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Does Oil Price Fluctuation Affect Stock Market Returns in Nigeria?

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ABSTRACT

This paper examined the responsiveness of the stock market returns to fluctuation in oil price in Nigeria using monthly dataset from January 1994 to December 2016. The autoregressive distributed lag estimation technique was applied to analyze the long-run model as well as the short-run dynamics whereas test for cointegarating relationships was conducted using the Bound testing method. The findings revealed that changes in oil price have had positive but insignificant impact on stock market returns both in the long-run and the short-run. Impact of inflation was positive and insignificant in the long-run but positively significant in the short-run. Real interest rate and log of exchange rate exerted negative influence on the stock market returns, where the short-run effect of real interest rate was significant, the long-run impact was found to be insignificant. The error term indicates that deviation from long-run equilibrium is corrected at the speed of 8.2% on annual basis. The Bound test result showed that no long-run relationships exist between the oil price and stock market returns during the period under study.

Keywords: Stock Market Returns, Oil Price, Autoregressive Distributed Lag, Bound Testing
JEL Classification: C32, Q43, E44

1. INTRODUCTION

Oil is an important commodity and crucial for the world's economy. Consequently, fluctuating oil prices exert a significant impact on the economy. Rapid Oil prices variation makes oil a key macroeconomic factor, which creates unstable economic conditions and affects global financial stability (Naifar and Al Dohaiman, 2013).

Studies in the energy finance literature have documented various channels through which oil price shocks are transmitted to stock markets. Narayan and Narayan (2010) explain that oil prices can impact stock prices (returns) through two channels. First, oil is considered largely as an input in the production process. A rise in the oil price raises the cost of production and reduce the productivity of labour and capital (Yıldırım and Öztürk, 2014), which in turn will depress aggregate stock prices. Second, expected oil prices also affect stock returns through the discount rate, which comprises the expected inflation rate and the expected real interest rate. Oil prices thus affect both expected inflation and interest rates. Investors and other market participants are faced with uncertainties associated with volatility spill over via oil price or stock returns. In view of this, it remains a general agreement that investors, within a given time period, require a larger expected return from a security that is riskier(Glosten et al., 1993).

Syriopoulos et al. (2015) identified Significant return and volatility transmission dynamics between the US and BRICS stock markets and business sectors, which is a critical input that can impact efficient global portfolio diversification and risk management strategies, which confirmed the Asian-Pacific case (Zhu et al., 2014). For a net importer of oil, a rise in oil price will put upward pressure on the country's domestic inflation rate and downward pressure on foreign exchange rate. A higher expected inflation rate causes the discount rate to rise, which has a negative effect on stock returns (Arouri et al., 2011).

Dynamic return links and volatility transmission across capital markets attract greater attention of the financial community with the increasing trend of financial globalisation across the globe. Ratti and Vespignani (2016) maintain that, at global level, money, industrial production and prices are cointegrated. And if return and volatility are found to spread from one market to another, portfolio managers and policymakers would have to adjust their actions to essentially prevent contagion risks in the event of market crashes or crises (Arouri et al., 2011; Henriques and Sadorsky, 2008).

2. LITERATURE REVIEW

Gokmenoglu and Fazlollahi (2015) emphasise that understanding the volatility of crude oil price is very critical, because it may generate uncertainty in all sectors of the economy, and may give rise to instability in the economy for both oil exporting and importing economies. Oil indexation has long been the leading pricing mechanism in the energy market (Hulshof et al., 2016). Oil is widely considered as the lifeblood of modern economies. As countries advance and modernise their demand for oil increases significantly.

Predicting future oil demand is difficult but it is generally highly correlated with the growth in industrial production. Consequently, countries experiencing rapid economic growth, like the emerging economies, are the ones most likely to considerably increase their demand for oil (Basher and Sadorsky, 2006). Gupta (2015) adds that oil price shock is broadly acknowledged to have significant influence the economic activity of the country. For an oil dependent nation, the oil-supply poses strong signal to revenue generation and thriving economic activities (Mustapha and Sulaiman, 2015). An increase in economic growth in developing countries, for instance, may be linked to a higher expected growth for commodity demand than an increase in growth in developed countries (Ratti and Vespignani, 2015).

