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EMPIRICAL ANALYSIS OF THE OIL SHOCKS-STOCK RETURNS RELATIONSHIP: A SECTORAL DISAGGREGATION FOR NIGERIA

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Abstract

This paper investigated the impact of crude oil price shocks on the returns and volatility of the Nigerian stock market. Since not all industries are expected to be equally affected by oil price changes, we conducted our study at the disaggregate firm level for two sectors namely Banking and Oil &Gas. A bivariate VAR-GARCH model was employed for the daily observations of Brent crude oil price and the closing share values of the 12 firms over the period January 1, 2000 to December 31, 2015. The empirical findings showed that the returns on stock market are significantly affected by their own past values suggesting some evidence of short-term predictability in stock market changes. For the Banking sector past oil shocks drive stock price volatility in all firms, except for ACCESS Bank. The response of stock returns to oil impact is negative in the case of FIRST Bank, UBA and WEMA Bank and positive for GUARANTY Trust Bank, UNION Bank and ACCESS Bank. In the Oil & Gas sector on the other hand, we found that innovations in the oil market had effects on the stock volatility in three firms (BOCGAS, CONOIL and OANDO). The largest response to oil effects was observed in the case of CONOIL followed by BOCGAS. Overall, our findings showed that direct volatility transmission is insignificant for each pair of oil firms, because the volatility transmission runs more often from oil market to firms than from the firms to oil market. Considering the intensity of volatility spillover, it seems to vary from sector to sector, depending especially on their degree of oil dependence and industrial characteristics. The impact has a direct link in the Oil & Gas sector, while in the Banking sector the impact is indirectly linked. This suggests that investors should closely watch the happenings in the oil market to have better forecasts of stock market volatility and make appropriate investment decisions.

Keywords: *Oil prices, Banking sector, Oil & Gas sector, volatility transmission, firm-level, VAR-GARCH model*

JEL Classification: *G110, G320, G210, Q350*

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1.0 Introduction

The stock market has been viewed as a market where most elements that feed into the development of a nation's economy operate. In Nigeria, the Nigerian Stock Exchange (NSE), which is one of the fastest growing stock markets in Africa and among the emerging stock markets in the world, has recorded phenomenal growth. As at 2002, of the eight sub-Saharan markets analyzed, only Nigeria, South Africa and Zimbabwe were considered 'frontier markets' and were thus included in the IFC Global Composite Index (Magnusson and Wydick, 2002). Moreover, the recent global financial crisis that led to a downward movement of stock prices also posed a great threat to an emerging economy like Nigeria. For instance, daily stock prices on the floor of the Nigerian Stock Exchange show that by the last week of June 2008, the prices of bank stocks had decreased by between 15 and 51 percent within a period of one month. The Equity market capitalization as at February 2008 was N12.5 trillion but fell to N9.7 trillion as at August of the same year. The Nigerian stock market witnessed a remarkable turn-around in May 2013 following the Bearish run experienced in April 2013. From a negative growth of 0.29% in April 2013, the market returned 13.02% as indicated by the All Share Index (ASI) during the month of April. This growth almost competes with the position of the ASI in January 2013, the only time the Index appreciated by double digits of 13.44% (NSE, 2013). The activities witnessed in the month of May 2013 resulted in the sale of 8.48 billion shares worth N94.36 billion, which were executed in 123,954 deals.

Consequently, the aggregate volume and value of securities traded from January to May 2013 stood at 48.61 billion and N444.77 billion respectively, indicating 36.81% and 64.27% appreciation when compared with 35.53 billion units of securities worth N270.76 billion traded in the corresponding period of 2012. The favourable improvement in the prices of equities resulted in an appreciation of 13.02% in value of the ASI; a move similar to the performance in January 2013 when the index gained 13.44%. It rose steadily from 33,440.57 points in April 2013 and attained a peak value of 38,016.80 points on 30th May, 2013 before ending the month at 37,794.75 points. The market capitalization of debt securities and the only listed Exchange Traded Fund (ETF) on the other hand, closed lower at N4.658 trillion and N0.862 billion thus recording a decline of 6.21% and 4.52% respectively in May 2013.

Hence, total market capitalization of all listed securities stood at N16.738 trillion during the month, a 6.86% appreciation when compared with N15.664 trillion in the preceding month. Equity market capitalization accounted for 72.16% of May's total market capitalization, up from 68.28% in the previous month. This significantly reduced the coverage of the debt capitalization to 27.83% from

31.71% in April 2013 while capitalization of ETF remained static at 0.01%. Out of the eleven (11) equities market sector classification of the NSE, the Financial Services, Industrial Goods and Consumer Goods sectors still controlled larger portions in terms of market capitalization, accounting for 32.58%, 29.98% and 28.96% respectively while the other sectors contributed the paltry balance of 8.47%.

Nevertheless, as of the 4th week of January 2015, the NSE All-Share Index and Market Capitalization appreciated by 0.38% to close the week at 23,916.15 and N8.225 trillion respectively. Similarly, all other Indices finished higher during the week, with the exception of the NSE Insurance Index, NSE Consumer Goods Index and NSE Industrial Goods Index that declined by -1.60%,-0.44% and -1.47% respectively, while NSE ASeM Index closed flat. The performance of the NSE ended poorly in 2015 as reflected by the market indicators, the market capitalisation and the All-Shares Index. During the year, the Nigerian Stock Exchange slumped below its three-year low due to what market analysts attributed to dwindling crude oil price, foreign exchange problems and exodus of foreign portfolio investors. A total of 92.90 billion shares worth N952.49 billion were exchanged by investors in 941,602 deals between January and December 2015. This was against 108.47 billion shares valued at N1.34 trillion traded in 1,335,572 deals in the same period in 2014. Data as at December 31, 2015 showed that the equity market dipped by 17.36 per cent year-to-date (YTD) compared with a decline of 16.14 per cent posted in 2014. The All-Shares Index lost 6014.90 points or 17.36 per cent to close for the year at 28,642.25 on December 31, 2015 from the 34,657.15 with which it opened for the year (NSE, 2015; CBN, 2014, 2015). The market capitalization, which opened for the year at N11.478 trillion, lost N1.628 trillion to close at N9.850 trillion on Dec 31, 2015 due to huge price losses by some blue-chip companies (NSE, 2015; CBN, 2014, 2015).

There are a number of different factors that affect financial markets; however, many researchers believe there is a direct relationship between the price of oil and the stock market (Salisu and Oloko, 2015; Babatunde, et al, 2013). In many cases, economic indicators have a positive linear effect on the markets. On the other hand, oil prices are believed to have a negative correlation to the stock markets, which means that as oil prices go down, stock prices go up. Most of the literature showed that oil does not have a positive correlation to the stock markets but instead that financial markets can do well while the price of oil is rising. The majority of studies indicate that the price of oil has a negative correlation to the markets. Negative correlation is the most popularly accepted relationship between oil prices and the stock markets (e.g. Kang, et al, 2014; Fowowe, 2013; Adebiyi, et al, 2012; Papapetrou, 2001).

