lambda-26=\lambda+36=\lambda-36=\lambda+46=\lambda-46=0$). The F statistic and critical values are also used to give conclusion about H_0. If H_0 is rejected, there exists asymmetrical effect.Also, Wald test, functional form, Larange multiplier(LM) test, CUSUM (Cumulative Sum of Recursive Residuals) and CUSUMSQ (Cu-mulative Sum of Square of Recursive Residuals) are necessary to ensure the trust-worthiness and stability of NARDL model.

The NARDL model for this study was specified as follows: -

$\Delta MVOL_t =\alpha_0 + \rho MVOL_{t-1} + \beta_1^+OP^+_{t-1} + \beta^-_2OP^-_{t-1} + \sum_{t=1}^{-p} \alpha_1\Delta MVOl_{t-1} + \sum_{t=0}^{-p} \alpha_2 OP^+_{t-1} \sum_{t=0}^{-p} \alpha_3OP^-_{t-1} + \mu_t$ ....(4)

In the NARDL equation as modeled above, αi represent short run coefficients while βi stand for the long-term coefficients with i = 1....4th. While the short-term analysis relates to the immediate effect of the independent variable on the dependent variable, the long-term analysis reveals the speed of adjustment towards equilibrium. The variables $MVOL_t$ and OP_t in this model represent average monthly exchange rates and Brent spot oil prices respectively; t stands for time. Wald test is run to know the long run asymmetry $\beta=\beta+=\beta-$ and for short run asymmetry $\alpha=\alpha+=\alpha-$ for the selected variables.

4. Empirical Results

4.1 Descriptive statistics

Effect of oil price fluctuation on the trading volume of the Nigerian capital market

Table 1 presents the descriptive statistics for the data series as well as their stochastic properties. The monthly average OP is 57.72USD and MVOL has an average of 4.56E+09. On a monthly basis, the MVOL and OP reach their maximum value of 1.98E+11 and 133.9USD respectively. The two series are positively skewed. MVOL has a peaked kurtosis. The Jarque-Bera test indicates the non-normality of MVOL and OP oil price series.

Table 1: Descriptive Statistics

	MVOL	OP
Mean	4.56E+09	57.72750
Median	3.23E+09	55.72500
Maximum	1.98E+11	133.9000
Minimum	33671122	9.800000
Std. Dev.	1.21E+10	32.16818
Skewness	14.52289	0.451290
Kurtosis	232.5291	2.149733
Jarque-Bera	633406.1	18.19500
Probability	0.000000	0.000112
Sum	1.29E+12	16394.61
Sum Sq. Dev.	4.15E+22	292846.1
Observations	284	284

Sources: Researcher's computation

4.2 ARDLUnit Root Test for Stationarity

Table 2.1a Unit Root Test for Stationarity for Oil Price (OP) (At level)

Null Hypothesis: OP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.066324	0.2587
Test critical values:	1% level	-3.453400	
	5% level	-2.871582	
	10% level	-2.572193	

*MacKinnon (1996) one-sided p-values.
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OP)
Method: Least Squares
Date: 12/04/20 Time: 07:09
Sample (adjusted): 1997M03 2020M08
Included observations: 282 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OP(-1)	-0.023666	0.011453	-2.066324	0.0397
D(OP(-1))	0.159905	0.058968	2.711706	0.0071
C	1.443707	0.757448	1.906014	0.0577
R-squared	0.036984	Mean dependent var		0.084787

Adjusted R-squared	0.030080	S.D. dependent var	6.254042
S.E. of regression	6.159262	Akaike info criterion	6.484372
Sum squared resid	10584.29	Schwarz criterion	6.523116
Log likelihood	-911.2965	Hannan-Quinn criter.	6.499909
F-statistic	5.357337	Durbin-Watson stat	2.036816
Prob(F-statistic)	0.005211		

The result of unit root test for OP (at level) in table 2.1a indicates that the t-statistic -2.066324 and the p-value is 0.2587. Since p-value is greater than 0.05, the null hypothesis that OP has a unit root was rejected .This implies that OP is not stationary at level. Consequently, the test was repeated with OP at first difference (table 2.1.b).