A study from West Africa happened to have examined the above phenomenon. Lin et al. (2014) investigated the dynamic volatility and volatility transmission between oil price and Ghanaian stock market returns in a multivariate setting using the VAR-GARCH, VAR-AGARCH and DCC-GARCH frameworks. In turn, the models' results are used to compute as well as analyze the optimal weights and hedge ratios for oil-stock portfolio holdings. For comparison purposes, the Nigerian stock market is also included in the analysis. The findings point revealed the existence of significant volatility spillover and interdependence between oil and the two stock market returns. While spillover effects are stronger for Nigeria, the transmission of volatility is much more apparent from oil to stock than from stock to oil in the case of Ghana. On the whole, the findings for optimal hedge ratios were consistent with the view that oil assets should be an integral part of a diversified portfolio of stocks and suggested that a better understanding of volatility links is crucial for portfolio management in the presence of oil price risk.

Syriopoulos et al. (2015) identified Significant return and volatility transmission dynamics between the US and BRICS stock markets and business sectors, which is a critical input that can impact efficient global portfolio diversification and risk management strategies, which confirmed the Asian-Pacific case (Zhu et al., 2014). Similarly, an earlier study by Hammoudeh et al. (2004) explored the link between U.S. oil prices and oil industry equity indices. The cointegration analysis indicates that the oil industry equity system and the mixed oil/equity index system offered more opportunities for long-run portfolio diversification and less market integration than the pure oil price systems. The spillover analysis of crude oil transmission showed that the oil futures have a matching volatility on the stocks of some oil sectors and a volatility-dampening effect on the stocks of others.

From the emerging market standpoint, Basher and Sadorsky (2006) evaluated the impact of oil price changes on a large set of emerging stock market returns. The approach adopted in the paper was an international multi-factor model that allows for both unconditional and conditional risk factors to determine the relationship between oil price risk and emerging stock market returns. In general, the findings revealed strong evidence that oil price risk impacts stock price returns in emerging markets.

Narayan and Narayan (2010) modeled the impact of oil prices on Vietnam's stock prices using daily data for the period 2000–2008 and include the nominal exchange rate as an additional determinant of stock prices. The results showed that stock prices, oil prices and nominal exchange rates are cointegrated, and oil prices have a positive and statistically significant impact on stock prices. This result is inconsistent with theoretical expectations.

Diaz and De Gracia (2017) examined the impact of oil price shocks on stock returns of four oil and gas corporations listed on NYSE over the period January 1974–December 2015. The novelty evidence supports a significant positive impact of oil price shocks on stock returns in the short-run.

3. DATA AND METHODOLOGY

Data for the study are monthly data for the period 1994 January–2016 December and consisting of 276 observations. Oil price data as well as inflation, exchange rate and real interest rate dataset were obtained from the World Bank while the stock market data were sourced from the Central Bank of Nigeria Statistical bulletin 2016 editions. Our variables of interest comprises oil price and stock market returns while the inflation rate, exchange rate and real interest rates are the moderating variables. Augmented Dickey-Fuller (ADF) unit root test will be employed to ascertain the stationarity of the variables and the Multiple-Break point tests under the ADF framework was applied to determine the break date(s) for each of the variable. The bound testing test approach to cointegration was used to test for long-run association among our series while our dataset was analysed using auto regressive distributed lag (ARDL) model.

Our baseline equation function can be expressed as;

$$STKR_t=\beta_0+\beta_1 OILP_t+\beta_2 INF_t+\beta_3 RIR_t+\beta_4 LEXR_t+\varepsilon_t \quad (1)$$

Where t denotes time, and STKR = Stock market returns, OILP = Percentage change in oil price, INF = Inflation rate, RIR = Real interest rate, LEXR = Log of exchange rate and ε = Error term.

