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Oil Price-US Dollar Exchange Returns and Volatility Spillovers in OPEC Member Countries: Post Global Crisis Period's Analysis

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Abstract. We investigate returns and volatility spillovers from oil to foreign exchange (FOREX) markets in oil-exporting countries using VARMA-GARCH framework with particular focus on OPEC members. The results indicate significant bi-directional return spillovers between oil and FOREX markets in OPEC countries. Local currencies of oil exporting countries appreciated against the US dollar with increases in oil prices, and vice versa. These findings are of importance to decision makers in the control of oil price inflationary shocks and exchange rates management in oil-exporting countries, as the framework provides proxy measurement for comparing oil-FOREX management in those countries.

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Résumé. Nous enquêtons sur la volatilité des rendements et les retombées provenant de l'huile au marché des changes(FOREX) les marchés dans les pays exportateurs de pétrole au utilisant VARMA-cadre GARCH aves un accent particulier sur les membres de l'OPEP. Les rêsultats font apparaître d'importantes retombées retour bidirectionnelle entre l'huile et des changes dans les pays de l'OPEP. Monnaies locales des pays exportateurs de pétrole s'est apprécié par rapport au dollar américain avec des augmentations des prix du pétrole, et vice versa. Ces constatations sont d'importance pour les décideurs dan le contrôle des prix de pétrole les chocs inflationnister et les taux de change dans les pays exportateurs de pétrole, comme le Cadre fournit la mesure de comparaison de proxy-FOREX pétrole gestion dans ces pays.

1. Introduction

For about two decades, international economic and financial markets have become more volatile as a result of deregulation of financial markets and economic integration (Liu *et al.* (2016)). Thus, the speed at which information is transmitted across markets is increased and this has an aftermath effect on the propagation of risks in the form of price shocks in the market system. As a result, there has been increasing interests of financial analysts, and scholars in studying market volatility, particularly volatility in the oil price. As oil market integration increases and volatility becomes persistent, asset and commodity prices that depend on oil become more responsive to events such as deregulation, socio-political unrests especially in oil producing states and other unforeseen events (Anandan and Ramaswamy (2015)).

Large increases in the price of oil, a naturally occurring non-renewable energy source, are known to be associated with economic recessions, inflationary pressures, trade deficits and unpredictable out-turn in investment in stocks and bonds especially in oil-importing countries. For oil-exporting countries, a sharp drop in price will generate balance of payments challenges as is currently being witnessed by oil and gas dependent economies especially Nigeria and Venezuela. Since the main invoicing and settlement currency in international oil market is the US dollar, oil price shock is transmitted to the real economy and financial markets through the exchange rate channel. Hence, changes in the US dollar exchange rates will have effect on both oil-exporting and oil-importing economies. Thus, a weak US dollar makes oil to be more attractive in oil-importing countries except the United States of America (USA), and this leads to an increase in their purchasing power in oil and other US dollar-denominated financial assets. Whereas in oil-exporting countries, a weak US dollar implies appreciation of local currencies against the US dollar, and oil becomes less attractive since the purchasing power of oil is reduced (Roboredo *et al.* (2014); Turham *et al.* (2016)). Thus, giving the centrality of the US Dollar to oil trading at the international market, oil traders should therefore be more concerned not only on the dynamics of pricing of crude oil but also on the movement of US dollar foreign exchange (FOREX) rates (World Bank Group (2015); Akram (2004); Zhang *et al.* (2008)).

In more recent years, exchange rate has undergone increasing trend due to industrialization and the increasing financial dealings of international traders, whereas prices of crude oil is generally trending down due to competition at the oil market and other effects

(Gil-Alana *et al.* (2016)). For example, the prices of oil that oscillate between \$80 to \$110 per barrel between 2010 and 2014 started a downward spiraling crash in mid-2014. By 2015 it had crashed to around \$60 per barrel and maintained its price as low as \$30 to \$45 dollar per barrel at the three oil markets in 2016[1].

Oil as a major source of global energy affects both the financial and the economic sectors in importing and exporting economies. The role of oil price in explaining FOREX movement has been noted as far back as 1980s by scholars like Golub (1983) and Krugman (1983). Both authors found oil-exporting countries to experience FOREX appreciation during oil price rise, while there was FOREX depreciation during oil price falls (see Al-Mulali and Binti Che Sab (2012); Muhammad *et al.* (2012)). The case was the reverse for oil-importing countries, where there was FOREX depreciation during oil price rise and FOREX appreciation during oil price falls. The changing dynamics of oil price-FOREX was largely accounted for by availability and/or non-availability of revenue denominated in US Dollar for oil exporting countries during price rise and when price fall.

According to the International Energy Agency (IEA, 2008), oil accounts for about 34 percent of the total global energy needs. Both oil price and FOREX rates are susceptible to high volatility in the international oil market that results from either supply or demand shocks. Thus, portfolio investors in these assets prices are affected by the risk and uncertainties caused by the changes in market values, and therefore they diversify their portfolios, and this leads to less profits being realized by the portfolio managers (see Arouri *et al.* (2011a), Arouri *et al.* (2011b)).

Thus, the analysis of FOREX with respect to oil price is important for the design of policy by national governments, public policy decision makers, portfolio investors and risk managers in international finance. With this assumption, it becomes important to investigate shocks induced by changes in oil price as it affects FOREX markets, particularly in oil producing countries and oil-exporting countries. The volatility in the FOREX rates and transmission of volatility from oil to FOREX is therefore of important concern and a major determinants of international capital flows, foreign direct investment (FDI) and macroeconomic performance especially in oil exporting economies. After the global financial crash of 2009, most asset prices have recovered, but the current global trends in the behaviour of oil and FOREX have induced the interests of researchers towards studying the dynamics as it relates to the relationship between these assets prices, at the mean, or variance series level which is known as volatility.

The volatility in oil prices and how it induced changes in FOREX rates has been of concern to academicians, financial researches and portfolio managers. To this end, there is the need to understand the volatility transmission across different financial markets, particularly the transmission of oil volatility to other financial markets such as FOREX. This could also be bi-directional in the sense that the transmission can also move from FOREX to oil. Most works that have focused on volatility transmission considered the transmission

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[1] These are oil markets at Organization of the Petroleum Exporting Countries (OPEC), West Texas Intermediate (WTI) in USA, and European Brent markets

between oil and other asset prices (see Malik and Hammoudeh (2007); Yilmaz (2010); Arouri *et al.* (2012); Sadorsky (2000), among others). Most of these studies have applied variants of Constant Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity (CCC-GARCH) of Engle (2002) or Vector Autoregressive Moving Average-GARCH (VARMA-GARCH) model of Ling and McAleer (2003) to investigate volatility dynamics, co-volatility across markets, correlation and further investigate portfolio management and hedging strategy which is very important to policy makers within an economy and portfolio investment managers that operate in the financial market.