Table 2.1.b. Unit Root Test for Stationarity for Oil Price (OP) (at First Difference)

Null Hypothesis: D(OP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.40261	0.0000
Test critical values:	1% level	-3.453400	
	5% level	-2.871582	
	10% level	-2.572193	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OP,2)
Method: Least Squares
Date: 12/04/20 Time: 07:10
Sample (adjusted): 1997M03 2020M08
Included observations: 282 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(OP(-1))	-0.850886	0.059079	-14.40261	0.0000
C	0.074333	0.368937	0.201480	0.8405

R-squared	0.425565	Mean dependent var	0.014681
Adjusted R-squared	0.423513	S.D. dependent var	8.159340
S.E. of regression	6.195120	Akaike info criterion	6.492468
Sum squared resid	10746.26	Schwarz criterion	6.518297
Log likelihood	-913.4380	Hannan-Quinn criter.	6.502826
F-statistic	207.4352	Durbin-Watson stat	2.029434
Prob(F-statistic)	0.000000		

The result of unit root test for OP at first difference shows that the t-statistic is -14.40261 while the p-value is 0.0000. Since the p-value is less than 0.05, the null hypothesis that OP has a unit root was rejected in favor of the alternative hypothesis. This implies that OP is stationary at first difference.

Table 2.2 shows the result of the unit root test for MVOL (At Level).It indicates that the . t-statistic is -16.45382 while the p-value = 0.0000. The p-value is less than 0.05,Consequently the Null Hypothesis that MVOL has a unit root and it is not stationary was rejected.

This implies that MVOL does not have a unit root; that is, it is stationary at level form

In summary the results of the ARDL unit root tests show that while OP is stationary at first difference, MVOL is stationary at level form. i.e. I(0) order integration.

Table 2.2 Unit Root Test for Stationarity for Market Volume (MVOL) (At level)

Null Hypothesis: MVOL has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.45382	0.0000
Test critical values:	1% level	-3.453317	
	5% level	-2.871546	
	10% level	-2.572174	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MVOL)
Method: Least Squares
Date: 11/03/20 Time: 02:38
Sample (adjusted): 1997M02 2020M08
Included observations: 283 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MVOL(-1)	-0.981135	0.059630	-16.45382	0.0000
C	4.49E+09	7.71E+08	5.816672	0.0000

R-squared	0.490691	Mean dependent var	16547363
Adjusted R-squared	0.488879	S.D. dependent var	1.70E+10
S.E. of regression	1.21E+10	Akaike info criterion	49.28523
Sum squared resid	4.14E+22	Schwarz criterion	49.31099
Log likelihood	-6971.860	Hannan-Quinn criter.	49.29556
F-statistic	270.7282	Durbin-Watson stat	2.001119
Prob(F-statistic)	0.000000		

4.3 Short and Long-term Relationship: Bounds Test

Table 3 shows the result of the bound test**. It shows that** the F-Statistic is equal to 8.341642. The Critical Value of the lower bound of I(0) is 3.1 at 5%. We reject the Null hypothesis that there is no cointegration among the variables is rejected since 8.341642 is greater than critical values of I(0).Hence**,**there is cointegration among the variables. This means that there is long run relationship between the variables.

Table 3: Short and long term relationship: Bounds Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(LMVOL)
Selected Model: ARDL (4, 0, 1)
Case 2: Restricted Constant and No Trend
Date: 11/11/20 Time: 07:14
Sample: 1997M01 2020M08
Included observations: 280

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.735577	1.691710	5.754872	0.0000
LMVOL(-1)*	-0.502764	0.087759	-5.728906	0.0000
LOP_POS**	0.442049	0.122307	3.614249	0.0004
LOP_NEG(-1)	0.313522	0.121285	2.584993	0.0103
D(LMVOL(-1))	-0.222361	0.083132	-2.674799	0.0079
D(LMVOL(-2))	-0.185030	0.073453	-2.519016	0.0123
D(LMVOL(-3))	-0.176534	0.059302	-2.976855	0.0032
D(LOP_NEG)	-0.644785	0.495191	-1.302095	0.1940

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOP_POS	0.879237	0.194642	4.517210	0.0000
LOP_NEG	0.623596	0.221463	2.815803	0.0052
C	19.36410	0.204919	94.49639	0.0000