The long run relation in Eq. (1) can be modified to allow for the short-run dynamic adjustment process. In line with Engle and Granger (1987), we represent Eq. (1) in an error correction model in the flowing form:

$$\Delta STKR_{t,j} = \begin{aligned} &\beta_0 + \sum_{i=1}^{m1}\beta_{1i,j}\Delta STKR_{t-1,j} + \sum_{i=0}^{m2}\beta_{2i,j}\Delta OILP_{t-1,j} + \\ &\sum_{i=0}^{m3}\beta_{3i,j}\Delta INF_{t-1,j} + \sum_{i=0}^{m4}\beta_{4i,j}\Delta RIR_{t-1,j} + \\ &\sum_{i=0}^{m5}\beta_{5i,j}\Delta LEXR_{t-1,j} + \delta\varepsilon_{t-1,j} + \mu_t \end{aligned} \quad (2)$$

Where Δ represents differencing operator, m_i is the number of lags, is the speed of adjustment parameter and ε_{t-1} is the one period lagged error correction term, derived from the residuals of Eq. (1). This method of estimation proposed by Engle and Granger (1987) assumes that for a co-integration relationship to be established, all variables must be I(1) and the error term I(0). Where, however, the variables in Eq. (1) have mixed order of integration, comprising strictly of I(1) and I(0) we may adopt a alternative co-integration method suggested by Pesaran et al. (2001). This approach is known as ARDL that replaces ε_{t-1} in Eq. (2) with its equivalent from Eq. (5). By linear combination of the lagged variables, ε_{t-1} is substituted as represented in as in Eq. (3).

$$\Delta STKR_{t,j} = \begin{aligned} &c_0 + \sum_{i=1}^{n1}c_{1i,j}\Delta STKR_{t-1,j} + \sum_{i=0}^{n2}c_{2i,j}\Delta OILP_{t-1,j} + \\ &\sum_{i=0}^{n3}c_{3i,j}\Delta INF_{t-1,j} + \sum_{i=0}^{n4}c_{4i,j}\Delta RIR_{t-1,j} + \\ &\sum_{i=0}^{n5}c_{5i,j}\Delta LEXR_{t-1,j} + c_6 STKR_{t-1} + \\ &c_7 OILP_{t-1} + c_8 INF_{t-1} + \\ &c_9 RIR_{t-1} + c_{10} LEXR_{t-1} + v_t \end{aligned} \quad (3)$$

To arrive at Eq. (3), we solve Eq. (1) for ε_t and lag the solution equation by one period. Then we substituted the solution for ε_{t-1} in Eq. (2) to arrive at Eq. (3) which is a representation of the ARDL process to co-integration. Further, we can obtain the ARDL representation of the Error Correction Model (ECM), and then estimate the speed of adjustment within the bounds testing procedure. Hence, in accordance to Pesaran et al. (2001) the lagged level variables in Eq. (3) are replaced by ECT_{t-1} as expressed in Eq. (4), and where a negative and statistically significant estimation of represents the speed of adjustment:

$$\Delta STKR_{t,j} = \begin{aligned} &\alpha_0 + \sum_{i=1}^{k1}\alpha_{1i,j}\Delta STKR_{t-1,j} + \sum_{i=0}^{k2}\alpha_{2i,j}\Delta OILP_{t-1,j} + \\ &\sum_{i=0}^{k3}\alpha_{3i,j}\Delta INF_{t-1,j} + \sum_{i=0}^{k4}\alpha_{4i,j}\Delta RIR_{t-1,j} + \\ &\sum_{i=0}^{k5}\alpha_{5i,j}\Delta LEXR_{t-1,j} + \delta ECT_{t-1,j} + \mu_t \end{aligned} \quad (4)$$

4. RESULTS AND DISCUSSIONS

The results reported in Table 1 show that null hypothesis of unit root is rejected in case of STKR, INF, RIR and LEXR variables in first difference at 1% level of significance; and are integrated of order one [I(1)], while OILP is stationary at level and is integrated at order zero [I(0)]. Under these circumstances when we have faced with mix results or varied orders of integration, estimating our model using the ARDL model is the efficient estimator for determining the long-run association among our variables.

