Oil Volatility spillover into Equity-Sector Stock Return: Evidence from Major Oil Producing Countries

1.0. Introduction

The study on crude oil prices and stock market index volatility dynamics has been on the front and center of the energy financial literature over the recent periods. In fact, the energy economics discipline is largely focused on addressing the influence of oil price fluctuations on stock market returns (Cuando and de Garcia, 2014; Kang et al., 2015; Bouri et al., 2016). Following the recent developments of increased interdependence between financial markets and the financialization of commodity markets which continues to provide new hedging and diversification opportunities for investors, studies on oil-stock volatility dynamics is very expedient and crucial for both investment and policy decisions (see, Domanski and Heath, 2007; Tang and Xiong, 2012; Basher and Sadorsky, 2016). Building on the premise of importance of oil and the corporate cash flows models which state that stock price is dependent on expected discounted earnings, strands of recent studies have sort to underscore the volatility linkage between oil prices and stock market returns (see, Sadorsky, 1999; Park and Ratti, 2008; Apergis and Miller, 2009; Narayan and Narayan, 2010; Arouri et al., 2011). The general consensus from most studies on the oil-stock nexus is that oil price shocks have negative impact on stock markets.

Having established that there is a growing literature that considers the empirical relationship between oil price shocks and stock market developments, we should point out that we know little about the effects of these shocks on different equity sector indices, especially from the perspective of emerging markets (see, Degiannakis et al., 2013; Bouri et al., 2016). In the production process, crude oil serves as intermediate input and as a results the effects of oil price shocks and linkage will not be equal across all equity-sectors. The magnitude and linkage of oil shocks/volatilities with sectors will depend on how much each equity-sector receives from oil as inputs. For example, it is natural logic that industrial or manufacturing sectors would be the most affected given an adverse international oil market condition compared to service or telecommunication sectors. Given the diverse oil intensity in the various equity-sectors, a cross-sector heterogeneity studies on how oil affects equity-sector returns can afford portfolio managers to better diversify their portfolios across different equity sectors within a particular market or region to ensure maximum return and minimum risk. Such analysis may also provide
regulators a more accurate insight to formulate appropriate framework at the sector level. Another advantage for the sector studies is that it helps to unmask some specific but important effect from oil price shocks inherent in individual sectors which may go undetected using the aggregate stock return index\(^1\). The few empirical work on the line of equity-sector-oil relationship have focused mainly on developed markets particularly in Europe and the US (Malik and Ewing, 2009; Arouri and Nguyen, 2010; Arouri et al., 2012; Qinbin and Mohammad, 2012; Broadstock and Filis, 2014).

This study focuses on major oil producing countries to add to the dearth of literature. To this end, we propose to investigate the dependence relationship between oil prices and sector stock indices within OPEC markets and few major non-OPEC countries such as Russia and United States. More specifically, we examine the dynamic conditional correlation between five equity sector (financials, industrials, telecommunication, Oil and Gas, and consumer goods sectors) and crude oil prices. Our study objective is in twofold: First, to investigate the time-varying dynamics of the correlation pattern between oil prices and sector-stock indices and how each sector’s correlations respond to fluctuations or shocks in oil prices. Second, to explore how the origins of oil price shocks (supply-side or demand-side shocks) affect the correlation dynamics of the different sectors. Do some sectors display heterogeneous dynamic correlation pattern with different oil price shocks origins or do all sectors exhibit same correlation dynamics to the different oil price shock origins? In the oil-stock literature, it is argued that oil price shocks pose adverse effect to stock price indices. This evidence, however, is generally from national or aggregate markets studies only and the same conclusion might not hold for sectoral studies. Given that markets are made up of sectors with distinctive structures and energy requirements, we expect a heterogeneous rather than herding behavior in the dynamic correlation of sectors during periods of oil price shocks. The sector-level analysis of the correlation behavior between oil prices and equity sectors would therefore provide more comprehensive understanding of the oil-stock relationship.