This present study has important implications for economic policy decisions and portfolio management since it involves the development of accurate pricing volatility models for predicting oil and FOREX rates in oil producing economies. Specifically, the study aims at investigating returns and volatility transmissions between oil price and FOREX rates (especially the US Dollar) in oil-exporting OPEC[2] member countries using the VARMA-GARCH modeling framework. This model allows one to investigate directional spillovers in both the returns and volatility mechanisms, with the estimate of correlation measuring the long-run co-variances between oil and FOREX markets. The estimates of conditional variances and co-variances are further used in the computation of measures of portfolio allocation and hedge ratio between the markets. This work is different from other empirical studies such as that by Roboredo (2011) in the sense that it investigates both returns and volatility spillovers framework in relations to oil price-FOREX dynamics in oil-exporting countries. Also, we are particular to the sample period, after the global financial crisis, in order to know the current shift in returns, shocks and volatility spillovers across the two asset markets within this chosen time frame.

In presenting the result of our study, this paper is structured into six sections. Following this introduction is section two which deals with brief presentation of the history of OPEC and recent empirical literature relevant to the work. Section three presents the methodology adopted for the paper. Section four presents the data description and estimation results. The paper presents tools for the management of FOREX within the context of oil price volatility in section five, while section six concludes with policy recommendations.

2. Literature Review

This study focuses attention on the dynamics of the relationship that exist between the international oil price and FOREX in OPEC market, which is one of the three international oil marketers. The other two marketers are the West Texas Intermediate (WTI) of North

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[2] OPEC was constituted at a conference in Baghdad in Iraq in September 1960 with the mind of having a unified agreement on the supply of oil by each oil producing country, since oversupply could lead to drop of oil price. The founding members of the organization were Iran, Iraq, Kuwait, Saudi Arabia and Venezuela, and later from 1961, Qatar, Indonesia, Libya, United Arab Emirates (UAE), Algeria, Angola, Nigeria, Ecuador and Gabon signed their membership agreement with the organization. In 1995 and 2009, respectively, Gabon and Indonesia terminated their membership, and presently, there are 12 OPEC member countries.

America and the European Brent of North Sea region[3]. In 2008, oil price hit an all-time high of about $147.27 per barrel, but the price collapsed after the financial crisis. During the crisis period, OPEC maintained steady supply and announced a record output cut of 2.5 million barrels a day. Sequel to this tinkering with the supply side of the international oil market, oil price thereafter stabilized by 2009. On the contrary, in the late 2014, after failing to reach consensus on new quota and output restriction, OPEC decided to maintain its current production and supply levels despite the steady increase in non-OPEC oil production. The decision to maintain current production and supply as at then by members of the oil cartel was hinged on the need for OPEC to maintain its share of global oil market that was estimated at 47.3 percent (OPEC (2010), (2015)). The thinking, especially as advanceb by Saudi Arabia, OPEC major swing producer was that attempt at production cut and restricting will have the potential to give non-OPEC producers the chance to capture OPEC share of the market and might not result in significant appreciation of price as envisaged.

There is a well-established literature on the co-movement between oil and US Dollar FOREX rates in both oil-exporting and oil-importing countries. Authors have applied different statistical methodologies to prove the year-long relationship that exists between the two time series, each time there is global economic and financial structural changes. The statistical methods cut across cross-correlation, co-integration, vector autoregressive (VAR), error correction mechanism (ECM) (Amano and van Norden (1998); Sadorsky (2000); Akram (2004); Zhang and Wei (2010); Aloi et al. (2013); Zhang (2013); Roboredo et al. (2014)), copula and wavelet analysis (Benhmad (2012); Roboredo (2011); Roboredo (2012): Roboredo and Rivera-Castro (2014); Uddin et al. (2013); Bouoiyour et al. (2015)); and multivariate GARCH and volatility spillover modeling frameworks (Chen and Chen (2007); Narayan et al. (2008); Zhang et al. (2008); Wang et al. (2013)). Other econometric approaches have been considered and deployed by Obadi and Othmanova (2012), Hazarika (2015), Coudert and Mignon (2016), among others.

The oscillations in FOREX rate have different effects in oil-exporting countries when compared with oil-importing countries. A weak US dollar is known to increase the purchasing power parity (PPP) of oil-importing countries except the United States of America, thus local currency of the oil-exporting countries appreciates. With weak US dollar, oil-importing countries feel the crunch since they need more US dollar to bargain for oil. In that case, there seems to be a positive relationship between oil price and FOREX rates in such countries (Roboredo (2011); Roboredo (2012); Turham et al. (2016); Roboredo et al. (2014)). Roboredo (2011); Roboredo (2012) and Roboredo and Rivera-Castro (2014) examined the relationship between oil and US FOREX rates using correlation, copula and de-trended cross-correlation analysis of different exchange rates across developed countries and observed a low negative dependence between the asset series. It is also important to note that there was a clear divergence at the onset

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[3] The new OPEC Reference Basket of Crudes (ORB) is made up of the following: Saharan Blend (Algeria), Girassol (Angola), Oriente (Ecuador), Iran Heavy (Islamic Republic of Iran), Basra Light (Iraq), Kuwait Export (Kuwait), Es Sider (Libya), Bonny Light (Nigeria), Qatar Marine (Qatar), Arab Light (Saudi Arabia), Murban (UAE) and Merey (Venezuela).

of the global financial crisis for all the time scales considered in the studies.

Chen *et al.* (2016) investigated the impacts of oil price shocks on US dollar exchange rates and found oil to explain 10 to 20 percent of long-term variations in FOREX rates by either demand and supply shocks, and they further confirmed that the variations were greater after the 2008 global financial crisis. Coudert and Mignon (2016) in their work on empirical relationship between the real price of oil and the U.S dollar real effective exchange rate over the time series period between 1974 and 2015, employed the estimated nonlinear smooth transition autoregressive model and observed a negative link between oil and exchange rates. They noted that changes in the real oil price and US dollar are linked by a negative relationship going from the US dollar exchange rate to the real oil price. Moreover, it was also observed that the relationship was positive for sample periods in the mid-2000s.