Therefore, the impact of oil price volatility on the performance of the stock market, much as it has not been adequately explored, should not be ignored. As noted by Okonjo-Iweala (2006), a major challenge for the Nigerian economy was its macroeconomic volatility driven largely by external terms of trade shocks and the country's large reliance on oil export earnings. Moreover, Nigeria's economy ranked among the most volatile in the world for the period 1960 to 2000 (World Bank, 2003). The impact of oil price on stock markets in developing countries has not been sufficiently covered in the literature. Stock markets in emerging markets especially in Africa have gained prominence because the markets have developed a step further to the diversification of risk apart from the primary role of providing an alternative source of capital for investment. In Nigeria, the stock market has been greeted with a high rate of volatility attributable to high risk. Since most investors are risk averse, they tend to shy away from the market due to uncertainty in expected returns. High market volatility increases unfavorable market risk premium (Uyaebo, et al, 2015; Atoi, 2014). Therefore, it is significant to reduce the stock market volatility and ultimately enhance economic stability in order to improve the effectiveness of asset allocation decisions (Poon and Tong, 2010).

In spite of many studies that exist on the dynamic relationship between stock prices and oil prices, few have focused on emerging stock markets in Africa such as the Nigerian Stock Exchange (NSE). Specifically, previous empirical studies about the stock market in Nigeria focused more on the impact of the stock market (as a form of financial development indicator) on economic growth as well as on efficiency and performance (Adjasi and Osinubi, 2003; Adelegan, 2003; Magnusson and Wydick, 2002). However, recently some authors have found that oil price volatility plays an important role in explaining both stock market and economic activities (Papapetrou, 2001). Therefore, our effort to investigate whether changes in stock market volatility over time can be attributed to the volatility of oil price is not only timely but also in the right direction. The examination of the relationship between oil price and stock prices has been well documented in the literature on developed economies. The empirical explanation for this connection was pioneered by Huang et al. (1996) and Jones and Kaul (1996). For instance, Huang et al. (1996) investigate the dynamic interactions between oil futures prices traded on the New York Mercantile Exchange (NYMEX) and US stock prices and they found the return volatility spillover from oil futures to stocks to be very weak. However, a similar submission can hardly be made for emerging and developing markets, as there is still a dearth of research in this area.

Furthermore, most of the studies in the literature consider the relationship between oil price and total (aggregate) stock market indices (Vo, 2011; Balcilar and Ozdemir 2012; Fowowe, 2013; Antonakakis et al, 2014; Mollick and Assefa, 2013; Salisu and Oloko, 2015). Therefore, to the best of our knowledge, no study on Nigeria has examined the effect of oil price changes on individual firms on the Nigerian Stock Exchange. We reckon that aggregate stock market indices may mask the individual characteristics of the activity sectors in relation to oil prices. Therefore, this study examines the relationship between oil price and stock prices at the disaggregate level. We deployed the industrial classification of firms and selected the sectors likely to be most affected by oil prices, namely, the *Banking* and *Oil & Gas* sectors.

Following the introduction in section 1, the remainder of the article is organized as follows. Section 2 discusses the findings of selected previous works on the relationship between oil price and stock markets. Our empirical methodology and data issues are treated in Section 3. Section 4 presents the empirical results and discussion of findings. Section 5 provides the summary and conclusion.

2.0 Literature Review

Many authors argue that oil price effect on stock markets is indirect and is fed through the macroeconomic indicators. According to Bjornland (2009) and Jimenez-Rodriguez and Sanchez (2005), an oil price increase is expected to have a positive effect in an oil-exporting country, as the country's income will increase. The consequence of the income increase is expected to be a rise in expenditure and investments, which in turn creates greater productivity and lower unemployment. Stock markets tend to respond positively to this sequence of events.

The study by Faff and Brailsford (1999) investigated the sensitivity of Australian industry equity returns to an oil price factor over the period 1983-1996. The paper employed an augmented market model to establish the sensitivity. The key findings were as follows. First, a degree of pervasiveness of an oil price factor, beyond the influence of the market, was detected across some Australian industries. Second, they found significant positive oil price sensitivity in the Oil and Gas and Diversified Resources industries. On the contrary, they found significant negative oil price sensitivity in the Paper and Packaging, and Transport industries. Generally, they found that long-term effects persisted, although they hypothesized that some firms had been able to pass on oil price changes to customers as a means to hedge the risk.

Employing an error correction representation of a VAR model, Papapetrou (2001) concluded that oil price is an important factor in explaining the stock price movements in Greece, and that positive oil price shocks depressed real stock returns. Maghyereh (2004) studied the relationship between oil price changes and stock returns in 22 emerging markets, working with a VAR model from 1998 to 2004, without finding any significant evidence that oil prices had an impact on stock index returns in these countries. In contrast to this conclusion, Basher and Sadorsky (2006), analyzing the impact of oil price changes on a large set of emerging market stock returns for the period 1992 to 2005, showed that emerging economies are less able to reduce oil consumption and are thus more energy intense, and more exposed to oil prices than more developed economies. Therefore, oil price changes are likely to have a greater impact on profits and stock prices in emerging economies. Cong et al (2008) applied multivariate vector autoregression methodology to analyze the interactive relationship between oil price shocks and Chinese stock market activity. The authors found evidence that oil price shocks had no significant effect on stock returns except for manufacturing index and some oil companies. Elyasiani et al (2011) examined the impact of changes in the oil returns and oil return volatility on excess stock returns and return volatilities of thirteen U.S. industries using the GARCH (1,1) technique. They found strong evidence in support of the view that oil price fluctuations constitute a systematic asset price risk at the industry level as nine of the thirteen sectors analyzed show statistically significant relationships between oil-futures return distribution and industry excess return. These industries are affected either by oil futures returns, oil futures return volatility or both. In general, excess returns of the oil-user industries are more likely to be affected by changes in the volatility of oil returns, than those of oil return itself. Volatilities of industry excess returns are time-varying, and return volatility for a number of sectors, appear to have long memory.