Furthermore, the sector-level analysis of oil price shocks is essential as there may be industry specific response to oil price shocks or even the magnitude of response may differ from sector to sector. Policy makers, investors as well as sector’s participant need to be aware of these responses. Additionally, national or aggregate stock market indices of different countries do not tell the whole story, as each country’s industrial base in terms of energy intensity may be significantly different. Thus, studies which use aggregate indices tend to mask certain characteristics inherent to various sectors hence, such results should be treated with caution. Unlike previous work on sector level analysis of oil price shocks, we consider not only the dynamic nature of the correlation linkage but also we account for origins of the oil price shocks and how the various sectors respond (in terms of correlation) to the different oil price shocks origins. More specifically, we examine the oil price shocks in terms of aggregate demand

\(^1\) According to Arouri et al. (2012, p.2) "*the use of equity sector indices is, in our opinions, advantageous because market aggregation may mask the characteristics of various sectors*"
induced shocks, supply-side shocks and/or precautionary demand induced shocks. In the energy literature, studies have opine that different shocks in crude oil market have different effects on stock market, thus the origin or shock factors should be considered in oil-stock analysis (see, Hamilton, 2009; Kilian, 2008; Kilian and Park, 2009). In fact, according to Hamilton (2009), there are demand driven and supply induced oil price shocks. Kilian (2009) decoupled the demand-side oil price shocks, into aggregate demand oil price shock and precautionary demand (or oil specific demand) oil price shocks and he argues that aggregate stock returns may respond differently depending on the cause or origin of the oil price shocks.

In order to account for the various shock origins, we split our data sample into sub-samples and for the sub-sample analysis, we adapt the oil price shocks classification by Kilian (2009) who identify three main different causes or origin of oil price shocks namely, Supply shock, Aggregate demand shock and the Precautionary demand shock. Thus, our study is in twofold: First, we use the full-sample for the entire sample period and examine the behavior of each sector’s dynamic correlation to determine whether correlation has increase or decrease over the period. Second, we split the full-sample into sub-sample to account for the various oil price shocks origins within the sample period. The full-sample period covers 2000-2015 and within this span a number of oil price shocks origins can be identified. We adapt Degiannakis et al., (2013), Hamilton (2009) and Kilian (2009) for the origins of oil price shocks date classification. The following are the various shock origins and dates: 2000-2003(aggregate and precautionary demand oil price shock); 2004-2007(aggregate demand oil price shock); 2008-2011(aggregate demand oil price shocks) and 2012-2015(supply-side oil price shock). To examine the dynamic time-varying correlation between the sectors and oil-price indices we proposed the Dynamic Conditional Correlation (DCC)-GARCH frameworks for the modelling part. We also propose the ADCC model to account for any possibility of asymmetric evidence within the time-varying correlations given both joint negative or positive news. The study also proposes the news impact curve (NIC) plots to further examine the dynamic correlation between oil prices and sector stock indices.

To the best of our knowledge, this study will be the first to apply the DCC and ADCC-GARCH models to emerging sector-stock markets returns and crude oil prices studies. The study provides an empirical-based evidence on the dynamic nature of the volatility correlation between crude oil and sector returns which is important for financial market investors and policy makers in portfolio selection and diversification, optimal hedging strategy, energy risk management and market regulations. In addition, our study accounts for oil price shock origins and provide evidence on how each sector responds to the various oil price shock regimes. Finally, this paper complements a growing literature on the crude oil-stock nexus from the perspective of sectoral indices which makes it possible to counter biases inherent to the use of country-level aggregate indices that may mask the characteristics, not necessarily uniform, of several sectors. The rest of paper is organized as follows. Section 2 discusses the relevant literature on the relationship between crude oil price and equity-sector markets. We present the econometric method and
estimation techniques in section 3. Section 4 presents summary of the dataset and its preliminary stochastic properties. We discuss the obtained results in section 5. Section 6 draws the conclusion.