Apart from price dynamics between oil and FOREX rates, it is of much interest to look at the transmission of returns as well as volatility across the two markets. While our study is with specific reference to oil-exporting countries, in particular OPEC member countries, however, it is important to note that this work is the first empirical study along this line of thought. Ding and Vo (2012) applied both stochastic volatility and multivariate GARCH models in analyzing oil and FOREX volatility interactions under structural breaks and found bi-directional spillover effects during the 2007/2008 global financial crisis. Salisu and Mobolaji (2013) found support for evidence of bi-directional returns and volatility spillovers between oil price and US dollar-Nigeria Naira exchange rate, and the results of their study called for effective hedging strategy between oil price and FOREX rates in Nigeria. In the midst of scarce literature on oil-FOREX returns and volatility spillovers among oil-exporting and oil-importing countries, we therefore consider the framework proposed in Salisu and Mobolaji (2013) in studying the transmission of returns and volatility, and building effective oil-FOREX hedging strategy among OPEC member countries of importance for this study. Herein lies the significance of this present study to knowledge and literature on the dynamics relationship that exists between oil price and FOREX and how volatility in oil price is transmitted through to the FOREX market especially in OPEC member states.

3. Methodology

3.1. The Multivariate Volatility modeling framework

A prominent MGARCH model of much practical application is the VARMA-GARCH model of Ling and McAleer (2003) and its asymmetric version used in McAleer *et al.* (2009). The VARMA-GARCH model is preferred to other earlier versions of MGARCH model since it allows one to simultaneously investigate the interdependency of the conditional returns, conditional volatility and conditional correlations in market prices of assets. Secondly, this model presents lesser computational burdens.

A bivariate VARMA-GARCH modeling framework employs two endogenous variables, say, for the oil price returns, $R_{oil,t}$ and $R_{e,t}$ for the FOREX returns as presented as equation (1). For both returns at first lag, $R_{oil,t-1}$ and $R_{e,t-1}$, each at time $t-1$ comes into the

estimation system to give first order auto-regression ϕ_{oil} and ϕ_e with current returns $R_{oil,t}$ and $R_{e,t}$ for both oil price and FOREX returns, respectively. The $\phi_{oil,e}$ and $\phi_{e,oil}$ measure the cross-correlation from FOREX (Oil) to Oil (FOREX), respectively. Thus, the parameter $\phi_{oil,e}$ measures the impact of FOREX market returns on the returns of oil market, and similarly, $\phi_{e,oil}$ measures the impact of oil market returns on the FOREX market returns.

The innovations process for the mean equations for oil price and FOREX returns are given as $\varepsilon_{oil,t}$ and $\varepsilon_{e,t}$, respectively, and these are independently and identically distributed. Thus, equation (2) conditioned the innovations on the conditional variances series, $\sigma_{oil,t}^2$ and $\sigma_{e,t}^2$, while H_t is a matrix of the conditional variances with diagonal element matrix $\mathbf{D}_t$ in equation (3). The $\mathbf{D}_t$ is the matrix of the conditional covariances, H_0 is the unconditional variance computed as $H_0 = \omega/(1 - \alpha - \beta)$, where ω, α and β are the corresponding univariate GARCH model. The standardized innovations $z_{oil,t} = \varepsilon_{oil,t}/\sigma_{oil,t}$ and $z_{e,t} = \varepsilon_{e,t}/\sigma_{e,t}$ assumed Gaussian distribution in this case for oil price volatility model innovations, and similarly for FOREX innovations.

$$\begin{pmatrix} R_{oil,t} \\ R_{e,t} \end{pmatrix} = \begin{pmatrix} \phi_{oil} & \phi_{oil,e} \\ \phi_{e,oil} & \phi_e \end{pmatrix} \begin{pmatrix} R_{oil,t-1} \\ R_{e,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{oil,t} \\ \varepsilon_{e,t} \end{pmatrix} \tag{1}$$

$$\varepsilon_t | I_{t-1} = \begin{pmatrix} \varepsilon_{oil,t} \\ \varepsilon_{e,t} \end{pmatrix} \sim N(0, \mathbf{H}_t) = N(0, \mathbf{D}_t R \mathbf{D}_t) \tag{2}$$

$$R = \mathbf{D}_t^{-1} \mathbf{H}_t \mathbf{D}_t^{-1} = \left\{ diag \begin{pmatrix} \sigma_{oil,t}^2 & 0 \\ 0 & \sigma_{e,t}^2 \end{pmatrix} \right\}^{-1} H_0 \left\{ diag \begin{pmatrix} \sigma_{oil,t}^2 & 0 \\ 0 & \sigma_{e,t}^2 \end{pmatrix} \right\}^{-1} \tag{3}$$

$$\begin{pmatrix} \sigma_{oil,t}^2 \\ \sigma_{e,t}^2 \end{pmatrix} = \begin{pmatrix} \omega_{oil} \\ \omega_e \end{pmatrix} + \begin{pmatrix} \alpha_{oil} & \alpha_{oil,e} \\ \alpha_{e,oil} & \alpha_e \end{pmatrix} \begin{pmatrix} \varepsilon_{oil,t-1}^2 \\ \varepsilon_{e,t-1}^2 \end{pmatrix} + \begin{pmatrix} \beta_{oil} & \beta_{oil,e} \\ \beta_{e,oil} & \beta_e \end{pmatrix} \begin{pmatrix} \sigma_{oil,t-1}^2 \\ \sigma_{e,t-1}^2 \end{pmatrix} \tag{4}$$

The conditional variance equation matrix is given in (4). The parameters ω_{oil} and ω_i are the non-negative constants in the model. The parameters α_{oil} and α_e measure the short run persistence or the ARCH effect of past shocks of oil and FOREX returns, respectively, at time $t-1$ on the present conditional variance series and this captures the impact of the direct effects of the transmitted shocks, $\varepsilon_{oil,t-1}^2$ and $\varepsilon_{e,t-1}^2$. Thus, the parameters β_{oil} and β_e measure the long run persistence or GARCH effect of past shocks of oil and FOREX returns, respectively, at time $t-1$ on the present conditional volatility series, that is capturing the direct impact of the effects of the transmitted conditional volatility series, $\sigma_{oil,t-1}^2$ and $\sigma_{e,t-1}^2$. The parameters $\alpha_{oil,e}$ and $\alpha_{e,oil}$ measure the cross value of the error terms $\varepsilon_{e,t-1}^2$ and $\varepsilon_{oil,t-1}^2$ on the current conditional variance series for oil and FOREX, respectively. That is, the parameters are shocks spillover coefficients, which measure the impact of volatility shocks between two different markets. Thus, $\alpha_{oil,e}$ measures the impact of FOREX market shocks on oil market, while $\alpha_{e,oil}$ measures the impact of oil market shocks on FOREX market shocks. Similarly, volatility spillovers between oil price and FOREX are measured by $\beta_{oil,e}$ and $\beta_{e,oil}$, where $\beta_{oil,e}$ measures the impact of volatility spillover of FOREX market to oil market, and $\beta_{e,oil}$ measures the impact of volatility of oil market on FOREX market.