In addition to the prominent papers considering oil price and stock markets in advanced and other emerging economies, some authors focused on the Nigerian economy. For instance, Adaramola (2012) examined the long-run and short-run dynamic effects of oil price on stock returns in Nigeria over 1985:1–2009:4 using the Johansen cointegration tests. A bi-variate model was specified and empirical results showed a significant positive stock return effect on oil price shocks in the short-run and a significant negative effect in the long-run. The Granger causality test showed strong evidence that the causation runs from oil price shocks to stock returns; implying that variations in the Nigerian stock prices are explained by oil price volatility. In a similar line, Okoro (2014) employed Augmented Dickey Fuller and Johansen Co-integration Tests in which the effect of oil price volatility, crude oil price and stock price was analyzed in a unifying model, using time series data spanning 1980 to 2013 for Nigeria. The result suggested that oil price volatility affects stock price both positively and negatively. Babatunde et al (2013) applied the multivariate vector auto-regression that employed the generalized impulse response function and the forecast error variance decomposition. Their results revealed that stock market returns exhibit insignificant positive response to oil price shocks but revert to negative effects after a period of time depending on the nature of the oil price shocks. The results were similar even with the inclusion of other variables. Also, the asymmetric effect of oil price shocks on the Nigerian stock returns indices is not supported by the statistical evidence.

Asaolu and Ilo (2012) used Cointegration analysis and the Vector Error Correction framework to analyze the impact of oil prices on the Nigerian stock market performance. They found that oil prices and stock market performance are associated in the long run. A rise in the price of oil leads to a decline in the return performance of the stock market. Somoye and Ilo (2008) examined the Nigerian stock market performance using vector-autoregressive (VAR). The study concluded that among the variables examined in the VAR model, the price of the Nigerian crude oil, exchange rate and inflation had the most significant influence on the aggregate stock market returns. Fowowe (2013) investigated the relationship between oil prices and returns on the Nigerian Stock Exchange. By using GARCH-jump models, he was able to model the volatility of stock returns and also take account of the effect of extreme news events on returns. The empirical results showed a negative but insignificant effect of oil prices on stock returns in Nigeria. Nwosa (2014) studied the relationship between domestic and international oil prices and stock prices in Nigeria with data for the period from January 1985 to April 2010. The test results which used the VECM analysis on quarterly data indicated that in the long run, there was a one-way relation between the two variables, i.e. the domestic oil prices affected stock prices. In contrast, there was no relationship between the domestic and international oil prices and stock prices in the short run. Using another data span, i.e. from January 1995 to December 2011, and a structural vector auto-regression (SVAR) model, Effiong (2014) found that the response of the stock market to oil supply shocks is insignificantly negative. However, the effect was significantly positive for aggregate demand and oil-specific demand shocks. The cumulative effects of the oil price shocks accounted for about 47 per cent of the variation in stock prices in the long run. These results suggest that the origin of oil price shocks is crucial for understanding the volatility in Nigeria's stock market.

Overall, compared to the previous literature, our investigation builds on the recently developed VAR-GARCH model, and moves from the market-level and sector-level analyses to an individual firm-level analysis by taking the stock prices of twelve firms in two sectors (*Banking* and *Oil & Gas*) in Nigeria. This paper, to the best of our knowledge, is a pioneer attempt in this direction in the literature, particularly for Nigeria.

3.0 Methodology and Data issues

3.1 Methodology

In the empirical finance literature, the generalized autoregressive conditional heteroscedasticity (GARCH) model of Bollerslev (1986) is one of the most widely used specifications on modeling and forecasting volatility of commodities prices. Empirical works indicated that the use of such types of models has centered on the evaluation of their forecasting performance (Fariz et al 2016; Uwubanmwe and Omorokunwa 2015; Amin and Amin 2014; Mollick and Assefa 2013; Elyasiani et al 2012; Kang et al., 2009; Sadorsky, 2006) and their application to Value-at-Risk (VaR) estimations (Aloui and Mabrouk, 2010; Giot and Laurent, 2003; Sadeghi and Shavvalpour, 2006).

However, as far as the major concern is about volatility transmission among multiple financial variables, it is commonly accepted that multivariate GARCH specifications such as the BEKK (full parameterization) model of Engle and Kroner (1995), the CCC-GARCH model of Bollerslev (1990) or the DCC- GARCH model of Engle (2002) with dynamic covariances and conditional correlations are more relevant than univariate representations. The superiority of these models and their ability to effectively capture the stylized facts of commodity-price volatility has been extensively confirmed in the literature (see, e.g. Malik, 2007; Agnolucci, 2009; Kang et al., 2009; Arouri et al., 2011, among others).

Nonetheless, the above-mentioned models are excessive in parameters, many of which lack empirical explanations, and often encounter convergence problems during estimation processes especially when additional exogenous variables are introduced to the conditional mean and variance equations. To tackle this problem, the current study uses the multivariate VAR (k)–GARCH (p,q) model proposed by Ling and McAleer (2003) as an interesting alternative. This model has two major advantages. First, it has an analysis advantage since it is relatively less excessive in parameters and allows the modeler to focus more on the estimation of meaningful and interpretable parameters. Second, it permits a multivariate analysis of conditional volatility of the series under investigation as well as of conditional cross-effects and volatility spillovers between the series. This model has previously been used to study the dynamic properties of different financial and economic phenomena (see for instance, Chan et al., 2005; Abdalla, 2013;

Boubaker and Jaghoubi, 2011; Chang et al. 2011; Chaibi and Ulici, 2014; Kumar, 2014; Arouri et al, 2011, 2012).

In this model, the conditional mean equation can be expressed as follows:

$$\begin{cases} R_t = \mu + \Pi R_{t-1} + \varepsilon_t \\ \varepsilon_t = H_t^{1/2} \eta_t \end{cases} \quad (1)$$

Where

$R_t = \left(r_t^s, r_t^o\right)$ with r_t^s and r_t^o being the of returns on the individual firms listed on the NSE stock market under the *Banking* and the *Oil & Gas* sectors and oil market returns at time t respectively.

$\mu = \left(\mu_t^s, \mu_t^o\right)$ is the vector of constant terms.

Π is a (2×2) matrix of coefficients allowing for cross-sectional dependency of conditional mean between stock market and oil prices of the following form:

$$\Pi = \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix}$$

$\varepsilon_t = \left(\varepsilon_t^S, \varepsilon_t^O\right)'$ is the vector representing the error terms of the conditional mean equations for stock and oil returns respectively.