2.0. Relevant Literature

As indicated in our introduction, there is colossal and growing literature investigating volatility dynamics between equity stocks and various commodities including crude oil (e.g. Park and Ratti, 2008; Apergies and Miller 2009; Filis et al, 2011; Arouiri et al, 2012; Mollick and Assefa, 2013; Chang et al, 2013; Lin et al, 2014; Guesmi and Fattoum, 2014). Since equity-sector-oil relationship is the focused of this paper, we limit our discussion to short review of relevant papers that shed light directly on sector-stock and oil volatility interactions. Nandha and Faff (2008) are among the first major work to investigate whether oil moves equity prices among 35 Datastream® global industry indices from April 1993 to September 2005. Their findings suggest that positive oil price shocks have negative effects on all sectors except Mining and Oil&Gas industries. Malik and Ewing (2009) follow similar research line to examine volatility spillover between oil prices and five US equity sector indices (Financials, Consumer Services, Technology and Health Care). Employing a bivariate GRACH framework using weekly data from January 1992 to April 2008, the authors’ evidence significant transmission of shocks and volatility between oil prices and the five sectors investigated albeit at different magnitudes. Their findings among others support the idea of cross-market hedging of common information by investors. Kilian and Park (2009) second these conclusions suggesting that the reactions of stock returns to oil price changes differ depending on the industrial sector. More specifically, they examine four US industrial sectors ((Petroleum and Natural Gas, Automobile and Trucks, Retails and Precious Metals) and argue that, investors need to consider differences in the response across sectors in terms of their portfolio adjustments in response to oil price shocks. Arouiri and Nguyen (2010) follow in same spirit and investigate the short-term linkage between oil and stock prices in the aggregate as well as sector-by-sector in Europe. Their findings from various econometric techniques suggest that the sensitivity of sector stock returns to oil price fluctuations varies from sector to sector. In particular, they find that the Food and Beverages, Health Care and Technology sectors respond negatively to oil price increases, whereas the response is positive for the Financial, Oil & Gas, Industrials, Basic Materials and Personal and Household Goods sectors. More interestingly, their out-of-sample analysis shows that adding oil assets to a diversified portfolio of stocks provides a substantial diversification advantage as doing so significantly improve the portfolio’s risk-return characteristics.

Arouiri et al. (2011) employ the generalized VAR-GARCH models using weekly data from January 1998 to December 2009 to examine volatility spillovers between oil and stock market sectors in the US and Europe. The authors evidence a unidirectional spillover effect from oil to stock markets in Europe and a bidirectional spillover effect between oil and the US stock market sectors. In their paper on 560 US firms listed on the NYSE, Narayan and Sharma (2011) apply simple univariate GARCH framework to explore the relationship between oil prices and firm returns. Their findings reveal that oil prices demonstrate asymmetric effect depending on the sector in which they are listed in. The authors however argue that results are firm size
dependent and that small firm’s stock prices tend to be favored by oil price increases, whereas the reverse holds for the larger firms. Scholtens and Yurtsever (2012) who investigate 38 industries in 15 European countries reach the same conclusion and suggest that the impact of oil price shocks substantially differ along industries over the period of 1983-2007. Their findings reveal that most industries/sectors will benefit from negative oil prices; however, Oil, Mining and Gas industries would benefit from oil price increases. In addition, Arouri et al. (2012) apply VAR-GARCH models to explore volatility interactions between crude oil and European equity markets. Employing a weekly data from January 1998 to December 2009, the analysis reveal evidence of volatility spillovers between oil prices and sector stock returns. The authors also reveal among others, that optimal hedge ratios differ from one sector to another. Qinbin and Mohammad (2012) investigate the US industry-level returns and oil price predictability nexus. Their findings show among others that, oil price predictability is in a relatively small number of industry-level returns and changes in oil futures prices have virtually no predictive power for industry-level returns. They also document that with a percentage changes in oil spot prices as the predictor, approximately one fifth of industry-level returns are oil-predictable.