The constant correlation $R = \rho_{oil,e}$ simplified by the conditional covariance matrix $\mathbf{D}_t$ measures the constant correlation between the two market returns. The asymmetric version of our bivariate $VAR(1,1) - GARCH(1,1)$ model is specified by replacing the classical $GARCH(1,1)$ model of Bollerslev (1986) by any other asymmetric volatility versions. Due to the flexibility of Glosten,

Jaganathan and Runkle (GJR-GARCH) model, we considered it in this framework. Thus, we obtained VAR-Asymmetric GARCH ($VAR(1,1) - AGARCH(1,1)$) model specification given in (5),

$$\begin{pmatrix} \sigma^2_{oil,t} \\ \sigma^2_{e,t} \end{pmatrix} = \begin{pmatrix} \omega_{oil} \\ \omega_e \end{pmatrix} + \begin{pmatrix} \alpha_{oil} & \alpha_{oil,e} \\ \alpha_{e,oil} & \alpha_e \end{pmatrix} \begin{pmatrix} \varepsilon^2_{oil,t-1} \\ \varepsilon^2_{e,t-1} \end{pmatrix} + \begin{pmatrix} \beta_{oil} & \beta_{oil,e} \\ \beta_{e,oil} & \beta_e \end{pmatrix} \begin{pmatrix} \sigma^2_{oil,t-1} \\ \sigma^2_{e,t-1} \end{pmatrix} + \begin{pmatrix} \gamma_{oil} I\left(\varepsilon_{oil,t}\right) \varepsilon^2_{oil,t-1} \\ \gamma_e I\left(\varepsilon_{e,t}\right) \varepsilon^2_{e,t-1} \end{pmatrix} \quad (5)$$

The only difference between the model in (4) and (5) is the inclusion of the leverage parameters, γ_{oil} and γ_e which measure the asymmetric impacts of volatility at oil and FOREX markets, respectively, using the indicator variables $I\left(\varepsilon_{oil,t}\right)$ and $I\left(\varepsilon_{e,t}\right)$ conditioned such that $I\left(\varepsilon_{oil,t}\right) = 1$ for $\varepsilon_{oil,t} \leq 0$ and 0 otherwise (same as $I\left(\varepsilon_{e,t}\right) = 1$ when $\varepsilon_{e,t} \leq 0$). Thus, the off-diagonal elements of the covariance series are set to zero, and the diagonal elements are $\sigma^2_{oil,t}$ and $\sigma^2_{e,t}$.

For a given pair of returns series, the 17 parameters are to be estimated for the case of symmetric specification, (19 for asymmetric specification). These parameters are labeled as,

$$\Theta = \phi_{0oil}, \phi_{0e}, \phi_{oil}, \phi_{oil,e}, \phi_{e,oil}, \phi_e, \omega_{oil}, \omega_e, \alpha_{oil}, \alpha_{oil,e}, \alpha_{e,oil}, \alpha_e, \beta_{oil}, \beta_{oil,e}, \beta_{e,oil}, \beta_e, \gamma_{oil}, \gamma_e, \rho_{oil,e} \quad (6)$$

The estimation of these parameters is achieved by numerical maximization of the joint likelihood function under the distributional assumption of this model. For a sample of N observations, the log-likelihood function to be maximized with respect to the parameter set Θ is,

$$L\left(\Theta\right) = \sum_{t=1}^{N} l_t\left(\Theta\right) = -N \ln 2\pi - \frac{1}{2} \sum_{t=1}^{N} \ln \left|\mathbf{H}_t\left(\Theta\right)\right| - \frac{1}{2} \sum_{t=1}^{N} \varepsilon'_t\left(\Theta\right) \mathbf{H}_t^{-1} \varepsilon'_t\left(\Theta\right) \quad (7)$$

where N is the size of the returns series, the innovation matrix $\varepsilon'_t = \begin{pmatrix} \varepsilon_{oil,t} & \varepsilon_{e,t} \end{pmatrix}$ obtained from (2), and Θ is the parameters set of the model. The likelihood function is therefore optimized using Broyden Fletcher Goldfarb Shanno (BFGS) algorithm. This is implemented in RATS 9.1 econometric software distributed by Estima.

3.2. Pre-tests and Model Specification tests

It is necessary to carry out appropriate pre-tests on the log-returns series (differences of log-transformed series multiplied by 100) before proceeding for volatility investigation via modeling. Thus, exploratory data analysis (EDA) and graphical representation of log-returns or actual asset prices may be necessary. The analysis of serial correlations on returns and squared returns at appropriate lag is necessary before testing for the ARCH effect, conducted based on Lagrange Multiplier (LM) statistic as detail in Engle (1982). The ARCH test regresses the squared residual series on lag of the squared residuals and the test statistic is distributed as χ^2 with degree of freedom under the null hypothesis of no ARCH effects. The appropriate order for the ARCH model is then determined by the maximum log-likelihood and information criteria estimates. The F-statistic equivalent of the LM test is often implemented in most software packages. In order to distinguish between symmetric and asymmetric model, Engle and Ng (1993) proposed asymmetric test which applies to both univariate and multivariate frameworks. This is otherwise known as sign and bias test. The test uses a dummy variable S_t^- which assumes value when $\hat{\varepsilon}_t < 0$, and a dummy variable S_t^+ which assumes value 0 when $\hat{\varepsilon}_t > 0$, thus $S_t^+ + S_t^- = 1$. This test examines whether the innovations, $\hat{\varepsilon}_t^2 < 0$ is predicted by S_t^-, $S_t^- \varepsilon_t^-$ and/or $S_t^+ \varepsilon_t^+$ which corresponds to testing the

significance of the parameters a_1, b_1 and c_1 in the regressions,

$$\varepsilon_t^2 = a_0 + a_1 S_{t-1}^- + u_t \qquad Sign\ bias\ test \tag{8}$$

$$\varepsilon_t^2 = b_0 + b_1 S_{t-1}^- \varepsilon_{t-1} + u_t \qquad Negative\ size\ bias\ test \tag{9}$$

$$\varepsilon_t^2 = c_0 + c_1 S_{t-1}^+ \varepsilon_{t-1} + u_t \qquad Positive\ size\ bias\ test \tag{10}$$

through t-test statistics, for testing sign bias, negative size bias and positive size bias tests, respectively. These three tests can also be combined in one regression model,

$$\varepsilon_t^2 = d_0 + d_1 S_{t-1}^- + d_2 S_{t-1}^- \varepsilon_{t-1} + d_3 S_{t-1}^+ \varepsilon_{t-1} + u_t \tag{11}$$

for testing a joint test corresponding to $H_0 : d_1 = d_2 = d_3$ which is χ^2 distributed with degree of freedom 3[4].