$\eta_t = \left(\eta_t^s, \eta_t^o\right)'$ is a sequence of independently and identically distributed $(i.i.d)$ random errors;

$H_t = \begin{pmatrix} h_t^s & h_t^{so} \\ h_t^{so} & h_t^o \end{pmatrix}$ is the matrix of conditional variances of stock and oil returns with h_t^s and h_t^o being the conditional variances of r_t^s and r_t^o respectively. Their time series dynamics are modeled as follows:

$$h_t^s = C_s^2 + \beta_{s1}^2 h_{t-1}^s + \alpha_{s1}^2 \left(\varepsilon_{t-1}^S\right)^2 + \beta_{s2}^2 h_{t-1}^o + \alpha_{s2}^2 \left(\varepsilon_{t-1}^O\right)^2 \quad (2)$$

$$h_t^o = C_o^2 + \beta_{o1}^2 h_{t-1}^o + \alpha_{o1}^2 \left(\varepsilon_{t-1}^o \right)^2 + \beta_{o2}^2 h_{t-1}^s + \alpha_{o2}^2 \left(\varepsilon_{t-1}^s \right)^2 \quad (3)$$

According to Equations. 2 and 3, negative and positive shocks of equal magnitude have identical effects on conditional variances. The equations also show how volatility is transmitted over time and across the two markets under investigation. The cross values of error terms, $\left(\varepsilon_{t-1}^o \right)^2$ and $\left(\varepsilon_{t-1}^s \right)^2$, represent the return innovations in the oil market and to the corresponding stock rate at time $(t-1)$, and thus capture the direct effects of shocks transmission. The transfer of risk between the two markets is accounted for by the lagged conditional volatilities, h_{t-1}^o and h_{t-1}^s.

To guarantee stationarity, the roots of the equation $|I_2 - AL - BL| = 0$ must be outside the unit circle where the expressions $(I_2 - AL)$ and BL satisfy some other identifiability conditions as proposed by Jeantheau (1998). L is a lag polynomial, I_2 is a (2×2) identity matrix, and A and B are defined as:

$$A = \begin{pmatrix} \alpha_{s1}^2 & \alpha_{s2}^2 \\ \alpha_{o2}^2 & \alpha_{o1}^2 \end{pmatrix} \text{ and } B = \begin{pmatrix} \beta_{s1}^2 & \beta_{s2}^2 \\ \beta_{o2}^2 & \beta_{o1}^2 \end{pmatrix}$$

The conditional covariance between oil returns and stock market returns in the bivariate VAR (1)-GARCH (1, 1) is modeled as:

$$h_t^{so} = \rho * \sqrt{h_t^s} * \sqrt{h_t^o} \quad (4)$$

where ρ is the constant conditional correlation (CCC) coefficient. Overall, the proposed empirical model simultaneously allows us to capture both return and volatility spillover effects between the crude oil and stock market. Note that the CCC assumption can be viewed as restrictive given that correlation coefficient is likely to vary over time according to changes in economic and market conditions. The quasi-maximum likelihood estimation (QMLE) method of Bollerslev and Wooldridge (1992) is used to estimate the empirical model in order to take into account the fact that the normality condition is often rejected for the majority of macroeconomic and financial series.

3.2 *Data Employed*

The data set used in this study consists of daily observations of crude oil prices (Brent) and the closing prices of the individual firms listed on the NSE under the *Banking* and the *Oil & Gas* sectors. Both series span the period January 1, 2000 to December 31, 2015. Daily frequency is used because it affords an opportunity to capture the intensity of the dynamics of the relationship between the key variables. Crude oil prices expressed in USD per barrel for Brent spot prices is used to represent the international crude oil market given that this serves as pricing benchmark for two-thirds of the world's internationally traded crude oil supplies (see Alloui et al., 2013; Maghyereh, 2004).

Data on crude oil prices was extracted from the US Energy Information Administration (EIA) database, OPEC database, IMF, and Bloomberg. The data for the NSE index prices are obtained from the NSE database and CashCraft Assets Management. Daily returns on the two variables was computed by taking the difference in logarithm of two successive prices as follows:

$$r_t^o = log\left(\frac{p_t^o}{p_{t-1}^o}\right)*100 \quad (5)$$

$$r_t^s = log\left(\frac{p_t^s}{p_{t-1}^s}\right)*100 \quad (6)$$

Here, p_t^o and r_t^o are the daily crude oil prices and their returns respectively. p_t^s and r_t^s denote daily closing prices of the NSE stock market and their returns respectively.

It is pertinent to note that while preparing the data for subsequent analysis, we encountered the problem of non-synchronous trading days. In order to deal with this issue, we carefully traced and removed the asynchronous trading days using Brent (oil market) trading days as the gauge. At the end of this fairly cumbersome exercise, we had 3,633 and 3,628 usable observations for *Banking* and *Oil & Gas* sectors respectively.

4.0 Empirical results and Discussion

4.1 Descriptive Statistics of Stock Market and Crude Oil Prices

In this section, we examine the statistical properties of the returns series and confirm relevant stylized facts about financial time series variables. In essence, we present descriptive statistics and conduct appropriate tests for serial correlation and time-varying autoregressive conditional heteroskedasticity i.e. ARCH effects. Table 1 shows the descriptive statistics augmented with the results for serial correlation using Ljung–Box Q-statistics test and for ARCH effects using ARCH–LM test by Engle (1982). Also included is the result for unconditional correlation between Brent returns and companies' stock returns.

Average daily returns on stock prices are negative for *FIRST BANK*, *UNITED BANK FOR AFRICA*, *UNION BANK OF NIGERIA* and *WEMA BANK* while *ACCESS BANK*, *GUARANTY TRUST BANK* and *Brent* are positive over our sample period. The stock price of *FIRST* bank realized the worst performance (-0.044), followed by *UNITED BANK FOR AFRICA*, *UNION BANK OF NIGERIA* and *WEMA BANK*. Conversely, *Brent*, *ACCESS* and *GUARANTY TRUST* experienced positive average returns, with *GUARANTY* having the highest average stock price return.

From Table 1, all the returns series show wide margins between minimum and maximum values, which suggests the presence of large variance. Meanwhile, as indicated by the standard deviation statistic, *FIRST BANK* stock appears to be the most volatile of the return series followed by *UNION BANK OF NIGERIA*, while *Brent* appears to be the least volatile return series. In addition, the skewness statistic shows that the return series for *Brent*, *FIRST BANK* and *GUARANTY TRUST* are negatively skewed while it is positively skewed for *ACCESS*, *UNITED BANK FOR AFRICA*, *UNION BANK OF NIGERIA* and *WEMA BANK*.

Moreover, Kurtosis coefficients are important in size and highly significant, indicating that outliers may occur with a probability higher than that of a normal distribution. The kurtosis statistic, which compares the peakedness and tailedness of the probability distribution with that of a normally distributed series, shows that all the return series were found to have a leptokurtic behaviour (i.e., their distributions have fatter tails than corresponding normal distributions). This suggests that each of the mean equations should be tested for the existence of conditional heteroskedasticity. Meanwhile, the Jarque–Bera statistic, which measures normality of the distribution using both the skewness and kurtosis statistics, shows that we can reject the null hypothesis for normality for all the return series at all conventional significance levels.