EC = LMVOL - (0.8792*LOP_POS + 0.6236*LOP_NEG + 19.3641)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	8.341642	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5
			Finite Sample:	
Actual Sample Size	280		n=80	
		10%	2.713	3.453
		5%	3.235	4.053
		1%	4.358	5.393

4.5 Heteroskedasticity Test

Table 5 presents the result of heteroskedasticity test. It indicates that the p-value is 0.6474for the t-statistic show that we accept the null hypothesis **which** states that residual is homoskedastic. It means that the residual is homoskedastic

Table 5: Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.729112	Prob. F(7,272)	0.6474
Obs*R-squared	5.157127	Prob. Chi-Square(7)	0.6408
Scaled explained SS	35.08485	Prob. Chi-Square(7)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/11/20 Time: 18:23
Sample: 1997M05 2020M08
Included observations: 280

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.260689	5.249514	0.049660	0.9604
LMVOL(-1)	-0.086139	0.184216	-0.467596	0.6404
LMVOL(-2)	0.073264	0.190936	0.383710	0.7015
LMVOL(-3)	-0.108045	0.190877	-0.566044	0.5718
LMVOL(-4)	0.160244	0.184020	0.870796	0.3846
LOP_POS	0.367958	0.379529	0.969511	0.3332
LOP_NEG	0.821380	1.536616	0.534538	0.5934
LOP_NEG(-1)	-0.324503	1.609055	-0.201673	0.8403

R-squared	0.018418	Mean dependent var	0.680361
Adjusted R-squared	-0.006843	S.D. dependent var	2.588073
S.E. of regression	2.596913	Akaike info criterion	4.774679
Sum squared resid	1834.357	Schwarz criterion	4.878531
Log likelihood	-660.4551	Hannan-Quinn criter.	4.816334
F-statistic	0.729112	Durbin-Watson stat	1.888626
Prob(F-statistic)	0.647424		

4.6 Serial Autocorrelation LM Test

Table 6 displays the result of serial autocorrelation LM test . **The** F-statistic has a p-value of 0.0072. Consequently, the null hypothesis which states that residual exhibit no serial auto correlation was rejected This means that the residuals exhibit serial autocorrelation

Table 6: Serial Autocorrelation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	5.018213	Prob. F(2,270)	0.0072
Obs*R-squared	10.03512	Prob. Chi-Square(2)	0.0066

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 11/11/20 Time: 18:24
Sample: 1997M05 2020M08
Included observations: 280
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMVOL(-1)	0.778718	0.309992	2.512056	0.0126
LMVOL(-2)	0.060344	0.319568	0.188829	0.8504
LMVOL(-3)	-0.117924	0.097432	-1.210326	0.2272
LMVOL(-4)	-0.060914	0.062070	-0.981371	0.3273
LOP_POS	-0.558571	0.219533	-2.544358	0.0115
LOP_NEG	0.171029	0.491261	0.348143	0.7280
LOP_NEG(-1)	-0.550256	0.542049	-1.015142	0.3109
C	-12.74927	4.499846	-2.833268	0.0050
RESID(-1)	-0.827050	0.313390	-2.639043	0.0088
RESID(-2)	-0.296893	0.291073	-1.019997	0.3086

R-squared	0.035840	Mean dependent var	-4.09E-15
Adjusted R-squared	0.003701	S.D. dependent var	0.826317
S.E. of regression	0.824787	Akaike info criterion	2.487677
Sum squared resid	183.6737	Schwarz criterion	2.617491
Log likelihood	-338.2747	Hannan-Quinn criter.	2.539745
F-statistic	1.115159	Durbin-Watson stat	1.981157
Prob(F-statistic)	0.352000		

4.7 Stability Test

A perusal at figure 1 discloses that the graph extended beyond the 5% significance boundary. This implies that the model became unstable in the long run.

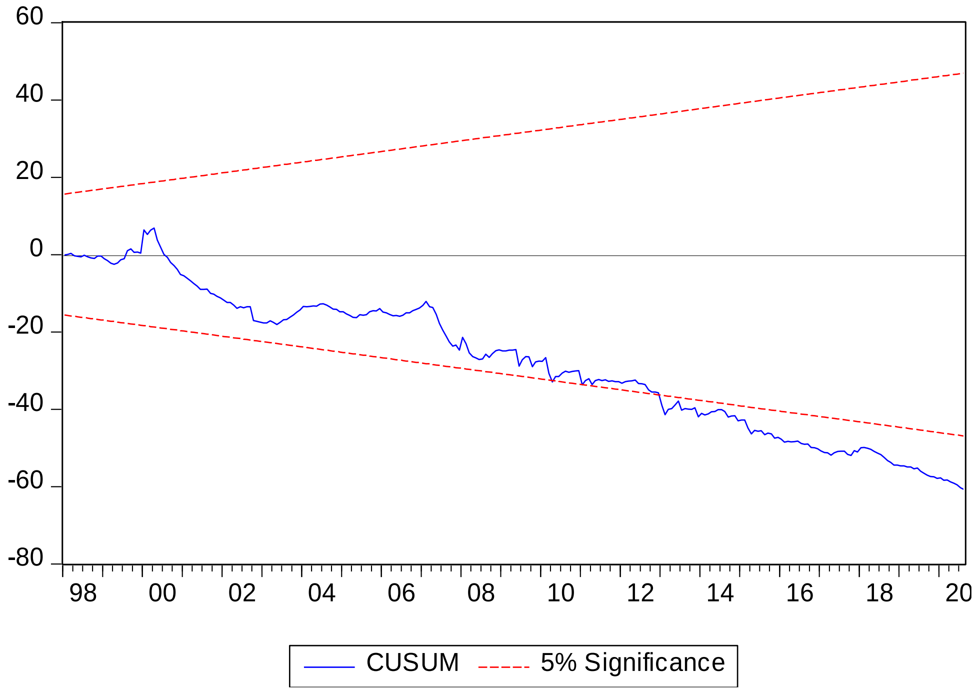

Fig. 1 CUSUM test gragh

4.8 NARDL Dynamic Estimation Result

Table 7:Dynamic Estimation result

Dependent Variable: LMVOL
Method: ARDL
Date: 11/11/20 Time: 07:12
Sample (adjusted): 1997M05 2020M08
Included observations: 280 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LOP_POS LOP_NEG
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(4, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LMVOL(-1)	0.274875	0.059366	4.630210	0.0000
LMVOL(-2)	0.037331	0.061531	0.606700	0.5446
LMVOL(-3)	0.008496	0.061512	0.138112	0.8903
LMVOL(-4)	0.176534	0.059302	2.976855	0.0032
LOP_POS	0.442049	0.122307	3.614249	0.0004
LOP_NEG	-0.644785	0.495191	-1.302095	0.1940
LOP_NEG(-1)	0.958307	0.518535	1.848106	0.0657
C	9.735577	1.691710	5.754872	0.0000

R-squared	0.692949	Mean dependent var	21.38210
Adjusted R-squared	0.685047	S.D. dependent var	1.491219
S.E. of regression	0.836882	Akaike info criterion	2.509889
Sum squared resid	190.5012	Schwarz criterion	2.613740
Log likelihood	-343.3844	Hannan-Quinn criter.	2.551544
F-statistic	87.69224	Durbin-Watson stat	2.062755
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

4.8.1 Long Run Asymmetric Effect: The Response Of Market Volume to Positive and Negative Changes of Oil Price

Asymmetric Co-integrating Equation

The results of the NARDL dynamic estimation in table 7 show that one unit increase in oil price (LOP_POS) is associated with 0.879237 or (87%) increase in market volume. There is a significant effect of oil price increase on market volume since the p-value is 0.0000, which is less than 0.05. Consequently, the null hypothesis that there is no significant effect of oil price increase on market volume was rejected.

In addition, one unit decrease in oil price (LOP_NEG) is associated to 0.623596 or (62%) decrease in market volume. There is a significant effect of oil price decrease on market volume since the p-value is 0.0052 which is less than 0.05. Consequently, the null hypothesis that there is no significant effect of oil price decrease on market volume was rejected.Hence, there is a significant effect of oil price decrease on market volume. In summary, oil price fluctuations have significant and positive effect on the trading volume in the Nigerian capital market.

4.9 Testing for Long-Run Asymmetries using Wald Test

We determined if the difference between the coefficient of the POS and NEG changes was significant. We would conclude that the relationship between MVOL market volume and Oil Price LOP is asymmetric.if the difference was found to be significant,

We already noticed in table 8 that both POS and NEG changes in LOP has significant impact on MVOL but needed to find out if the the positive and negative impacts were of the same magnitude (symmetric effect) or different (asymmetric effect).The null hypothesis is that the two impacts are the same,that is that there is no long-run asymmetry. The result in table 8 shows that there is no evidence of long run asymmetric (nonlinear) relationship between market volume and oil price Both positive and negative changes in oil price LOP have the same effect on market volume MVOL.Hence, there is no asymmetric effect.

Table 8:

Wald Test:
Equation: NARDL09

Test Statistic	Value	Df	Probability
t-statistic	-1.751391	272	0.0810
F-statistic	3.067371	(1, 272)	0.0810
Chi-square	3.067371	1	0.0799

Null Hypothesis: C(3)=C(4)
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(4)	-0.168039	0.095946

Restrictions are linear in coefficients.

4.9 Discussion of results

This study examined the effect of oil price fluctuations on the trading volume in the Nigerian capital market. It employed the Nonlinear autoregressive lag model to capture the possible short-, medium-, and long-term causal effects between the variables of the study as well as the asymmetric nature of their relationship. The NARDL estimation was done after ex-raying the summary characteristics of the variables and ensuring their stationarity. In addition, tests were carried out to establish the serial correlation,find out the status of the data series, the short and lungrun relationship among the variables, the homoeskedasticity or heteroskedasticity of the date series, long run stability and asymmetry of the relationship as well as the suitability of NARDL for analysis. The NARDL eequation was estimated with oil price as exogenous variable to trading vollume. The global oil prices are determined by the economic conditions in the international market which are external to the Nigerian economy. The results of the study indicate the presence of short run asymmetric effect between oil price and all-share index and that there is no long run relationship between them.In addition,

The results of the study suggest that oil price fluctuations have significant and positive effect on the trading volume in the Nigerian capital market.

These results are in conformity with theoretical a priori expectation for an oil exporting country like Nigeria that an increase or decrease in the international oil price should have positive effect on Nigeria;s stock market performance. The results agree with the findings of several empirical studies that propose a positve relationship between oil price and stock market return such as Alsharif(2020),Agbo and Nwankwo(2019), Asaolu and Ilo (2012) and Akinlo (2014). However, the results vary disagree with Kelikume and Muritala(2019), Miller and Ratti(2009)that suggest negative connections between the two variables. In addition,while this study finds no long run relationship oil price between and trading volume,for some earlier works like Asaolu and Ilo (2012), Akinlo (2014), Ojikutu, Onolemhemhen and Isehunwa (2017), there is a long-term relationship between the macroeconomic variables and crude oil. One of the policy implication of the findings is that short term energy policy would be appropriate for oil price and stock market performance relationship in Nigeria. The disagreement among results could have arisen because the causal effects between oil and stock markets depend heavily on whether research is conducted using aggregate stock market indices, sectorial indices, or firm-level data and whether stock markets operate in net oil-importing or net oil-exporting countries. In addition, conclusions vary depending on whether studies use symmetric or asymmetric changes in the price of oil, or whether they focus on unexpected changes in oil prices (Degiannakis, Filis & Arora, 2018). Also, such divergence in result could have arisen partly because some methods considered only a short-run relationship as against the others which captured long-run associations(Kelikume and Muritala, 2019) One of the policy implications of the findings of this study is that diversifying in both oil and stock markets will not create benefits for the investors holding the portfolio because of the integration of the markets (Anoruo and Mustafa, 2007).

5.Conclusion

This study explored the effect of oil price fluctuation on the trading volume of the NNigerian capital market using monthly frequency data that cover the period from January,1997 to August 2020. It employed the non-linear autoregressive distributed lag approach for data analysis. The results of the empirical analysis suggest that oil price fluctuations have significant and positive effect on the market volume in the Nigerian capital market and that there is no asymmetric effect between the variables. The study recommends that Nigeria should devise strategies that can ensure stability in their capital markets .It can do this by vigorously pursuing pro-growth policies irrespective of the fluctuations in oil price and other macroeconomic variables.

References

Abbas, T. & Terfa, W.A. (2010). The Impact of Oil Price Volatility on the Nigerian Stock Market: Evidence from Autoregressive Distributed Lag Model. Conference Paper. Nasarawa State University, Conference on Managing the Challenges of the Global Financial Crisis in Developing Economies. Retrievedfromhttps://www.researchgate.net/publication/202165614_

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

Adebiyi, M. A.; Adenuga, A.O.; Abeng, M. O. & Omanukwue, P. N. (2010). Oil price shocks, exchange rate and stock market behavior: Empirical review from Nigeria. Retrievedfromhttp://africanetics.org/document/conference09/papers/adebiyiAdenugaAbeng Omanukwue.pdf

Agbo, E.I. & Nwankwo, S. N. P. (2019). Effect of oil price shocks on the market capitalization of Nigeria, Advance *Journal of Management, Accounting and Finance Adv. J. Man. Acc*. 4(11) ISSN: 2364 – 4219

Akinlo, O. O. (2014). Oil prices and stock market: Empirical evidence from Nigeria. *European Journal of Sustainable Development*, 3(2), 33-40.

Akomolafe,K. J.& Danladi, J. D. (2014). Oil Price Dynamics and the Nigerian Stock Market: An Industry Level Analysis.International Journal of Economics, Finance and Management, 3, (6),1-9.

Al-hajj, E., Al-Mulali, U. & Solarin, S. A. (2018). Oil price shocks and stock returns nexus for Malaysia: Fresh evidence from Malaysia

Allen, D.E. & McAleer, M. (2020). A Nonlinear Autoregressive Distributed Lag (NARDL) Analysis of West Texas Intermediate Oil Prices and the DOW JONES Index, *Energies,13,4011,1-11,*

Alsharif, M. (2020). The Relationship between the Returns and Volatility of Stock and Oil Markets in the Last Two Decades: Evidence from Saudi Arabia, International *Journal of Economics and Financial Issues,* 10(4), 1-8. ISSN: 2146-4138 available at http: www.econjournals.com

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.

Anoruo, E., Mustafa, M. (2007). An Empirical Investigation into the Relation of Oil to Stock Market Prices. *North American Journal of Finance and Banking Research,* 1(1), 22-36.

Arouri, M. E. H. & Rault, C. (2009). On the influence of oil prices on stock markets: Evidence from panel analysis in GCC countries. *CESifo Working Paper*, No. 2690.

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.

Arouri, M. H. & Nguyen, D. K. (2010). Oil Prices, Stock Markets and Portfolio Investment: Evidence from Sector Analysis in Europe over the Last Decade, Working Papers hal-00507823, HAL.

Asaolu, T. O. & Ilo, B. M. (2012). The Nigerian stock market and oil price: A co-integration analysis. Kuwait chapter of Arabian *Journal of Business and Management Review,* 1 (5), 39 – 54.

Aye, G. C. (2014). Does oil price uncertainty matter for stock returns in South Africa? *Investment Management and Financial*

Badeeb, R. A. & Lean, H. H. (2018). Asymmetric impact of oil price on Islamic sectoral stocks. Energy Economics, 71, 128-

Balcilar, M., Gupta, R. & Wohar, M. (2016).Common cycles and common trends in the stock and oil markets: Evidence from more than 150 years of data

Bernanke, B., Gertter, M. & Watson, M. (1997). Systematic monetary policy and the effect of oil price shocks. *Brookings papers on Economics Activity*. 1, 91 – 142

Bittlingmayer, G. (2005). Oil and stocks: Is it war risk?": University of Kansas manuscript, December 29, 2005

Burbidge, J. & Harrison, A. (1984). Testing for the effects of oil price rises using vector auto- regression. *International Economic Review,* 25, 459 – 484.

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

Degiannakis, S., Filis, G., & Kyzys, R. (2014). The effects of oil price shocks on stock market volatility.: Evidence from European data. *The Energy Journal*, 35(1), 35-56.

Degiannakis, S.A., Filis, G. & Arora, V. (2018).Oil Prices and Stock Markets: A Review of the Theory and Empirical Evidence. *The Energy Journal* 39(01)

Diaz, E. M., Molero, J. C. & de Gracia, F. P. (2016). Oil price volatility and stock returns in the G7 economies. *Energy Economics*, 54, 417-430

Ding, Z., Liu, Z., Zhang, Y. & Long, R. (2017). The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. *Applied Energy,* 187, 27-36. DOI: 10.1007/978-3-030-04200-4_27

Dutta, A., Nikkinen, J. & Rothovius, T. (2017). Impact of oil price uncertainty on Middle East and African stock markets. *Energy*, 123, 189-197.