4. Empirical results and discussion

4.1. Data, Description and Pretests

The data considered in this paper are daily time series of exchanges rates (see Table 1) of nine OPEC member countries, and daily oil price at the OPEC market (http://www.opec.org)[5]. The OPEC member countries are: Algeria, Iran, Iraq, Kuwait, Nigeria, Qatar, Saudi Arabia, United Arab Emirates and Venezuela. The labels for the corresponding FOREX series are given in the third column of the table. Each time series span between 12 March 2010 and 4 October 2016. This period covers the time of full recovery from the global financial crisis, when oil price rises to \$100 and above per barrel at the market. This period is also termed the birth of the shale revolution, when technological innovation makes the extraction of crude-oil from Shale fields possible and economically viable especially in the United States. The phenomenal rise of production from Shale field led to oversupply of crude oil into the international market as a result of the competitions at the WTI, European Brent and OPEC markets (see Gil-Alana *et al.* (2016)).

Figure 1 presents bivariate plots of daily oil price and FOREX rates for the period under investigation. The figure clearly shows varying prices of oil over time, and the corresponding changes in FOREX rates. It is very clear to observe the two series responding to each other. In most of the plots, as oil price increased, FOREX rates decreased and this is very conspicuous after 2014 when the price of oil start its downward spiral. The corresponding divergence in the prices of the two assets at the time frame is clearly observed, except in the case of USD_QAR and USD_AED FOREX rates. Thus, as the price of crude oil was increasing at the OPEC market, FOREX rates in oil-enriched exporting countries was reducing implying appreciation of local currencies against the US Dollar.

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[4] Harris and Sollis (2003), *pg 236* provide a more detailed expositions on the sign and size bias tests.

[5] The countries have been selected from the 12 current member countries of OPEC based on availability of consistent exchange rates data within the time series span.
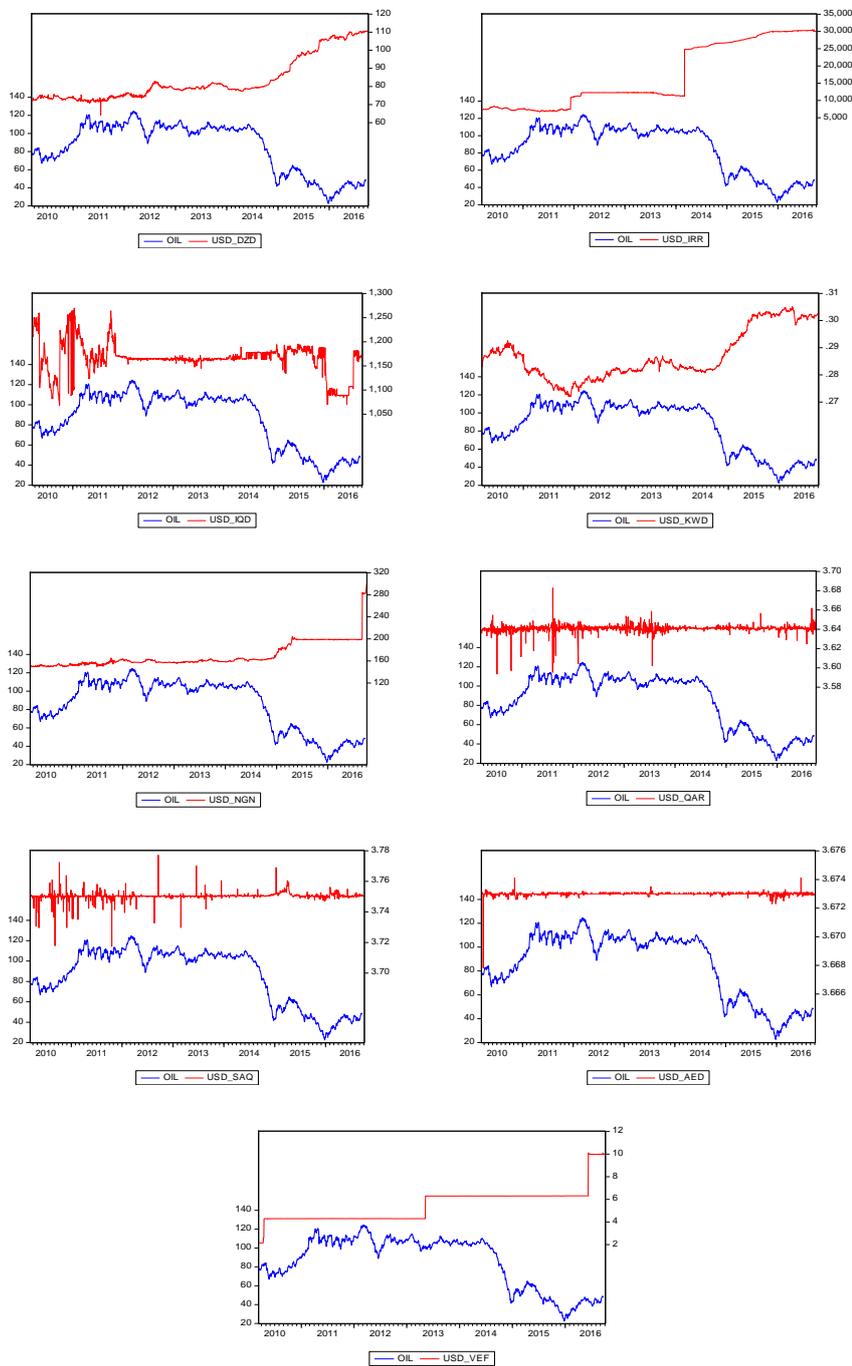
Fig. 1. Bivariate Time plots of Oil price and FOREX series

Table 1. Data Description and Summary

Country	Currency	Exchange rate
Algeria	Algerian Dinar	USD_DZD
Iran	Iranian Rial	USD_IRR
Iraq	Iraqi Dinar	USD_IQD
Kuwait	Kuwaiti Dinar	USD_KWD
Nigeria	Nigerian Naira	USD_NGN
Qatar	Qatari Riyal	USD_QAR
Saudi Arabia	Saudi Arabian Riyal	USD_SAQ
UAE	Emirati Dirham	USD_AED
Venezuela	Venezuelan Bolivar	USD_VEF

To clearly investigate the time series for volatility, we observe the continuously compounded daily returns using the logarithmic filter:

$$r_{i,t} = 100 \times (\log P_{i,t} - \log P_{i,t-1}) \tag{12}$$

where $r_{i,t}$ and $P_{i,t}$ are the daily log-returns obtained in percentage, and the closing asset price, i (oil or FOREX) at time t, respectively.