The trends of these variables, in their appropriate model - ARDL (1, 0, 1, 1, 0), is presented in Figure 1. Moreover, we ascertain the break point dates for each variable as shown in Table 1. While the summary break point test by Quandt-Andrews revealed that stock market returns and changes in oil price have break points in January and August 2008, respectively. The break-point for oil price may be connected to the global financial crisis which held sway at that time. Inflation rate and real interest rate share the same break date at July 1997 whereas break date for exchange is in January 1999. The break-points reveal moments of significant shocks on each of the variables.

4.1. Model Selection

The Akaike information criterion (AIC) is used to select the optimum number of lag in the ARDL mode where the model with the lowest AIC is considered more appropriate as shown in Figure 2. The selected model is ARDL (1, 0, 1, 1, 0) out of 20 possible models. The trend of our variables based on the selected model is presented in Figure 2.

4.2. Regression Results

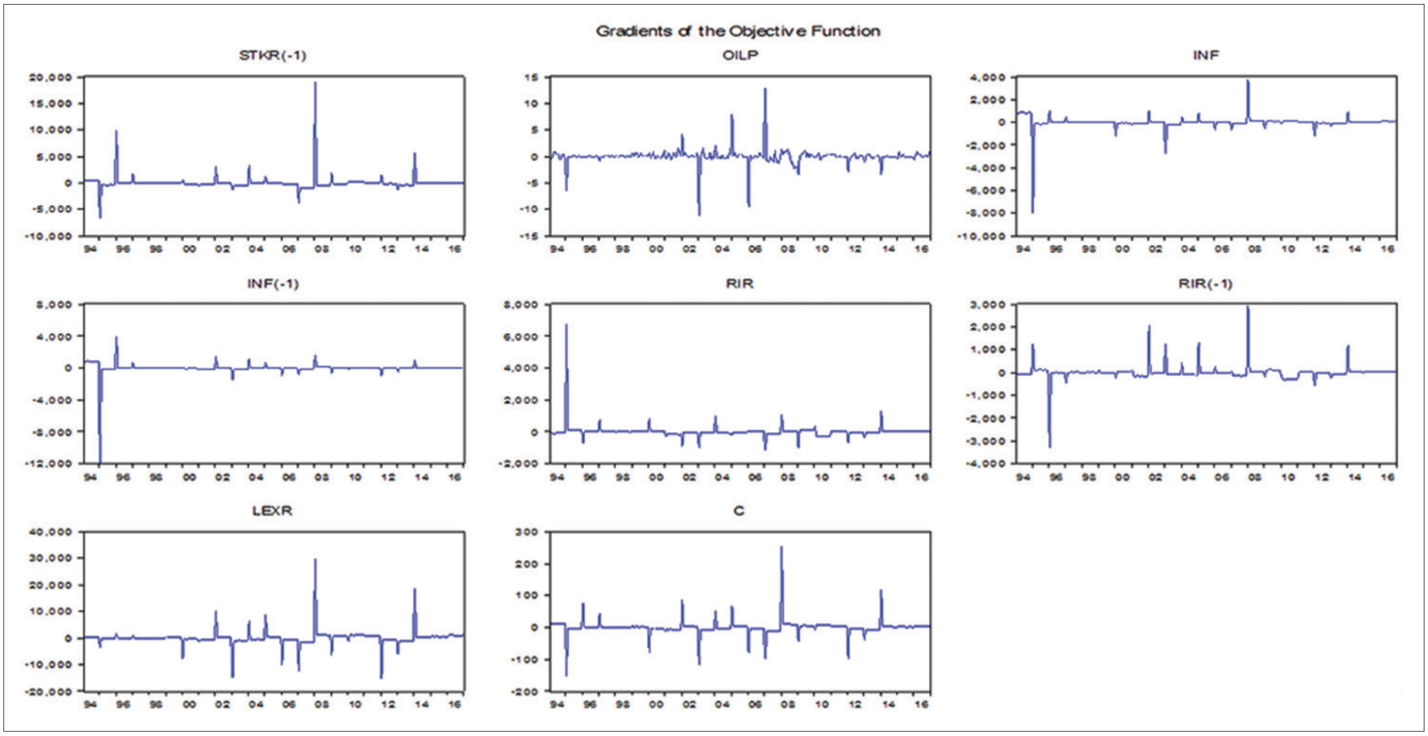
The ARDL long-run form presented in Table 2 shows that change in oil price and the inflation level are positively but not significantly