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

Engle,R.F & Granger,C.W.J.(1987).Co–Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica,* 55(2), 251–276.

Ftiti, Z., Guesmi, K. & Abid, I. (2016). Oil price and stock market co-movement: What can we learn from time-scale approaches? *International Review of Financial Analysis*, 46, 266-280.

Ghosh, S. & Kanjilal, K. (2016). Co-movement of international crude oil price and Indian stock market: Evidences from nonlinear cointegration tests. *Energy Economics*, 53, 111-117.

Gil-Alana, L. A. & Yaya, O. S. (2014). The relationship between oil prices and the Nigerian stock market. An analysis based on fractional integration and cointegration. Energy Economics, 46, 328-333.

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

Gourène, G. A. Z. & Mendy, P. (2018). Oil prices and African stock markets co-movement: A time and frequency analysis. *Journal of African Trade*, 5(1-2), 55-67.

Gupta, R. & Modise, M. P. (2013). Does the source of oil price shocks matter for South African stock returns? A structural VAR approache. *Energy Economics*, 40, 825-831.

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 nonlinear denoised based quantile and Granger-causality analysis. *Energy Economics*, 80, 536-552

Hamilton, J. D. (1983). Oil and the macro economy since World War II. *Journal of Political Economy*, 91, 228 – 248

Hamilton, J. D. (1996). This is what happened to the oil price–macroeconomy relationship. *Journal of Monetary Economics,* 38(2), 215-220

Harris, R. & Sollis, R. (2003). Applied Time Series Modelling and Forecasting, West Sussex: Wiley.

Hooker, M. A. (1999). Oil and the macro economy revisited. Finance and Economics Discussion Series #43, Federal Reserve Board of Governors.https://www.sciencedirect.com/science/article/pii/S2452315117301352

Hu, C., Liu, X., Pan, B., Chen, B. & Xia, X. (2018). Asymmetric impact of oil price shock on stock market in China: A combination analysis based on SVAR model and NARDL model. *Emerging Markets Finance and Trade,* 54(8), 1693-1705.

IEA. (2016). The International Energy Agency-World energy outlook. Retrieved on January 18, 2019 from https://www.iea.org/news room /news/2016/november/world-energy-outlook-2016.html.

Iheanacho, E. (2016). Dynamic relationship between crude oil price, exchange rate and stock market performance in Nigeria. *International multidisciplinary Journal,* Ethiopia, 10 (4). DOI: http://dx.doi.org/10.4314/afrrev.v10;4.16.

Ji, Q., Liu, B. Y., Zhao, W. L. & Fan, Y. (2018). Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. *International Review of Financial Analysis,* doi:10.1016/j.irfa.2018.08.002.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors*, Journal of Economic Dynamics and Control*, 12(2–3), 231–254.

Kang, W., de Gracia, F. P. & Ratti, R. A. (2017). Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *Journal of International Money and Finance,* 70, 344-359.

Karpoff, J. M. (1986). A theory of trading volume. *The Journal of Finance,* 41(5);1069-1087

Kelikume, I. & Muritala,O.(2019). The Impact of Changes in Oil Price on Stock Market: Evidence from Africa. *International Journal of Management, Economics and Social Sciences,* 8(3), 169 – 194. ISSN 2304 – 1366,http://www.ijmess.com

Lawal, A. I., Somoye, R. O. C. & Babajide, A. A. (2016). Impact of oil price shocks and exchange rate volatility on stock maket behaviour in Nigeria. *Binus Business Review,*7(2), 171 – 177. A01 10.21512/b.b.r.v 7i2 1453

Lo, A. W. & Wang, J. W. (2000). Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory. *NBER Working Paper* No. 7625 March

Luo, X. & Qin, S. (2017). Oil price uncertainty and Chinese stock returns: New evidence from the oil volatility index. *Finance Research Letters*, 20, 29-34

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

Miller, I.J., Ratti, A.R. (2009). Crude Oil and Stock Markets: Stability, Instability, and Bubbles. *Energy Economics*, 31(4), 559-568

Mordi, C. N. O., Michael A. & Adebiyi, A. M. (2010). The asymmetric effects of oil price shocks on output and prices in Nigeria using a structural VAR model. *Economic and Financial Review, 481*, 1 – 32

Namovsky, S. (2018). The impact of oil prices on trade. *Review of International Economics*, 27(1).https://doi.org/10.1111/roie.12383

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), 1-17.