The descriptive statistics for the daily log-returns $r_{i,t}$ as well as necessary pre-tests for heteroscedasticity in the returns are reported in Table 2. The summary results suggest that highest positive return is observed in USD_VEF (3.8E-02%) followed by USD_IRR (3.5E-02%), that is Venezuelan Bolivar and Iranian Rial US dollar exchange rates, respectively. Negative FOREX returns are observed in USD_IQD (-1.1E-03%) and USD_AED (-1.4E-06%), for both Iraqi Dinar and UAE Emirati Dirham US dollar exchange rates. Thus, it implies the general increase in FOREX rates in seven of the nine OPEC member countries considered in this paper. Looking at the oil price, the average log-return is -2.8E-02% which implies the general decrease in the oil price during the sampled period. Highest risk in FOREX returns, as approximated by a standard deviation of 0.93% is observed in USD_IRR FOREX returns, and next to this value is 0.84% for USD_VEF FOREX returns. Oil price returns also present very high risk approximated by 1.58% standard deviation. Both positive and negative skewness values were observed. Negative values are observed for USD_DZD, USD_KWD, USD_SAQ and USD_AED FOREX returns, while positive skewness are observed for the remaining five log-return series. Thus, there is a higher probability for investors to experience daily positive returns in FOREX trading in these countries. Furthermore, kurtosis values were extremely high above the range for normal distribution. When subjected to ADF unit root tests, the hypothesis of nonstationarity of returns were quite rejected in all the cases meaning that all the return series are pure stationary series. We carried tests of correlation of current return on past log-returns and squared returns, up to lag 10 and observed significant dependencies in most of the cases. Finally, heteroscedasticity test by means of ARCH Lagrange Multiplier (LM) test was unable to reject the null of no heteroscedasticity only in the case of USD_IRR log-returns.

Table 2. Descriptive Statistics and Pre-tests on Log-Returns

Returns	Mean	Std. Dev.	Skewness	Kurtosis	ADF	$LB(10)$	$LB^2(10)$	ARCH (5)
USD_DZD	1.00E-02	0.273	-0.036	183.51	**-42.93**	**298.87**	**440.08**	**66.8**
USD_IRR	3.50E-02	0.928	32.289	1139.26	**-42.05**	0.642	0.012	0.055
USD_IQD	-1.10E-03	0.493	0.383	91.95	**-16.15**	**170.44**	**755.69**	**25.61**
USD_KWD	1.40E-03	0.065	-0.097	7.05	**-52.35**	**100.98**	**383.11**	**15.52**
USD_NGN	1.80E-02	0.425	20.283	666.82	**-43.35**	7.376	0.0988	**46.18**
USD_QAR	3.90E-06	0.064	2.084	64.86	**-22.44**	**436.67**	**396.39**	**160.3**
USD_SAQ	4.50E-06	0.039	-0.062	38.17	**-18.53**	**281.53**	**286.81**	**123.4**
USD_AED	-1.40E-06	0.002	-0.008	442.96	**-23.54**	**410.69**	**440.71**	**173.86**
USD_VEF	3.80E-02	0.839	23.12	549.95	**-21.06**	**36.59**	7.58	**6.17**
Oil Price	-2.80E-02	1.582	0.251	7.468	**-32.74**	**100.2**	**756.56**	**49.48**

Note: ADF test is Augmented Dickey Fuller unit root test on the log-returns; $LB(10)$ and $LB^2(10)$ are computed Q-statistics for auto-correlations of log-returns and squared-log returns at 5% level, and ARCH(5) tests the significance of heteroscedasticity in the returns series. In bold, significance of the tests at 5% level.

4.2. Return and volatility dependencies

It is quite necessary to carry out both constant correlation and asymmetry pre-tests before specifying MGARCH models. Actually, test of constant conditional correlation (CCC) against dynamic conditional correlation (DCC) by Engle and Sheppard (2001) was carried out on each pair of oil and FOREX return series, i and we found the hypothesis of constant correlation to be accepted in all the cases[6]. The results of asymmetry on log-returns, based on Engle and Ng (1993) test are presented in Table 3. Here, based on four levels of the test, the null hypothesis of no asymmetry in the log-returns is accepted in all the cases except for USD_AED log-return series. Thus, we specify 10 $VARMA(1,1) - GARCH(1,1)$ models and one $VARMA(1,1) - AGARCH(1,1)$ model. We present the results, here in Table 4.

Table 3. Asymmetry Test on Log-returns

FOREX	USD_DZD	USD_IRR	USD_IQD	USD_KWD	USD_NGN
Sign bias test	0.8974	0.4896	1.799	0.8847	0.0194
Negative size bias test	0.4969	0.8791	0.1231	0.4658	0.4002
Positive size bias test	0.3604	0.0054	0.5164	0.4674	1.2992
Joint bias test	0.855	1.8689	3.3864	0.8422	2.0733

FOREX	USD_QAR	USD_SAQ	USD_AED	USD_VEF	Oil Price
Sign bias test	1.3993	0.0255	13.424	1.5651	0.8188
Negative size bias test	0.7894	0.7938	33.816	1.1327	0.283
Positive size bias test	0.047	0.0748	0.1275	0.0496	0.3117
Joint bias test	2.2665	0.6778	1148	2.5807	1.4636

Note: In bold, significance of the test at 5 percent level.

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[6] The results obtained are not presented here in this paper but are available on request.

Table 4. VARMA-GARCH modelling results

Parameters	USD_DZD	USD_IRR	USD_IQD	USD_KWD	USD_NGN	USD_QAR	USD_SAQ	USD_AED	USD_VEF
$\hat{\phi}_{oil}$	-0.00424	-0.0258	-0.0423	-0.0432	-0.0324	-0.0421	-0.0575	-2.30E-03	-0.0244
$\hat{\phi}_{e}$	-0.0384	0.0248	0.0369	-0.2763	-0.0164	-0.8625	0.3477	-3.20E-03	0.0151
$\hat{\phi}_{oil,e}$	-0.092	-0.0437	-0.3778	-0.1858	-0.2717	-0.4483	-0.3518	-0.3538	-0.0946
$\hat{\phi}_{e,oil}$	-0.0006	-0.0656	-0.0101	-0.0017	-0.0026	-2.30E-06	-0.0012	6.40E-05	-0.8105
$\hat{\omega}_{oil}$	0.0046	0.003	1.90E-03	0.0071	0.0065	0.0054	0.0061	0.0483	-0.0002
$\hat{\omega}_{e}$	-3.20E-05	0.8158	-2.20E-04	1.20E-05	0.0006	0.0001	5.80E-05	4.60E-06	-0.0241
$\hat{\alpha}_{oil}$	0.0612	0.0669	0.0226	0.066	0.0677	0.0654	0.0569	0.2251	0.0105
$\hat{\alpha}_{e}$	0.2554	0.2675	0.1539	0.0492	0.892	0.8914	0.1334	0.2205	27.194
$\hat{\alpha}_{oil,e}$	0.0377	0.0166	-0.0308	-0.1189	0.092	-0.2562	-0.636	1.10E-03	0.0639
$\hat{\alpha}_{e,oil}$	-0.0089	-0.6198	0.0227	-0.0011	-0.0284	0.0009	-0.0038	-2.20E-04	1.0479
$\hat{\beta}_{oil}$	0.9259	0.9298	0.9727	0.9322	0.9182	0.9288	0.9397	0.7411	0.9849
$\hat{\beta}_{e}$	0.6933	-0.0038	0.8546	0.9337	0.5046	0.3395	0.8509	2.20E-03	0.0064
$\hat{\beta}_{oil,e}$	-1.7099	-0.1761	-0.1634	-2060.5	-0.9173	-25.063	2.6043	4.00E-03	-0.083
$\hat{\beta}_{e,oil}$	-0.08548	2.8077	-0.3753	39.6645	-0.2418	-3.7979	0.0029	0.0177	-5.4097
$\hat{\gamma}_{oil}$	xxx	xxx	xxx	xxx	xxx	xxx	xxx	0.0519	xxx
$\hat{\gamma}_{e}$	xxx	xxx	xxx	xxx	xxx	xxx	xxx	-0.0743	xxx
$\hat{\rho}_{oil,e}$	-0.0272	-0.0243	-0.0377	-0.0368	-0.0424	-0.0017	-0.0284	-0.0392	-0.078
LogLik.	-1443.7	-4436.4	-2032.9	393	-1638.7	1179.0.	1617.8	6390.4	-3477.4
AIC	1.655	5.05	2.323	-0.429	1.876	-1.32	-1.818	-7.23	3.962
SIC	1.701	5.096	2.37	-0.382	1.923	-1.274	-1.772	-7.177	4.008

Note: The bivariate VARMA(1,1)-GARCH(1,1) model is estimated for each oil/FOREX nexus from 12 March 2010 to 4 October 2016. The optimal lag order for the VARMA model is determined using Akaike Information Criterion (AIC) and Swartz Bayesian Information Criterion (SBIC). In bold, significant VARMA-GARCH parameters at 5 level.

Regarding the mean equation for the returns, we observe significant AR parameter estimates ($\hat{\phi}$) for both oil price and FOREX returns in the case of USD_IRR, USD_NGN and USD_VEF models, these correspond to FOREX returns with high mean returns. This means that future returns in these markets can be predicted based on the immediate past observations in the markets. Looking at the coefficient of cross-market returns, that is, $\hat{\phi}_{oil,e}$ and $\hat{\phi}_{e,oil}$, we observe significant return spillover effect in both cases, while the spillover from FOREX markets to oil market is significant throughout all the 9 OPEC countries considered in the study. We do not observe significant oil to FOREX markets spillovers in the case of oil-USD_DZD, oil-USD_KWD and oil-USD_QAR nexi. Thus, the spillovers are negative bi-directional in the case of oil-USD_IRR, oil-USD_IQD, oil-USD_NGN, oil-USD_SAQ and oil-USD_VEF nexi, and positive and negative bidirectional in the case of oil-USD_AED nexus.

Next, we present the results of the conditional variance equations in the second panel of Table 4. We observe significant ARCH and GARCH effect coefficients, ($\hat{\alpha}_{oil}$, $\hat{\alpha}_e$, $\hat{\beta}_{oil}$, $\hat{\beta}_e$) throughout in all the market nexi. This suggests the adequacy of $MGARCH(1,1)$ model in predicting the conditional volatility of the return series. Consider the volatility spillover effect between oil and FOREX market returns, positive and negative shocks spillovers are observed across the markets. In most cases, bi-directional shocks spillovers are observed across the markets, except in oil-USD_KWD, oil-USD_QAR and oil-USD_AED nexi, where shocks spillover from FOREX to oil market is not significant. Similarly, volatility spillovers were both positive and negative bi-directional except in oil-USD_AED nexus, where there was a spillover from oil to FOREX market. Oil-USD_KWD nexus presented the highest FOREX-oil spillover coefficient of -2060.5, and this nexus also presented the highest oil-FOREX spillover coefficient of 39.7. Next to this nexus is oil-USD_QAR nexus with -25.1 and -3.8 FOREX-oil and oil-FOREX volatility spillover coefficients, respectively. For oil-USD_AED nexus, the asymmetric parameters are actually significant, confirming the rejection of no asymmetry by Engle-Ng asymmetry test. The fourth panel of this table presents the estimates for constant conditional correlations between oil and FOREX markets. These estimates are negative in all the cases implying the inverse relationship between oil price and FOREX rates/returns in oil-producing countries, as noted in the literature. In fact, the estimates show that the strongest negative correlation -0.078, was observed for oil-USD_VEF nexus. Next to this are oil-USD_NGN and oil-USD_AED nexi with correlation estimates -0.0424 and -0.0392, respectively. The fact that we obtain varying negative correlations using oil market returns in volatility relationship between FOREX market returns indicate the potential loss incurred by decision makers or portfolio managers investing in both asset prices in these economies. Now, it is advisable to know how to balance both oil and FOREX assets in oil-FOREX portfolio as a result of inverse relationship between the market values of oil and FOREX, and as well as between their corresponding conditional volatility series.