Table 1: Results of ADF unit root test

Variables	Test results		Order of integration	Bai-Perron multiple breakpoint test		Quandt-Andrews breakpoint test
	ADF-statistic	5% Critical values		Break test	Break dates	Single-break date
STKR	−16.46461	−3.991904***	I(1)	1 versus 2	1997M06, 2008M01	2008M01
OILP	−13.79645	−3.426251***	I(0)	1 versus 2	-	2008M08
INF	−16.78729	−3.426311***	I(1)	1 versus 2	1997M06	1997M07
RIR	−8.232713	−3.427004***	I(1)	1 versus 2	1997M06	1997M07
LEXR	−16.63869	−3.426311***	I(1)	1 versus 2	1999M01, 2009M01	1999M01

***Significance at 1%. ADF: Augmented Dickey-Fuller

Figure 1: Gradient graph of variable proxies



related to stock market returns whereas real interest rate and log of exchange rate exerted negative influence on the regressand. The result indicate that our regressors are jointly significant in explaining the dependent variable and explained about 89.5% of the variations in stock market returns as indicated by the coefficient of determination. The results of the cointegrating equation in Table 2 appear similar to the long-run estimates in direction but differ in magnitude.

Table 3 shows that OILP is positively related to STKR. INF has significant positive impact on STKR whereas RIR and EXR exerted negative impact on STKR, but the impact of RIR is shown to be significant. The coefficient of the error term is negative and statistically significant; being the speed of adjustment but also provides an alternative means of supporting co-integration between the variables (Mehdi and Reza, 2011). The error term indicates that deviation from long-run equilibrium is corrected at the speed of 8.2% annually.

Full ARDL (1^{STKR}, 0^{OILP}, 1^{INF}, 1^{RIR}, 0^{LEXR}) Cointegrating Test Equation:

D(STKR)=3.944595415839*D(OILPR)+0.802497199121*D(INF)−0.725439971373*D(RIR)−0.002063303322*D(LEXR)−0.082378943632*ECT(−1)(STKR−(47.88353968*OILPR(−1)+1.22899901*INF−1.05821298*RIR(−1)−0.02504649*LEXR(−1)+5.21296339*Intercept)).

4.3. Bound Testing for Long-run Relationship

The long-run relationship among our variables is test using the bound testing as presented in Table 4. From the results, the null hypothesis of that no long-run relationships exist cannot be rejected given that the F-statistic is low compared to the critical values at

Table 2: ARDL long-run coefficients estimate

Selected model: ARDL (1, 0, 1, 1, 0)				
Dependent variable: STKR				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
OILP	47.883540	109.747965	0.436305	0.6630
INF	1.228999	0.752732	1.632717	0.1037
RIR	-1.058213	0.614639	-1.721681	0.0863
LEXR	-0.025046	0.182527	-0.137221	0.8910
Intercept	5.212963	30.177790	0.172742	0.8630

The Schwartz Bayesian criterion is used to select the optimum number of lag in the ARDL mode. R^2=0.895, Adj. R^2=0892, F-statistic (prob.)=323.98 (0.000), D-W stat=1.933. ARDL: Auto regressive distributed lag