Odupitan,E.(2017). Effects of crashing crude oil prices on oil producing countries Nigeria's perspective, Thesis, Centria University of Applied Sciences, Business Management

Ojikutu, O. T., Onolemhemhen; R. U, & Isehunwa, S. O. (2017). Crude oil price volatility and its impact on Nigeria stock market performance (1985 – 2014). *International Journal of Energy Economics and Policy,* 7 (5). 302 – 311

Okany, C. T. (2014). Effect of oil price movement on stock prices in the Nigeria

Omisakin, O., Adeniyi O. and Omojolaibi, A. (2009). A Vector Error Correction Modelling of Energy Price Volatility of an Oil Dependent Economy: The Case of Nigeria, *Pakistan Journal of Social Sciences 6*(4), 207-213

Pal, D. & Mitra, S. K. (2019). Oil price and automobile stock return co-movement: A wavelet coherence analysis. *Economic Modelling*, 76, 172-181.

Pesaran, M. H. & Pesaran, B. (1997). Microfit 4.0 (Window Version), Oxford University Press.

Pesaran, M. H., Shin, Y. & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships, *Journal of Applied Economics*, 16(3), 289–326.

Phong, L. H., Bao, H. H. G. & Van, D.T.B. (2017). The Impact of Real Exchange Rate and SomeMacroeconomic Factors on Vietnam's Trade Balance: An ARDL Approach, *Proceedings International Conference for Young Researchers in Economics and Business*, 410–417.

Phong, L. H., Bao, H. H. G. & Van, D. B. T. (2018). Testing J–Curve Phenomenon in Vietnam: An Autoregressive Distributed Lag (ARDL) Approach. In: Anh L., Dong L., Kreinovich V.,Thach N. (eds) *Econometrics for Financial Applications, Studies in Computational Intelligence*, Springer, Cham, 760, 491–503.

Phong, L. H., Van, D. T. B. & Bao, H. H. G. (2019). A Nonlinear Autoregressive Distributed Lag(NARDL) Analysis on The Determinants of Vietnam'sStock Market, Email:lhphong@hcmulaw.edu.vn∗,bachvan@ueh.edu.vn,hhgbao@hcmulaw.edu.vn

Rafailidis, P. & Katrakilidis, C. (2014). The relationship between oil prices and stock prices: a nonlinear asymmetric cointegration approach. Applied Financial Economics, 24(12): 793-800

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics,* 21(5): 449-469

Shin,Y., Yu, B. & Greenwood-Nimmo, M. (2014). Modeling Asymmetric Cointegration and Dynamic 'Multipliers in a Nonlinear ARDL Framework',In: W. C. Horrace and R. C. Sickles,Eds., Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications, SpringerScience & Business Media, New York, 281–314.

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,1-8.Retrievedfrohttp://dx.doi.org/10.1016/jikjss2017.09.004.

Tursoy, T. & Faisal, F. (2018). The impact of gold and crude oil prices on stock market in Turkey: Empirical evidences from ARDL bounds test and combined cointegration. *Resources Policy*, 55, 49-54

Wang, L. (2015). Dynamical models of stock prices based on technical trading rules. : *IEEE Trans. on Fuzzy Systems* 23(4), 1127-1141

Wong, V. S. & El-Massah, S. (2018). Recent Evidence on the Oil Price Shocks on Gulf Cooperation Council Stock Markets. *International Journal of the Economics of Business,* 25(2): 297-312.

Xiao, J., Zhou, M., Wen, F. & Wen, F. (2018). Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market

Yoshino, N., Rasoulinezhad, E. & Chang, Y. (2019). Trade linkages and transmission of oil price fluctuations. *Energy Policy,* 133;1-23.

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/licences/by/4.0/1-22.

Zhu, H. M., Li, S. F. & Yu, K. (2011). Crude oil shocks and stock markets: A panel threshold cointegration approach. *Energy Economics*