5. FOREX Management in the Presence of Oil risk

The applicability of VARMA-GARCH modeling framework goes beyond looking at the estimates of volatility, co-volatility and correlations. These estimates are further used to build an optimal portfolio allocation for risk management decisions and portfolio allocation as decision tools for policy makers, portfolio investors and risk managers in these economies. Two measures of financial decision are obtained from our bivariate $VARMA(1,1)-GARCH(1,1)$ model. These are the portfolio weight and hedge ratio measures. As applied in Kroner and Sultan (1993) and Arouri *et al.* (2011a), an attempt was made to minimize the risk without reducing the expected market returns by using the estimates of the conditional variances and co-variances to obtain the portfolio weight measure. This

is given as a measure of portfolio weight of holding an oil/FOREX portfolio which is given as,

$$w_{oil,e,t} = \frac{\sigma_{e,t}^2 - \sigma_{oil,e,t}^2}{\sigma_{oil,t}^2 - 2\sigma_{oil,e,t}^2 + \sigma_{e,t}^2} \qquad (13)$$

$$w_{oil,e,t} = \begin{cases} 0 & if\, w_{oil,e,t} < 0 \\ w_{oil,e,t} & if\, 0 \le w_{oil,e,t} \le 1 \\ 1 & if\, w_{oil,e,t} > 1 \end{cases} \qquad (14)$$

where $w_{oil,e,t}$ is the weight of oil in 1 US dollar crude oil-FOREX market portfolio at time t, $\sigma_{oil,e,t}^2$ is the conditional covariance series between oil price market returns and FOREX market returns, $\sigma_{e,t}^2$ is the conditional variance series for the FOREX market returns and $\sigma_{oil,t}^2$ is the conditional variance series for oil market returns. The optimal weight of FOREX in the oil-FOREX market portfolio is therefore evaluated as $1-w_{oil,e,t}$. The summary statistics obtained for the portfolio weight computed for the $VARMA(1,1) - GARCH(1,1)$ models are presented in Table 5. The results show that the average highest portfolio weight for the oil/FOREX portfolio is 0.7670 for oil-USD_VEF nexus. Next to this are oil-USD_IRR, oil-USD_NGN and oil-USD_IQD with 0.5257, 0.2919 and 0.2544, respectively. These indicate that for a portfolio of \$1, about 77 cents, 53 cents, 29 cents and 25 cents should be invested in oil markets by Venezuelan, Iranian, Nigerian and Iraqi decision makers or portfolio managers, while, correspondingly, 23 cents, 47 cents, 71 cents and 75 cents should be invested in FOREX markets in the four OPEC economies. In oil-USD_AED, oil-USD_SAQ and oil-USD_QAR portfolios, corresponding to UAE, Saudi Arabia and Qatar, respectively, very small proportion of oil as compared to FOREX is expected to be invested in every oil-USD_FOREX portfolio.

Table 5. Estimates of Optimal Portfolio Weights and Hedge Ratio

Parameters	USD_DZD	USD_IRR	USD_IQD	USD_KWD	USD_NGN
$w_{oil,e,t}$	0.0815	0.5257	0.2544	0.0046	0.2919
$1 - w_{oil,e,t}$	0.9185	0.4743	0.7456	0.9954	0.7081
$\beta_{oil,e,t}$	-0.0677	-0.019	-0.041	-0.0003	-0.0282

Parameters	USD_QAR	USD_SAQ	USD_AED	USD_VEF	
$w_{oil,e,t}$	0.0058	0.0028	0.0023	0.767	
$1 - w_{oil,e,t}$	0.9942	0.9972	0.9977	0.233	
$\beta_{oil,e,t}$	-0.0139	-0.5036	-0.714	-0.0017	

Regarding the risk-minimizing hedge ratios between oil and FOREX markets, Kroner and Sultan (1993) proposed using the hedge ratio measure $\beta_{oil,e,t}$ adapted as,

$$\beta_{oil,e,t} = \frac{\sigma_{oil,e,t}^2}{\sigma_{e,t}^2} \qquad (15)$$

with low ratio of $\beta_{oil,i,t}$ suggesting that oil asset can be hedged at the market by taking a short position in FOREX markets during turbulent periods. To minimize the risk incurred in \$1 long of the first asset, the investor is expected to short \$$\beta$ of the second asset. The results obtained for $\beta_{oil,i,t}$ are presented in Table 5. These values are generally low, suggesting the effectiveness of herding strategy. They are negative as a result of negative co-variances $\sigma_{oil,e,t}^2$ indicating the inverse relationship between oil price and FOREX returns, thus the absolute values of these ratios

have been obtained. Specifically, a \$1 long position in oil can be hedged for about 7 cents with a short position in FOREX in oil/USD_DZD portfolio whereas a \$1 long position in oil can be hedged for 71 cents with a short position in FOREX in oil/USD_AED portfolio. In oil/USD_NGN portfolio, a \$1 long position in oil can be hedged for about 3 cents with a short position in FOREX. Thus, highest hedge ratio is found in oil/USD_AED portfolio while lowest hedge ratio is found for oil/USD_KWD portfolio.

6. Conclusion

We have considered both return and volatility spillovers between oil price and exchange rates in OPEC member countries using daily data from March 2010 to October 2016. During the period, oil price has fully recovered from the global financial shocks which ended in 2009, and oil market is facing serious problem of oversupply at the three markets since none of the marketers was ready to cut supply.

For oil-exporting OPEC countries, fall in oil price leads to depreciation of local currency as against the US dollar. From the preliminary results obtained in this paper, generally, we found inverse relationship between oil price and FOREX in the OPEC member countries, confirming the assertions of previous authors on the co-movements between oil price and FOREX at price and returns levels (Roboredo *et al.* (2014); Turham *et al.* (2016)). The transmission of returns between the two asset prices are bi-directional, while volatility spillover is bi-directional, except in the case of UAE where the spillover only runs from oil market to FOREX market. The results also predict negative conditional correlation between the two markets confirming the oil price-FOREX relationship in oil-exporting countries. Portfolio management and hedging strategies indicates wide ratios of investment in oil-FOREX portfolio by decision makers and interested investors in trading in OPEC member countries, and inclusion of more oil in the investment implies reduction of FOREX investment in the portfolio. Due to the possibility of return spillover from FOREX to oil market among oil-exporting countries, there is the need to strengthen the economy against local or global macroeconomic shocks such as stocks and inflations (see Fratzscher *et al.* (2014)). The findings will be of importance to decision makers in the control of oil inflationary shocks and exchange rates since this will help in dollar-pegging policies of oil-exporting countries.

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