More recently, Degiannakis et al. (2013) employ time-varying multivariate heteroskedasticity framework to investigate the correlation between oil prices returns and European industrials sector indices returns. Using dataset from 10 European sectors, the authors document a contemporaneous correlations between oil prices and sector returns thus, suggesting that the relationship between sector indices and oil prices changes over time and are industry/sector specific. Among other findings, the authors argue both the origin of oil price shocks and the type of industry are important determinants of the correlation level between industrials sectors’ return and oil prices. They however acknowledged that the studies did not consider the time-varying fluctuations of the correlation and thus a direct comparison should be treated with caution. Furthermore, Bouri et al. (2016) investigate the mean and variance causality between world oil prices and sectoral equity returns in Jordan before and after the Arab Uprising. Employing the cross-correlation functions (CCF) that are computed from standardized residuals of a GARCH process for Financials, Industrials, and the Service sectors, the study document that oil impacts vary across the equity sectors. More specifically, the authors argue that oil return shocks significantly affect Financials and the Service sectors, while the impact is insignificant on the Industrials sector. From the aforementioned studies, it is evident that the impact of oil price shocks largely differ from one sector to another. We may also observe that majority of literature is akin to the developed markets particularly Europe and the US. Apart from Bouri et al. (2016), there is little evidence on the sectoral-level responses to oil price shocks from the perspective of Major oil producing markets. More besides, there is lack of evidence in literature on the time-varying correlations linkage between sector-returns and crude oil prices. Thus, the above literature ignored the importance of examining the oil-sector stocks nexus in a dynamic environment. Additionally, literature is silent on comparative analysis between country-level aggregate stock indices and sector-level indices to explore possibility of heterogeneous responses during oil price shocks. Again, literature fail to consider how equity-sector returns responds (in terms of correlation) to oil price changes under different time regimes. Our study thus, comes as
complement to literature to fill this void by examining the dynamic conditional correlations link between equity sector-stock indices and oil prices within five equity sectors from oil producing countries. More specifically, we explore the time-varying fluctuations in the correlations using DCC (dynamic conditional correlation) and asymmetric (DCC) ADCC-GARCH framework and we also consider the different time regimes in the oil price shocks.