Table 3: Estimated error correction model

Dependent variable: STKR				
Variable	**Coefficient**	**SE**	**t-Statistic**	**Prob.**
D(OILP)	3.944595	9.018265	0.437401	0.6622
D(INF)	0.802497	0.248654	3.227371	0.0014
D(RIR)	−0.725440	0.111317	−6.516910	0.0000
D(LEXR)	−0.002063	0.015120	−0.136460	0.8916
ECT(−1)	−0.082379	0.024314	−3.388183	0.0008

Table 4: ARDL bounds test result

Null hypothesis: No long-run relationships exist		
Test statistic	**Value**	**k**
F-statistic	2.590435	4
Critical value bounds		
Significance (%)	**Lower bound**	**Upper bound**
10	2.45	3.52
5	2.86	4.01
2.5	3.25	4.49
1	3.74	5.06

Table 5: Serial-correlation, heteroskedasticity and Ramsey RESET test results

Breusch-Godfrey serial correlation LM test			
F-statistic	0.395710	Prob. F (2.265)	0.6736
Obs*R^2	0.818840	Prob. Chi-square (2)	0.6640
Heteroskedasticity test: Breusch-Pagan-Godfrey			
F-statistic	1.119606	Prob. F (7.267)	0.3509
Obs*R^2	7.841880	Prob. Chi-square (7)	0.3467
Ramsey RESET test	Value	df	Probability
t-statistic	0.768576	266	0.4428
F-statistic	0.590708	(1, 266)	0.4428

Figure 2: The Akaike information criteria for model selection

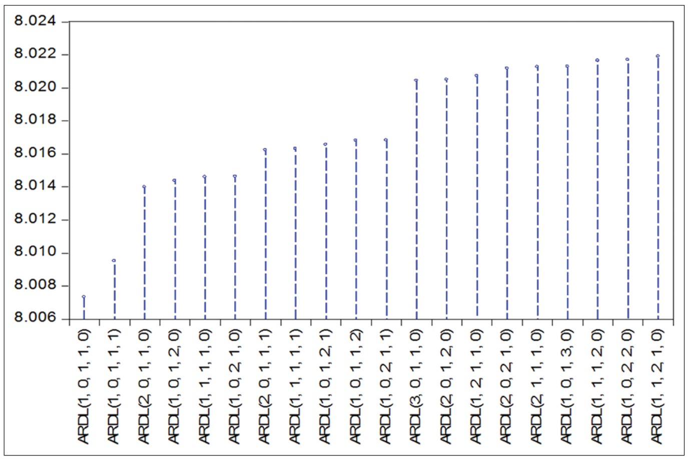
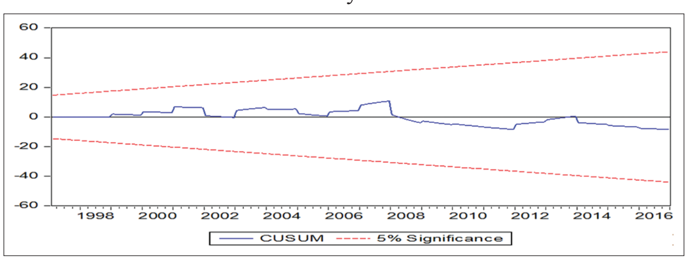


Figure 3: Plots of cumulative sum (CUSUM) statistics for coefficients stability tests



5% conventional level of significance.

4.4. Diagnostic Tests

From Table 5, breusch-godfrey serial correlation LM Test indicates that our model has no autocorrelation problems. This confirms the result of Durbin-Watson (DW) result in Table 2 which supports same result. The second test for Heteroskedasticity shows that our model is homoskedastic. The Ramsey RESET test in the third panel reveals that the null hypothesis that the model is correctly specified cannot be rejected. This also indicates that there are no specification errors in our model.

In Figure 3, we applied the cumulative sum (CUSUM) test to analyze the stability of our selected ARDL model specification. The null hypothesis that the regression equation is correctly specified cannot be rejected since the plot of this statistic remains within the critical bounds of the 5% significance level. Therefore, the model seems stable and correctly specified given that the CUSUM test statistic did not exceed the bounds of the 5% level of significance.

5. CONCLUSIONS

Recent empirical studies have sought to examine the likely impact of movements in oil price on the stock market returns. Mostly, the focus was on examining various channels through which oil price shocks are transmitted to stock markets. In this paper, we examined the responsiveness of the stock market returns to fluctuation in oil price in Nigeria.

The findings revealed that changes in oil price have had positive but insignificant impact on stock market returns both in the long-run and the short-run. Impact of inflation was positive and insignificant in the long-run but positively significant in the short-run. Real interest rate and log of exchange rate exerted negative influence on the stock market returns, where the short-run effect of real interest rate was significant, the long-run impact was found to be insignificant. The error term indicates that deviation from long-run equilibrium is corrected at the speed of 8.2% on annual basis. The Bound test result showed that no long run relationships exist between the oil price and stock market returns during the period under study.

REFERENCES

Arouri, M.E., Jouini, J., Nguyen, D.K. (2011), Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. Journal of International Money and Finance, 30(7), 1387-1405.

Basher, S.A., Sadorsky, P. (2006), Oil price risk and emerging stock markets. Global Finance Journal, 17, 224-251.

Diaz, E.M., De Gracia, F.P. (2017), Oil price shocks and stock returns of oil and gas corporations. Finance Research Letters, 20, 75-80.

Engle, R.F., Granger, W.J. (1987), Co-integration and error correction: Representation, estimation. Econometrica, 55, 251-276.

Gokmenoglu, K.K. (2015), The Interactions among gold, oil, and stock market: Evidence from S and P500. Procedia Economics and Finance, 25, 478-488.

Glosten, L., Jagannathan R. & Runkle D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779-1801.

Gupta, K. (2016), Oil price shocks, competition, and oil and gas stock returns - Global evidence. Energy Economics, 57, 140-153.

Hammoudeh, S., Dibooglu, S., Aleisa, E. (2004), Relationship among U.S. oil price industry equity indices. International Review of Economics and Finance, 13, 427- 453.

Henriques, I., Sadorsky, P. (2008), Oil prices and the stock prices of alternative energy companies. Energy Economics, 30, 998-1010.

Hulshof, D., Van Der, M.J., Mulder, M. (2016), Market fundamentals, competition and natural-gas prices. Energy Policy, 94, 480-491.

Lin, B., Wesseh, P.K., Appiah, M.O. (2014), Oil price fluctuation, volatility spillover and the Ghanaian equity market: Implication for portfolio management and hedging effectiveness. Energy Economics, 42(C), 172-182.

Musstapha, S.A., Sulaiman, L.A. (2015), Estimating the critical bands for Nigeria's crude oil price and production: Evidence from GARCH models and interval adjustments. Procedia Economics and Finance, 30(15), 573-585.

Narayan, P., Narayan, S. (2010), Modelling the impact of oil prices on Vietnam's stock prices. Applied Energy, 87, (1), 356-361.

Naifar, N., Saleh, M., Dohaiman, A. (2013), Author's personal copy nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. International Review of Economics and Finance, 27, 416-431.

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

Ratti, R.A., Vespignani, J.L. (2015). OPEC and non-OPEC oil production and the global economy. Energy Economics, 50, 364-378.

Ratti, R.A., Vespignani, J.L. (2016), Oil prices and global factor macroeconomic variables. Energy Economics, 59, 198-212.

Syriopoulos, T., Makram, B., Boubaker, A. (2015), Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. International Review of Financial Analysis, 39, 7-18.

Yıldırım, E., Öztürk, Z. (2014), Oil price and industrial production in G7 countries: Evidence from the asymmetric and non-asymmetric causality tests. Procedia - Social and Behavioral Sciences, 143, 1020-1024.

Zhu, H., Li, R., Li, S. (2014), Modelling dynamic dependence between crude oil prices and Asia-Pacific stock market returns. International Review of Economics and Finance, 29, 2013-2015.