We further carry out the stochastic test for autocorrelation and conditional heteroskedasticity to further verify stylized facts on financial time series variables. The ARCH–LM test by Engle (1982) was adopted for testing the significance of time-varying conditional variance (ARCH effects) while the Ljung–Box Q-statistic test was employed for testing the significance of autocorrelation. The results for these tests are also presented in Table 1 and they show that we can reject the null hypothesis of no ARCH effects for all the return series at 1% level of significance. In addition, Q-statistic results show that there is statistically significant autocorrelation in the return series for all the stock returns whereas return series for Brent are found to exhibit insignificant autocorrelations. We also compute the unconditional correlations between *Banking* Sector stock returns and oil returns. These correlations are weak on average and positive for *FIRST BANK, GUARANTY TRUST, UNITED BANK FOR AFRICA* and *UNION BANK OF NIGERIA*, while negative for *ACCESS* bank and *WEMA* bank, suggesting that oil price increases over the period were seen as indicative of higher expected corporate earnings for *FIRST* bank, *GUARANTY TRUST, UNITED BANK FOR AFRICA* and *UNION BANK OF NIGERIA*, and negative earnings for *ACCESS BANK* and *WEMA BANK*. *GUARANTY TRUST* has the highest positive correlation with oil (0.032), while the lowest positive correlation is observed between *UNION BANK OF NIGERIA* and oil market (0.013). *ACCESS BANK* and *WEMA BANK* have negative correlations between the oil market of (-0.014) and (-0.003) respectively.

Table 1: Descriptive statistics and statistical properties of return series for the Banking Sector

	RBR	RAC	RFB	RGU	RUBA	RUBN	RWE
Mean	0.01229	0.03401	-0.04359	0.04053	-0.04009	-0.03755	-0.01663
Median	0.03647	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Maximum	18.1297	68.9808	368.888	228.278	199.243	167.428	90.016
Minimum	-19.891	-31.916	-368.888	-228.278	-193.152	-155.256	-85.866
Std. Dev.	2.269	3.122	11.525	6.168	5.787	6.476	3.736
Skew.	-0.252	2.628	-0.448	-0.200	0.738	5.111	0.222
Kurt.	9.020	75.422	822.280	1035.75	734.032	356.825	173.617
J-B	5525.305	798131.7	1.02E+08	1.61E+08	80896252	18966752	4406558.
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ARCH	32.66	4.14	64.20	532.99	786.32	279.98	870.15
LB(Q)	2.59	55.27	426.21	493.15	276.68	258.74	22.48
Corr. with oil	1.000	-0.014	0.022	0.032	0.017	0.013	-0.003
Observations	3633	3633	3633	3633	3633	3633	3633

Notes: The table reports statistics of return series, including mean (Mean), standard deviation (Std. Dev.), skewness (Skew.), kurtosis (Kurt.), ARCH refers to the empirical statistics of the statistical test for conditional heteroskedasticity, LB (Q) is the empirical statistics of the Ljung-Box tests for autocorrelations applied to return series. J-B is the empirical statistics of the Jarque-Berra test for normality based on skewness and excess kurtosis. Corr. Denotes correlation coefficients. RBR, RAC, RFB, RGU, RUBA, RUBN, and RWE stand for returns on Brent, ACCESS, FIRST BANK, GUARANTY TRUST, UNITED BANK FOR AFRICA, UNION BANK OF NIGERIA and WEMA BANK respectively.

In addition, in Table 2, we report basic statistics of the return series for the *Oil & Gas sector*. On average, *FO* stock price realized the highest returns, then *TOTAL* stock, *MOBIL* stock and *Brent* oil market, which are positive. On the flip side, *BOCGAS* stock, *CONOIL* stock and *OANDO* stock all showed negative average returns over the sample period. There are also wide gaps between the minimum and maximum values on all the series. The standard deviation statistic indicated that *OANDO* stock appears to be the most volatile among all the series, which is followed by *FO*, *CONOIL*, *BOCGAS*, *MOBIL*, *TOTAL* and *Brent* is the least volatile, in that order.

Skewness is negative in most of the series, only *BOCGAS* and *FO* stocks being positively skewed. Kurtosis is higher than 3 in all the return series, with *OANDO* having the highest at (478.59). Statistical tests performed indicate that: i) there is rejection of the normality condition for all return series at 1% level (JB); ii) there is strong evidence of ARCH effects for all return series. By applying the Engle (1982) test, we observe that the null hypothesis of no ARCH effects is rejected at conventional levels in all cases, thus confirming that GARCH modeling is adequate for capturing any persistence in the volatility of stock and oil returns. All these facts support our choice of the quasi-maximum likelihood (QML) estimation method to estimate our VAR–GARCH models; iii) there is also significant autocorrelation for six out of the seven series.

We further computed the unconditional correlation between the *Oil & Gas* stock returns and *Brent* oil returns. These correlations are very low, with *BOCGAS* and *CONOIL* stocks having negative correlations, while *FO*, *MOBIL*, *OANDO* and *TOTAL* returns all have positive correlations with *Brent* returns.

	RBR	RBO	RCO	RFO	RMO	ROA	RTO
Mean	0.012	-0.014	-6.68E-05	0.078	0.027	-0.042	0.024
Median	0.036	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	18.130	35.797	39.900	91.707	23.502	120.149	37.168
Minimum	-19.891	-35.797	-39.900	-91.707	-29.779	-145.405	-37.168
Std. Dev.	2.266	2.818	3.048	4.155	2.456	4.415	2.403
Skewness	-0.240	0.148	-0.138	0.056	-1.021	-4.535	-0.135
Kurtosis	9.029	20.037	31.284	219.663	19.019	478.587	35.955
Jarque-Bera	5529.296	43891.91	120945.5	7096225.	39421.61	34203794	164182.3
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	32.89	726.54	802.22	839.99	233.70	567.12	759.94
LB(Q)	13.07	51.78	57.24	80.96	14.16	71.12	8.44
Corr. with oil	1.000	-0.016	-0.001	0.021	0.008	0.013	-0.010
Observations	3628	3628	3628	3628	3628	3628	3628

Notes: The table reports statistics of return series, including mean (Mean), standard deviation (Std. Dev.), skewness (Skew.), kurtosis (Kurt.), ARCH refers to the empirical statistics of the statistical test for conditional heteroskedasticity, LB (Q) is the empirical statistics of the Ljung-Box tests for autocorrelations applied to return series. J-B is the empirical statistics of the Jarque-Berra test for normality based on skewness and excess kurtosis. Corr. Denotes correlation coefficients. RBR, RBO, RCO, RFO, RMO, ROA and RTO represent returns on Brent, BOCGAS, CONOIL, FORTESOIL, MOBIL OANDO and TOTALOIL respectively.

4.2 *Empirical Results*

It is now possible to proceed with modeling the response of the *Banking* and *Oil & Gas* stock returns to oil price fluctuations by employing a VAR(1)-GARCH(1,1) model. The proposed model is estimated using maximum likelihood method under the assumption of bivariate normal distributed error terms. The log likelihood function is maximized using Marquardt's numerical iterative algorithm to search for optimal parameters.

4.2.1 *Oil market and the Banking sector in Nigeria*

The empirical findings from our VAR (1)-GARCH (1, 1) estimation results are reported in Table 3 for the oil-stock market (six *Banking* sector companies) pairs. Primarily, we note that the one-period lagged values of stock price returns are discovered to have a significant explanatory power on their current values in all the series considered in the Banking sector. The one-period lagged terms corresponding to returns on oil market are not significant in all cases, implying that past oil returns do not determine future oil returns.

With respect to the interdependence of returns in the mean equations, the findings showed that lagged oil returns insignificantly affected stock market returns in all the cases under consideration, except for *FIRST BANK* and *UBA BANK*. In the same vein, previous stock returns do not have significant effect on oil market returns. Thus, similar to results obtained for Nigeria by Fowowe (2013); Kuwait by Mohanty et al. (2011); Kuwait, Saudi Arabia, U.A.E. by Arouri et al. (2011); UK by Jammazi (2012); and Bahrain, Kuwait, Oman, Saudi Arabia, UAE by Hammoudeh and Choi (2006), returns on the Nigerian stock market are not affected by oil price returns. The effect of oil on stock prices is positive for five out of six companies in the *Banking* sector with *WEMA BANK* being negatively impacted.

Turning to the conditional variance equations, the estimates of ARCH and GARCH coefficients are statistically significant based on generally accepted levels in most cases. We can observe in the stock market that the sensitivity to past own conditional volatility (h_{t-1}^{s}) appears to be significant for *FIRST BANK, UBA, UNION Bank* and *WEMA BANK*, while it is insignificant for *ACCESS BANK and GUARANTY TRUST BANK* at 1% level. From the results, it can also be seen that the present value of conditional volatility of stock returns in the *Banking* sector also rely on past unexpected shocks $(\varepsilon_{t-1}^{s})^2$ affecting returns dynamics since the associated coefficients are highly significant in all cases except for *GUARANTY Trust Bank*. However, the relatively large size of ARCH coefficients suggests that conditional volatility changes very rapidly under the influence of returns innovations, and it tends to fluctuate gradually over time as evident from the large magnitude of GARCH coefficients. Furthermore, the past unexpected shocks of stock market $(\varepsilon^s_{t-1})^2$ is not significant to the oil market for all the series. The past conditional volatility is negative for *FIRST Bank, ACCESS Bank, GUARANTY Trust, UBA Bank and WEMA Bank;* and positive for *UNION Bank.* The stock market past conditional volatility (h^s_{t-1}) for *FIRST Bank, ACCESS Bank, UBA* and *WEMA Bank* are significant to the oil market while *GUARANTY Trust* and *WEMA Banks* are insignificant to the oil market. It is negative in *ACCESS, UNION and WEMA banks; and positive in FIRST Bank, GUARANTY Trust and UBA.*

In addition, the past conditional volatility of oil market h^o_{t-1} is highly significant in *FIRST Bank, ACCESS Bank, UBA Bank and WEMA Bank* and very insignificant in *GUARANTY Trust Bank and UNION Bank.* The cross-market unexpected past shocks $(\varepsilon^o_{t-1})^2$ from oil to stock is significant in all the series except in *ACCESS Bank.*

Next, we consider the volatility spillover effect between oil and stock (*Banking* sector) markets in Nigeria. We first observed that there is direct transmission of volatility h^o_{t-1} from oil market to stock market in *FIRST Bank, ACCESS Bank, UBA, and WEMA Bank,* but not in *GUARANTY Trust Bank* and *UNION Bank.* The cross-volatility coefficients (return innovation and volatility) are significant at conventional levels. More specifically, past oil shocks $(\varepsilon^o_{t-1})^2$ have significant effects on stock market volatility in *FIRST Bank, GUARANTY Trust Bank, UBA, UNION Bank* and *WEMA Bank* except in *ACCESS Bank.* Past oil return volatility strongly affects stock market volatility in *FIRST Bank, ACCESS Bank, UBA, WEMA Bank,* but not in *GUARANTY Trust Bank* and *UNION Bank.* Therefore, our results suggest an intensification of volatility spillovers from oil to the *Banking sector* of the stock market.

Summing up the *Banking* sector as a whole, the observed spillover effects from the oil market to the stock market are significant at the 1% level. This volatility relationship is not unexpected because oil price increases tend to have a serious effect on consumer and investor confidence and demand for financial products, while rising financial stock prices are often indicative of oil consumption due to increasing productive activity.

The estimates for the constant conditional correlation (CCC) between oil and individual firm (*Banking* sector) stocks are found to be positive for all but *ACCESS Bank* stock returns. This is not surprising, as there existed a negative cross-volatility between oil market and *ACCESS Bank* stock returns. Moreover, on a general note the CCC are somewhat low and weak. The positive outcome for CCC is in favour of plausible gains from investing in both stock and oil markets.

4.2.2 *Oil Market and the Oil & Gas Sector in Nigeria*

Estimation results of the VAR (1)-GARCH (1, 1) model for the six oil-stock market pairs for the *Oil & Gas* sector are reported in Table 4. As regards the conditional return generating processes, we find that one-period lagged oil returns insignificantly affected their current values in all cases. Thus, this suggested that there is no evidence of short-term predictability in oil price changes. The autoregressive terms corresponding to stock return equations are also insignificant in all cases except for *FO and OANDO*, implying that past stock returns do not help to better predict future stock returns in most cases. These results are inconsistent with the findings of some recent papers showing that the weak-form efficiency of the crude oil market is rejected (Arouri et al., 2010; 2011b; and 2012).

The estimates of ARCH and GARCH coefficients in the conditional variance equations are statistically significant in most cases at conventional levels. For the oil market segment, the sensitivity to past own conditional volatility (GARCH-term) appears to be significant for all the series. This finding typically suggests that past values of the conditional volatility in the oil market can be employed to forecast its future volatility. However, the current conditional volatility of the oil market does not depend on past shocks affecting return dynamics since ARCH-terms are not significant for all series considered.

A closer examination of the coefficients in Table 4 reveals that in general conditional volatility does not change very rapidly as the ARCH-terms measuring the impact of past shocks on conditional volatility are relatively small in size. On the other hand, the large magnitude of GARCH-term estimates, which capture the impact of past volatility on current volatility, indicates gradual fluctuations of conditional volatility over time.

Turning to the empirical findings regarding the volatility transmission between oil and stock *(Oil & Gas)* returns, we first observed that the conditional volatility of the stock market is affected by innovations in the oil market as indicated by the significance at the 1% level of the coefficients on $(\varepsilon_{t-1}^{o})^2$ in three cases: *BOCGAS, CONOIL* and *OANDO*. Apparently, a shock originating from the oil market leads to increased stock market volatility in those cases. In addition, there is a strong evidence suggesting that past volatility of the oil market is transmitted to the stock market because the coefficients associated with h_{t-1}^{o} is very much significant except for *OANDO stocks*. On the other hand, the statistical insignificance of the coefficients of $(\varepsilon_{t-1}^{s})^2$ in the conditional volatility equation for oil returns suggests that oil market volatility behaves independently from changes or shocks that occurred in the *Oil & Gas* sector.

Observing the *Oil & Gas* sector as a whole, we concluded that the relationship between oil and stock market is rather unclear. We noticed that there are no cross innovations effects from both oil and stock markets. This finding is thus somewhat surprising given that firms operating in the *Oil & Gas* sector are majorly involved in petroleum-related activities. One would thus expect that these firms will be highly influenced by the changes in the oil market.

As expected, the estimates of *CCC* between oil market and firms in the *Oil & Gas* sector are positive for *CONOIL, FO, MOBIL* and *OANDO* and negative for *BOCGAS* and *TOTAL*. They are small in general, which again suggests the existence of potential gains from investing in both oil and stock markets.

Broadly comparing across the two sectors (*Banking and Oil & Gas*), our findings showed that past unexpected shocks of stock returns do not significantly affect the current value of the oil market volatility in the *Oil & Gas* sector. However, past innovations in only three firms (*BOCGAS, CONOIL and OANDO*) exert significant influence from oil market to stock market volatility. This notwithstanding, there is conditional volatility spillover from both markets (*Oil and Oil & Gas* sector). Considering the *Banking* sector, we found similar results concerning conditional volatility as indicated for the *Oil & Gas* sector above. It is seen that past conditional volatility of stock (*Banking* sector) returns significantly affected the current value of the oil market volatility and vice versa, in all the firms. Oil market unexpected past shocks in all the firms except one (i.e. *ACCESS Bank*) exercise significant influences on stock market volatility, while oil price volatility is unaffected by past stock market shocks in all the firms.

In sum, the intensity of volatility spillover seems to vary from sector to sector, depending especially on their degree of oil dependence and industrial characteristics. It is equally imperative to note that some sectors are subject to indirect impacts of oil price changes. For instance, increases in oil price are likely to exert influence on the *Banking* sector through their effects on monetary policy, interest rates, employment and consumer confidence. Consequently, to better forecast stock market volatility and make appropriate investments decisions, investors need to closely watch what is happening in the oil markets.

Table 3: Estimate of Bivariate VAR (1)-GARCH (1, 1) Model for Six Banking Sector Firms

Notes: The bivariate VAR (1)-GARCH (1, 1) model is estimated for each firm over the period January 2, 2001 to December 31, 2015. The optimal lag order for the VAR model is selected using the AIC and SBC information criteria. Standard errors are given in parenthesis. Oil, Stock and CCC are oil price returns, firm stock returns and constant conditional correlation respectively. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Variables	First Bank		Access Bank		Guaranty Trust Bank		UBA		Union Bank		WEMA Bank	
	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil
Mean Equation												
Constant	-1.9111*** (0.0021)	0.0399*** (0.0116)	-0.0422 (0.0411)	0.0387 (0.0264)	-0.0497* (0.0272)	0.0330*** (0.0008)	-0.4289*** (0.0397)	0.0516** (0.0250)	-0.0278*** (0.0011)	0.0360* (0.0196)	-0.0187*** (0.0026)	-0.0012 (0.0232)
Stock(1)	-0.5262*** (0.0019)	0.0034** (0.0006)	0.1013*** (0.0169)	0.0123 (0.0098)	0.1464*** (0.0001)	-0.0002*** (0.0000)	-0.1768*** (0.0166)	0.0107*** (0.0006)	0.2687*** (0.0041)	-0.0022 (0.0018)	0.1992*** (0.0179)	0.0010 (0.0049)
Oil(1)	0.7466*** (0.0012)	0.0033*** (0.0072)	0.0749*** (0.0217)	0.0417*** (0.0100)	0.0529*** (0.0014)	0.0209** (0.0104)	0.1131*** (0.0210)	0.0036 (0.0155)	0.0213*** (0.0014)	0.0160*** (0.0001)	-0.0277*** (0.0009)	0.0863*** (0.0125)
Variance Equation												
Constant	1.2215*** (0.0674)	0.0050 (0.0020)	2.5369*** (0.0148)	-0.0164*** (0.0015)	22.6227*** (0.0195)	0.0135*** (0.0025)	1.5316*** (0.1491)	-0.0016 (0.0049)	0.7191*** (0.0021)	0.0173*** (0.0026)	0.0011 (0.0008)	0.0595*** (0.0100)
$(\varepsilon^s_{t-1})^2$	5.4212*** (0.0069)	-0.0079*** (0.0006)	0.2738*** (0.0095)	-0.0230*** (0.0023)	0.0992*** (0.0070)	-0.0014 (0.0025)	0.4189*** (0.0144)	-0.0063*** (0.0002)	0.2692*** (0.0009)	0.0103*** (0.0029)	0.3054*** (0.0029)	-0.0129*** (0.0037)
$(\varepsilon^o_{t-1})^2$	-1.5661*** (0.0179)	0.0492*** (0.0007)	0.0099 (0.0275)	0.0507*** (0.0003)	0.3459*** (0.0059)	0.0511*** (0.0009)	-0.3173*** (0.0165)	0.0472*** (0.0043)	0.3668*** (0.0001)	0.0533*** (0.0009)	-0.1109*** (0.0045)	0.0754*** (0.0033)
h^s_{t-1}	0.1146*** (0.0007)	0.8429*** (0.0555)	-0.0451*** (0.0019)	-1.4107*** (0.0158)	-0.0170*** (0.0000)	0.0072 (0.3411)	0.7538*** (0.0075)	0.2889** (0.0382)	0.8228*** (0.0001)	-0.0498 (0.0835)	0.7641*** (0.0019)	-0.5972*** (0.2037)
h^o_{t-1}	236.3689*** (2.4683)	0.9464*** (0.0006)	-48.3745*** (0.1317)	0.9233*** (0.0003)	-0.0273 (0.2689)	0.9483*** (0.0008)	-4.8130** (1.9275)	0.9420*** (0.0038)	-0.0992 (0.0656)	0.9455*** (0.0009)	5.1848*** (0.0554)	0.9202*** (0.0020)
CCC between oil and stocks		0.0017*** (0.0000)		-0.0164*** (0.0000)		-0.0002 (0.0018)		0.0228*** (0.0025)		0.0030*** (0.0002)		0.0058*** (0.0003)
Log-likelihood		-20096.9089		-16793.6567		-18590.6015		-17870.7924		-17909.3707		-15477.8730
AIC		11.076		9.257		10.246		9.850		9.871		8.532
SBC		11.105		9.286		10.275		9.879		9.900		8.561
No. of Obrns		3632		3632		3632		3632		3632		3632

Table 4: Estimate of Bivariate VAR (1)-GARCH (1, 1) Model for Six Oil & Gas Firms

Notes: The bivariate VAR (1)-GARCH (1, 1) model is estimated for each firm over the period January 2, 2001 to December 31, 2015. The optimal lag order for the VAR model is selected using the AIC and SBC information criteria. Standard errors are given in parenthesis. Oil, Stock and CCC are oil price returns, firm stock returns and constant conditional correlation respectively. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Variables	BOCGAS		CONOIL		FO		MOBIL		OANDO		TOTAL	
	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil	Stock	Oil
Mean Equation												
Constant	-0.0314 (0.0261)	0.0227 (0.0248)	-0.0761 (0.0508)	0.0189 (0.0293)	-0.0009*** (0.0002)	0.0585*** (0.0221)	-0.0211 (0.0326)	0.0267 (0.0292)	0.0069*** (0.0014)	0.0214 (0.0245)	0.0289 (0.0223)	0.0288 (0.0295)
Stock(1)	0.0321 (0.0228)	-0.0056 (0.0112)	0.0868*** (0.0201)	0.0018 (0.0101)	0.3580*** (0.0089)	0.0180*** (0.0018)	0.0283 (0.0182)	0.0147 (0.0120)	0.2109*** (0.0001)	0.0047*** (0.0005)	-0.0943*** (0.0193)	0.0032 (0.0121)
Oil(1)	-0.0461*** (0.0149)	0.0197 (0.0172)	0.0041 (0.0178)	0.0198 (0.0174)	0.0205*** (0.0056)	0.0238 (0.0149)	-0.0126 (0.0145)	0.0160 (0.0170)	0.0371*** (0.0044)	0.0198 (0.0148)	0.0144 (0.0126)	0.0187 (0.0180)
Variance Equation												
Constant	0.3656*** (0.0497)	0.0043 (0.0046)	1.4627*** (0.2372)	-0.0106 (0.0096)	5.9942*** (0.0000)	-0.0410*** (0.0002)	1.8156*** (0.1985)	0.0224*** (0.0052)	13.315*** (0.0183)	0.0099*** (0.0025)	0.4637*** (0.0091)	0.0034 (0.0026)
$(\varepsilon^{s}_{t-1})^2$	0.2876*** (0.0210)	0.0033 (0.0046)	0.1865*** (0.0182)	-0.0083* (0.0319)	0.2511*** (0.0000)	-0.0257*** (0.0000)	0.2388*** (0.0244)	0.0067 (0.0301)	0.2624*** (0.0036)	-0.0039*** (0.0022)	0.2546*** (0.0028)	-0.0141*** (0.0118)
$(\varepsilon^{o}_{t-1})^2$	-0.1280*** (0.0247)	0.0409*** (0.0051)	0.1535*** (0.0046)	0.0434*** (0.0043)	-0.0610*** (0.0010)	0.0402*** (0.0002)	0.0082 (0.0053)	0.0501*** (0.0054)	0.1096*** (0.0013)	0.0474*** (0.0008)	0.0332*** (0.0048)	0.0525*** (.0010)
h^{s}_{t-1}	0.5342*** (0.0297)	-13.1753 (13.7325)	0.4592*** (0.0570)	57.6308** (24.3517)	0.6844*** (0.0000)	2.5187*** (0.0000)	0.4881*** (0.0485)	114.1257*** (12.6774)	0.0302*** (0.0000)	0.0329** (0.0241)	0.6625*** (0.0027)	-0.6861*** (0.1767)
h^{o}_{t-1}	-193.8038 (215.2795)	0.9396*** (0.0071)	1103.5516*** (49.3849)	0.9424*** (0.0076)	-112.0223*** (0.0236)	0.9507*** (0.0002)	94.924*** (56.3998)	0.9330*** (0.0052)	0.0145 (0.0142)	0.9508*** (0.0008)	-2.8745*** (0.0501)	0.9378*** (0.0009)
CCC between oil and stocks		-0.0012 (0.0014)		0.0002*** (0.0001)		0.0050*** (0.0000)		0.0002*** (0.0000)		0.0309*** (0.0071)		0.0155*** (0.0007)
Log-likelihood		-16058.8771		-16524.9932		-17233.849		15844.98		17719.5798		-15575.9263
						5		45				
AIC		8.867		9.124		9.515		8.749		9.783		8.601
SBC		8.896		9.153		9.544		8.778		9.812		8.630
No. of Obrns		3626		3626		3626		3626		3626		3626

5.0 Summary and Conclusion

This study investigated the dynamic relationship between crude oil price fluctuations and the performance of the Nigerian stock market using two sectors over the period January 2, 2001 to December 31, 2015. The study employed a bivaraite VAR-GARCH model recently developed by Ling and Mcaleer (2003) to simultaneously estimate the conditional mean and conditional variance of returns on crude oil prices and the closing values of 12 firms in the *Banking* and *Oil & Gas* sectors. Empirical results of the conditional mean equations showed that there is evidence of short-run predictability on the firms' stock returns in the *Banking* sector and also revealed that crude oil prices had a significant impact on the *Banking* sector movements only in two firms (*FIRST BANK and UBA*). In the *Oil & Gas* sector on the other hand, our results showed that there is no evidence of short-run predictability in any of the firms (i.e. oil prices had no significant impact in the conditional mean equations). The study also investigated volatility transmission between the two markets (*Brent* and *Banking* and *Oil & Gas* sectors). Based on the conditional variance equations, our empirical findings indicated that the conditional volatility of the returns on the individual firms in the two sectors is affected not only by own volatility, but also by innovations in the oil market.

Our results also show the existence of significant volatility transmission between oil and stock markets in Nigeria, with the spillover effects being more apparent from oil to stock markets. However, it is important to underscore that the observed spillover effects come entirely from spillovers of volatilities, and that spillovers of shocks are mostly insignificant. Consequently, our empirical findings regarding interdependence of the oil and the stock market give an understanding of the true nature of the two markets for policymakers into building proper assets pricing models and to forecasts for the return and volatility of both markets. This will further help, for instance, portfolio managers and policymakers to adjust their activities in order to avert the spreading of market risks in the situation of market downturns. Finally, policymakers can use the results of this study as a starting point in their attempt to curtail higher volatility in the Nigerian stock market.

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