3.0. Empirical methodology

In the literature on financial volatility modeling the most widely used specification is the generalized autoregressive conditional heteroskedasticity (GARCH) model. Most of the empirical studies on volatility interdependence, correlations and hedge ratios between oil markets and other assets has applied multivariate GARCH frameworks such as CCC-MGARCH model of Bollerslev (1990), VARMA-MGARCH of Ling and McAleer (2003), the BEKK of Baba, Engle, Kraft and Kroner (1990) or the DCC-MGARCH of Engle(2002). While it is true that these models are more relevant in the multivariate analysis compared to the univariate models, the multivariate GARCH frameworks does pose serious challenges when dealing with large data sets. In fact, one of the biggest challenges in multivariate GARCH modeling is the issue of identifying the tradeoff between generality and feasibility which is often referred to as the “curse of dimensionality”. For example, when the BEKK model is used for more than two variables, the likelihood function most often tend to behave poorly which causes estimation difficulty (Basher and Sadorsky, 2016). The basic problem is that when the number of number of estimated parameters are increased, the likelihood function flattens thereby making optimization difficult, if not entirely impossible. Given the objective of our study which is to explore the linear dependence in terms of correlation dynamics between oil prices and sector-stock market indices and to investigate the volatility persistent among the series the above models provide naturally suitable options. However, some of these frameworks as earlier stated are excessive in parameters and many lack empirical explanation. In view of this, we consider two multivariate the (dynamic conditional correlation) DCC-GARCH model of Engle (2002) and the Asymmetric-DCC (ADCC) GARCH of Cappiello et al. (2006) to model the volatility dependence and conditional correlational dynamics between oil prices index and sector-stock market indices. The CCC-GARCH (constant conditional correlation) model is not considered in our study because it poses restriction on the conditional correlations. Even though the CCC-GARCH model has generally well-behaved likelihood function and can handle bigger data sets than the fully parameterized models, its assumption of constant conditional correlation seems too restrictive in the sense that correlation coefficient is likely to vary over time due to the changes in economic and market conditions. From this backdrop and to allow for dynamic (time-varying) responses in the conditional correlation, the DCC model proposed by Engle (2002) provides the best alternative.
The major advantage of DCC-MGARCH model is that it enables estimation of conditional covariance matrices for large number of assets in a two-step procedure with smaller number of parameters than most of the MGARCH specifications such as VECH, BEKK representations and so on. It also captures well persistence in volatility and correlation and time-varying correlations. The DCC-GARCH model however, does not allow for asset-specific news or any possibility of asymmetric responses in the time-varying conditional correlations between two assets. In fact, while leverage effect and volatility feedback are cited in most volatility studies as main reasons for asymmetries in return volatility, little theoretical framework is available to justify recent evidence of asymmetric response to joint bad news (negative returns) in correlation (Cappiello et al. 2006). One possible explanation may be the time-varying risk-premium. Given a CAPM-type world, a negative systematic shock will induce downward pressure on the return of any pair of assets and will consequently increase the variance of these securities. With betas unchanged, covariance will increase and without proportional changes in idiosyncratic variance, correlation will as well increase (see, Cappiello et al. 2006). Therefore, correlation may be higher following negative shock (“bad news”) than after positive shock (“good news”) of the same magnitude. Following the spectacular fluctuation episodes in the crude oil market, it is very expedient to investigate the possibility of asymmetric effects in the dynamic correlation between oil prices and sector-stock indices. To this point, we employ the ADCC (asymmetric dynamic conditional correlation) framework which is able to account for asymmetric responses in the dynamic conditional correlation between oil-sector stock indices. The advantage of the ADCC model is that it offers us an appropriate alternative to identify the heterogeneity in the correlation response of sector-stock indices to joint negative or positive innovations from the two market. The DCC-GARCH by Engle (2002) is estimated in two stages. In the first stage, univariate volatility GARCH model is fit for each of the assets under study and estimates of volatility are obtained. In the second stage, the standardized residuals (asset returns transformed by their standard deviations) are used to estimate the conditional correlation. Similar to previous studies, the optimal lag length selected for the univariate GARCH process is one by the AIC information criteria. All assets returns exhibit autocorrelation, volatility clustering and fat tails. This suggests an AR (1) mean equation for each GARCH model with multivariate Student $t$ distribution for the DCC and ADCC models. Consequently, we used lag one for both the conditional mean and variance equations for the markets we study. With an AR (1) process, the mean equation is expressed as

$$r_t = \mu + \alpha_1 r_{t-1} + \epsilon_t$$

(1)

$$\epsilon_t \mid \Omega_{t-1} \sim N(0, H_t)$$

where $r_t$ is the $n \times 1$ vector of the asset returns; $\mu$ is the intercept (constant) term; $\alpha_1$ is autoregressive (AR) parameter to account for serial correlation in the market returns and $\epsilon_t$ is vector of the residual terms. The residual vector $\epsilon_t$ is bivariate and conditionally normally distributed. $H_t$ represents the conditional covariance matrix measurable with respect to the
information set at time \( t \) from previous period, \((\Omega_t_{-1})\) and \( \Omega t-1 \) is the matrix of conditional previous information set.

All DCC class models (including the constant conditional correlation (CCC) GARCH of Bollerslev (1990)) use the fact that \( H_t \) can be decomposed as;

\[
H_t = D_t R_t D_t
\]  
(2)

\( H_t \) is an \( n \times n \) conditional covariance matrix, \( R_t \) is the time-varying correlation matrix and \( D_t \) is the diagonal matrix of time-varying standard deviations from the univariate GARCH models on the diagonal. Thus,

\[
D_t = \text{diag}(h_{i,t}^{1/2}, ..., h_{n,t}^{1/2})
\]  
(3)

\[
R_t = \text{diag}(q_{1,t}^{1/2}, ..., q_{n,t}^{1/2}) Q_t \text{ diag}(q_{1,t}^{1/2}, ..., q_{n,t}^{1/2})
\]  
(4)

The time-varying conditional variances, \( h_{i,t} \) (elements of \( D_t \) in the equation (2)) are computed from univariate GARCH models. For the GARCH (1, 1) the parameters of \( H_t \) can be expressed as:

\[
h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}
\]  
(5)

Where \( h_{i,t} \) is the conditional variances of assets \( i \) at time \( t \), \( \omega_i \) is the constant term, \( \alpha_i \) refers to the ARCH term which transmits news about volatility from previous period and \( \beta_i \) is the first order GARCH term which captures the effect of previous volatility on current volatility. \( Q_t \) from eq. (4) is a symmetric definite matrix and the DCC parameter is modeled as:

\[
Q_t = (1 - \theta_1 - \theta_2) \bar{Q} + \theta_1 \eta_{t-1} \eta_{t-1}' + \theta_2 Q_{t-1}
\]  
(6)

Where \( \theta_1 \) and \( \theta_2 \) are the non-negative scalar parameters which capture the effect of previous standardized shocks and dynamic conditional correlations on current correlations respectively. \( Q_t \) is the \( n \times n \) matrix of unconditional correlations of standardized errors \( \eta_t \). The DCC model is mean reverting as long as \( \theta_1 + \theta_2 < 1 \). The correlation estimator is,

\[
\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}}
\]  
(7)

Next, we estimate the ADCC-GARCH model. Capiello et al. (2006) expand the DCC model and the GJR model of Glosten et al. (1993) by adding an asymmetric term to create the Asymmetric DCC (ADCC) model. The univariate GJR-GARCH model is given as:

\[
h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1} I(\varepsilon_{i,t-1} < 0)
\]  
(8)
Where $I = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0 \\ 0 & \text{if otherwise} \end{cases}$

For the above specification, $d$ is the parameter which captures asymmetric effects from previous news and a positive value for $d$ means that negative residuals (news/innovations) tend to increase variance more than the positive ones of the same magnitude.

With the often observed stylized facts in financial assets data where an unexpected drop in asset prices (negative returns) tends to increase volatility more than an unexpected increase (positive returns) of the same magnitude, asymmetric or leverage effects models are designed to capture these characteristics. In other words, bad news (negative returns) increases volatility more than good news (positive returns) of the same magnitude. Since the DCC model does not allow for asset-specific news and asymmetries, we propose and estimate the Asymmetric DCC (ADCC) model to better capture the heterogeneity present in our data series. The ADCC model is expressed as:

$$Q_t = \left( \tilde{Q} - A'\tilde{Q}A - B'\tilde{Q}B - G'\tilde{Q}^rG \right) + A'\eta_{t-1}\eta_{t-1}' + B'Q_{t-1}B + G'\eta_t\eta_t'G$$

(9)

$A$, $B$, and $G$ are the $n \times n$ parameter matrices and $\eta_t$ are zero-threshold standardized errors which are equal to $\eta_t$ if $< 0$ and zero if otherwise. $\tilde{Q}$ and $\tilde{Q}^r$ are the unconditional matrices of $\eta_t$ and $\eta_t^r$ respectively.

### 4.0 Data

We are in the process of collecting the relevant data on equity sectors on major oil producing countries including US.

### References:


