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Oil Price and Exchange Rates: A Wavelet Analysis for Organisation of Oil Exporting Countries Members

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ABSTRACT

This paper studies the relationship between oil price and the exchange rates of Organization of Oil Exporting Countries (OPEC) members from February 1999 to March 2016. The wavelet method is applied to combine information from both time and frequency domains, which does not require stationary and decomposition of original time series data. The study found that the strength of the relationship between oil price and exchange rate divides into three main categories, namely oil price leads exchange rate, exchange rate leads oil prices, and the relationship keeps changing. Countries which currencies pegged to US Dollar are lagging against oil price changes, countries with floating exchange rates and countries with an undisclosed weighted basket of international currencies leads the changes in oil price, and countries which their currencies pegged to special drawing right experience changing relationships. This finding suggests that the central banks of OPEC member countries should give importance to shocks on oil prices, while formulating their own exchange rate policy.

Keywords: Wavelet Coherence, Oil Price, Exchange Rate, Organization of Oil Exporting Countries
JEL Classifications: C58, F31, Q02

1. INTRODUCTION

In an era of globalization, every country has different gross domestic product compositions that are affected by currency exchange. Research on the relationship between oil price and US dollar (USD) exchange rates found that oil price and exchange rates have a contagion and negative dependent relationship (Reboredo and Rivera-Castro, 2012). Fluctuation in the USD will affect oil trading, importing as well as oil exporting countries because USD is the major invoicing and settlement currency in the international oil market. Hypothetically, a weak USD has a negative impact on oil exporting countries but increases the purchasing power of oil importing countries. This premise is crucial as the Organization of Oil Exporting Countries (OPEC) member countries have adopted a different currency exchange system which has already “dollarized” the nation’s currency. This study examines the relationship between oil price and the currency of OPEC members.

Although it is widely accepted that oil prices influence the economy, it is unclear how the relationship changes depending upon the availability and usage of the oil in a particular country/region. The Statistical, Economic and Social Research and Training Centre for Islamic Countries (SESRIC) studied the proposal for a single currency for the Organization of Islamic Countries (OIC). It argued that if the OIC decided to pursue a single currency. Much work is required to eliminate the disparities and induce co-movement of the business cycle (SESRIC, 2012). Their results reflect the importance of choosing the right currency exchange system within the context of overall economic activity.

In this research, we focus on how the overall economic health of OPEC countries is dependent on the currency exchange and its correlation to fluctuations in oil price. It examines the causal relationship between oil prices and exchange rates in OPEC countries. Interestingly, despite being a major oil producing region, no such research has been conducted for OPEC countries.

This research paper is organized in five sections. The second section reviews literature on OPEC members and their currency exchange systems, and the relationship between currency exchange movement and fluctuations in oil price. The third section discusses the wavelet approach. The fourth section discusses the research methodology. The data and empirical findings are discussed in the fifth section and the last section concludes the study.

2. OPEC MEMBERS AND THE CURRENCY EXCHANGE SYSTEM: AN OVERVIEW

The OPEC has 13 members, which includes five founding members: Saudi Arabia, Venezuela, Iran, Iraq, and Kuwait and full members including Qatar, Indonesia, Libya, United Arab Emirates (UAE), Algeria, Nigeria, Ecuador, and Angola. Each country is distinct in both geographical location and currency exchange system (OPEC Secretariat, 2012). OPEC generates 41.7% of total global crude oil production and is home to 80% of reserves (OPEC, 2015).

Saudi Arabia has a fixed exchange rate regime, with the riyal pegged to the USD. The dollar/riyal exchange rate has remained fixed at SAR3.75/USD since June 1986. As foreign exchange is predominantly earned by the government, the Saudi Arabian Monetary Agency provides the foreign exchange needs of the private sector by selling dollars against Riyals to the domestic banks (Al-Jasser and Banafe, 2005). From 2003, former Venezuelan President Hugo Chaves introduced currency control to stem capital flight. From 2003 to date, the country has devalued the official exchange rate four times and alternated between single and multiple exchange rate system. The government also introduced three different exchange rates where the government sells dollars for 6.3, 12, and 172 bolivars per dollar. The first two rates are used for imports of government-authorized priority goods including food, medicine, and car parts. The third can be use by anybody not authorized by the government to buy dollars at the two preferential rates. From the 1970s until the March 2002 unification, the exchange rate system of the Islamic Republic of Iran was heavily controlled, featuring multiple exchange rate practices with associated exchange restrictions and import controls. The two remaining official exchange rates of the Iranian Rial were unified in March 2002, after which the authorities adopted a market-based managed floating exchange rate system (Celasun, 2003).

Between 5 January 2003 and 19 May 2007, the Kuwaiti Dinar (KWD) was pegged to the USD within margins around a parity rate effective the beginning of the year 2003. The then Governor, H.E. Sheikh Salem Abdulaziz Al-Sabah, announced the parity rate of the KWD exchange rate against the USD for the 1st day of business in January 2003 corresponding to Sunday 5 January 2003. The exchange rate was set at KWD 0.2996/USD with margins of ±3.5%. This parity rate was set based on the same principles and considerations approved historically by the Central Bank of Kuwait (CBK) in determining the KWD exchange rate under the previous system of the currency basket to ensure a smooth change from the currency basket peg to the dollar peg within margins. Effective 20 May 2007, the KWD exchange rate was re-pegged to an undisclosed weighted basket of international currencies of Kuwait's major trade and financial partner countries. Reverting to the exchange rate policy followed prior to 2003 aims at protecting the purchasing power of the national currency and containing inflationary pressures affecting the local economy, after having exhausted all attempts to absorb the adverse effects of USD depreciation against major currencies for an extended period of time (CBK). Similarly, the Libyan Dinar has experienced fluctuations until it was pegged to special drawing right (SDR) (Central Bank of Libya, 2014). In 1969, the International Monetary Fund (IMF) established SDR as a supplementary international reserve asset whereby its value based on four major currencies (IMF, 2015).

The Qatar Central Bank (QCB) adopted the exchange rate policy of its predecessor, Qatar Monetary Agency, by fixing the value of the Qatari Riyal (QAR) against the USD at a rate of QAR3.64/USD as a nominal anchor for its monetary policy. The peg has always been highly credible. The targeted peg was officially authorized substituting the de jure exchange rate policy of pegging to the SDR that was in effect since 1975. To date, QCB has continued implementing its exchange rate policy of hard pegging to the USD at an average price of QAR 3.64 per USD. Commercial banks domestically trade the USD on basis of price determined by QCB (nd). Ecuador has adopted the dollar as their official currency replacing the 116-year old "Sucre" since 2000. The USD became legal tender in Ecuador March 13, 2000, and Sucre notes ceased being legal tender on September 11, 2000.

The 1997 Asian financial crisis forced Bank Indonesia (Bank Central Republic Indonesia) to float the rupiah in August 1997 due to the dramatic depreciation against USD (The New York Times, 1997). The decision is still active although some have called for a peg with USD. In the case of Angola, Reuters (2009) stated that kwanza is a more liberal currency which can be floated freely after its unpegging with USD in October 2009. The decision was made after the increasing demand of USD for importing goods which caused the central bank to reduce the value of kwanza by 4%, however the local currency lost above 30% of its value in the black market. Hence unpegging will preserve the value of the local currency. The summary of exchange rate systems of OPEC member countries is presented in Table 1.

3. LITERATURE REVIEW

The dynamic relationships between crude oil prices and exchange rate have recently received much attention from many economic

Table 1: Summary of exchange rate system of OPEC

Country	Pegged exchange rate
Emirate	USD
Angola	Floating
Indonesia	Floating
Kuwait	Basket
Libya	SDR
Nigeria	Floating
Qatar	USD
Saudi Arabia	USD
Algeria	Floating
Iran	Floating
Ecuador	Floating

agents. Surges in oil price over the last decade and the continuing build-up of global imbalance due to increased globalization require a better understanding of the relationship between crude oil and foreign exchange for purposes of asset trading and market regulation.

How variation in oil prices can affect exchange rates have been excessively documented firstly in terms of trade. A raise in oil prices for oil importing countries will weaken the trade balance and decrease the value of the local currency (Backus and Crucini, 2000). The second factor is via wealth effects. Kilian and Park (2009) and Bodenstein et al. (2011) found that increase in oil prices will shift wealth from oil importing countries to oil exporting countries, which influence the exchange rate of oil importers through current account imbalances and portfolio reallocation.

Furthermore, there is a negative correlation between exchange rate and oil prices. More explicitly, exchange rates can change oil prices through its impact on oil supply, oil demand, and financial markets. Firstly, on the supply side of the oil market, a decrease in the USD value might lead oil exporting countries to limit oil supplies and increase oil prices to stabilise the purchasing power value of their export revenues in dollars (Wirjanto and Yousefi, 2005). Secondly, a decrease in the USD might lead to increased demand for oil for oil importing countries since it becomes cheaper in their local currency (De Schryder and Peersman, 2012). For countries with currencies pegged to the USD, such as China, a depreciation of USD could increase oil demand driven by higher exports (Fratzscher et al., 2014).

Some researchers found a co-movement between oil prices and exchange rates while others did not. The first category is supported empirically in Canada (Amano and Van Norden, 1995); in US (Amano and Van Norden, 1998); in Spain (Camarero and Tamarit, 2002); in Norway (Akram, 2004); in Fiji (Narayan et al., 2008); in India (Tiwari et al., 2013); and in Asia (Narayan, 2013).

Amano and Van Norden (1995) fund the evidence of linking the Canada-US real exchange rate with the terms of trade. More specifically, the results showed that causality runs from the terms of trade to the exchange rate. In another research, they (Amano and Van Norden, 1998) examined that the issue of the relative importance of monetary versus real shocks in explaining exchange rate movements. They found that a stable link between the US real effective exchange rate and oil price shocks over the post-Bretton Woods period. They support the idea that oil prices were the main source on the exchange rate shocks.

By applying panel cointegration techniques, Camarero and Tamarit (2002) studied the factors explaining the real exchange rate of the Spanish peseta. As an additional variable, they have included the real oil price and found that, in the case of the real oil prices, the results are not homogeneous; this variable turns out to be significant *viz*. the countries that are less oil dependent than Spain. Akram (2004) explored the possibility of a non-linear relationship between oil prices and the Norwegian exchange rate. Their studies revealed that there was a negative relationship between oil prices and the value of the Norwegian exchange rate.

Narayan et al. (2008) examined the relationship between oil price and the Fiji–US exchange rate by using the generalized autoregressive conditional heteroskedasticity (GARCH) and exponential GARCH models to estimate the impact of oil price on the nominal exchange rate. They found that a rise in oil prices leads to an appreciation of the Fijian dollar *viz*. the USD. Tiwari et al. (2013) studied the linear and nonlinear Granger causalities between oil price and the real effective exchange rate of the Indian currency, known as “rupee.” By applying wavelet methodology, they discovered that the linear and nonlinear causal relationships between the oil price and the real effective exchange rate of Indian rupee at higher time scales (lower frequency). Narayan (2013) conducted a research that whether oil price can predict exchange rate returns for 14 Asian countries. They found that the higher oil price leads to future depreciation of the Vietnamese dong but future appreciations of the local currencies of Bangladesh, Cambodia, and Hong Kong based on the generalized least squares-based time series predictive regression model.

The second category which found a weak correlation between the variables pertained to OECD by Chaudhari and Daniel (1998), Asia-Pacific countries (Chinn, 2000), China (Huang and Guo, 2007), and European countries (Czudaj and Beckmann, 2013).

By application of cointegration and causality tests, Chaudhari and Daniel (1998) demonstrated that the non-stationary behavior of USD real exchange rates, over the post-Bretton Woods era, is due to the non-stationary behavior of real oil prices. Based on a productivity-based model of East Asian relative prices and real exchange rates is tested by Chinn (2000) by applying calculated productivity levels for China, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand. Time-series regressions of the exchange rate on relative productivity ratios indicated that such a relationship for Japan, Malaysia, and the Philippines (and Indonesia and Korea when oil prices are included).

Huang and Guo (2007) investigated the relationship among the oil price shock and three other types of underlying macroeconomic shocks impact on the trend movements of China’s real exchange rate. Based on a four-dimensional structural VAR model, their results suggested that real oil price shocks would lead to a minor appreciation of the long-term real exchange rate due to China’s lesser dependence on imported oil than its trading partners included in the RMB basket peg regime and rigorous government energy regulations. By taking into account two previously neglected issues in its analysis of the relationship between oil prices and effective dollar exchange rates, namely, nonlinear adjustment dynamics and a distinction between nominal and real linkages and using a Markov-switching vector error correction model, Czudaj and Beckmann (2013) differentiated the long-run and time-varying short-run dynamics. Their findings indicated that not only that the results depend on the choice of the exchange rate measure, but also that the time-varying causality patterns mainly runs from nominal exchange rates to nominal oil prices.

As we seen from the above literatures, the previous empirical studies have suggested an ambiguous relationship between crude oil prices and exchange rates. Also we noted that, there are lesser studies on OPEC member countries despite they are the main oil producers. Therefore, we are going to study the behavior of crude oil prices and exchange rates for OPEC member countries by applying wavelet analysis.

4. METHODOLOGY

This paper uses the wavelet method rather than standard time series analysis can be conducted by time domain analysis, time series analysis, or frequency domain, spectral analysis. Time domain analysis studies the evolution of an economic variable with respect to time, whereas frequency domain analysis shows at which frequencies the variable is active (Masset, 2008). In other words, time period changes but not frequency in the first analysis, meaning its purpose to study the temporal properties of the variable at the specified frequency. Issues with time domain analysis arise when the variable depends on several frequency components not only one. However, frequency changes but not time periods, thus this analysis studies the properties of a variable over the frequency spectrum (Jia et al., 2015).

Wavelet is a small wave that grows and decays in a limited time frame. Madaleno and Pinho (2012) and Reboredo and Rivera-Castro (2013) stated that wavelet can be seen as an extension to spectral and Fourier analysis that does not face the weakness of Fourier analysis wherein the variable needs to be stationary which is not the case for economic and finance variables. It is important to note that each variable comprises three components: Trend, seasonal, and random effect. Making the variable stationary removes the long-term effect of the variable. Wavelength analysis also provides a more complete decomposition of original time series data compared to Fourier analysis. Briefly, Fourier analysis requires stationarity and does not provide decomposition and at the most provides for the short and long run only (2 time scales). These limitations are solved in wavelet analysis by using mathematical functions that transform the data into a mathematically equivalent representation enabling it to spilt the time series data into various components the decompose original series by considering both time and frequency.

Maslova et al. (2013) affirmed that wavelet is the best alternative to replace Fourier analysis because: (i) It combines information from both time domain and frequency domain; (ii) it does not require stationary; (iii) it allows us to extract the different frequencies driving any macroeconomic variable in the time domain by decomposing into its time scale components; (iv) it removes the noise from the raw data; and (v) the wavelet covariance decomposes the covariance between two stochastic processes over different time scales to better estimate the causality relationship between variables.

Gençay et al. (2002) proposed that there are two wavelet functions, the father wavelet (*S*) which captures the smooth or low frequency or trend part of signal, while mother wavelet (*D*) captures the detailed or high frequency or deviation from the trend part of the signal. *S* and *D* are stated as below:

$$S_{J,k}\left(x\right)=\int_{-\infty}^{\infty}\varnothing_{J,k}\,y\left(x\right)dx \tag{1}$$

$$D_{j,k}\left(x\right)=\int_{-\infty}^{\infty}\tau_{j,k}\,y(x)dx\ \ (j=1,2,\ldots,J) \tag{2}$$

The functions $S_J(x)$ and $D_j(x)$ are known as smooth and detailed approximations, respectively. The highest level approximation $S_J(x)$ is the smooth, while the details $D_1(x)$, $D_2(x)\ldots$, $D_j(x)$ are associated with oscillations of length 2-4, 4-8,…, 2^J-2^{J+1} (Reboredo and Rivera-Castro, 2013).

4.1. Continuous Wavelet Transform (CWT)

A number of authors have recently started to use the CWT in economics and finance research for example Tiwari (2013), Saiti et al., (2015). In the literature, Tiwari (2013) argues that the application of wavelet analysis is mostly limited to the use of one or other variants of discrete wavelet transformation especially in economics and finance. We have to consider several factors while applying discrete wavelet analysis, for example, up to what level we should decompose. Furthermore, it is also hard to understand the results of discrete wavelet transformation in an appropriate way. The time series data variations, what we may get by applying any method of discrete wavelet transformation at every scale, can be obtained and more easily with continuous wavelet analysis. On the other hand, under the CWT, it is not required to find out the structural breaks since this wavelet transformation can capture all the dynamics of financial time series (Saiti et al., 2015). The CWT maps the original time series, which is a function of just one variable time-separate into function of two different variables such as time and frequency. One major benefit CWT has over discrete wavelet transform (DWT)/maximum overlap DWT is that we need not define the number of wavelets (time-scales) in CWT which generates itself according to the length of data. Other than that, the CWT maps the series correlations in a two-dimensional figure that allows us to easily identify and interpret patterns or hidden information (Saiti et al., 2015).

Even though wavelets have very interesting features, it has not very popular among the economists due to two important reasons as suggested by Aguiar-Conraria et al. (2008) and Tiwari (2013). Aguiar-Conraria et al. (2008) stated that "(i) In most economic applications, the (discrete) wavelet transform has mainly used as a low and high pass filter, it being difficult to convince an economist that the same could not be learned from the data applying the more traditional, in economics, band pass-filtering methods, (ii) it is difficult to analyze simultaneously two (or more) time series. In economics, these techniques have either been applied to analyze individual time series or used to individually analyze several time series (one each time), whose decompositions are then studied using traditional time-domain methods, such as correlation analysis or Granger causality."

In order to overcome the above said problems and to accommodate the analysis of time-frequency dependencies between two time series, Hudgins et al. (1993) and Torrence and Compo (1998) developed techniques of the cross-wavelet power, the cross-wavelet coherency, and the phase difference. In this way, we can study the interactions between two time series at different frequencies and how they evolve over time with the usefulness of the cross-wavelet approaches (Tiwari, 2013).

In short, the cross-wavelet power of two time series demonstrates the confined covariance between the time series. The wavelet coherency can be treated as correlation coefficient in the time frequency space. The word "phase" can imply the position in the pseudo-cycle of the series as a function of frequency. By doing so, the phase difference provides us information "on the delay, or synchronization, between oscillations of the two time series" (Aguiar-Conraria et al., 2008; Tiwari, 2013).

In general, the time series application on a wavelet function is defined by $\varphi_{\theta}(\mu)$ with zero mean and localized both time (Δt) and bandwidth ($\Delta\omega$). The purpose of the CWT is to filter the time series by stretching its scale (s), i.e., the dimensionless time $(\mu) = t \times s$, and normalizing it to have unit energy. Therefore, the CWT coefficients of a time series (x_n, $n = 1,\ldots N$) with uninformed time steps (δt) is given by Grinsted et al. (2004) as:

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n=1}^{N} x_{n'} \varphi_{\theta}[(n' - n)\frac{\delta t}{s}] \tag{3}$$

The wavelet spectrum is defined as $\left|W_n^X(s)\right|^2$ which can be used to measure the local phase and variance of a time series on the time scale space. The CONE OF INflUENCE is introduced to treat the edge effect of edge artefacts of the CWT due to incomplete time localization of the wavelet. The area where the discontinuity at the edge has dropped to e^{-2} of the value which causing the wavelet power is considered as a cone of influence.

This paper applies the Monte Carlo methods used by Torrence and Compo (1998). Under the null, according to Torrence and Compo (1998), the corresponding distribution for the white and red noise wavelet power spectrum each time (t) and scale (s) is given as:

$$D\left(\frac{\left|W_n^X(s)\right|^2}{\sigma_X^2} < p\right) = \frac{1}{2} P_{\varepsilon} \chi_v^2(p) \tag{4}$$

Where, v is equal to 1 for real and 2 for complex wavelets and P_{ε} is the Fourier power spectrum of an autoregressive process with lag-1 autocorrelation and Fourier frequency index is (ε) is given by Allen and Smith (1996) as:

$$P_{\varepsilon} = \frac{1-\alpha^2}{\left|1-\alpha e^{-2i\pi\varepsilon}\right|^2} \tag{5}$$

4.2. Cross Wavelet Transform

The cross wavelet transform of given two wavelet transforms $W_n^X(s)$ and $W_n^Y(s)$ of time series X_n and Y_n, respectively, is defined as $W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s)$, where * donates the complex conjugate of $W_n^Y(s)$ which is used to expose the local relative phase, covariance, among two time series on the time scale space. The cross wavelet power spectrum is further defined as $|W_n^X Y(s)|^2$ which discloses the coincident events of two times series on the time scale space. By using Monte Carlo methods to assess the statistical significant of the cross wavelet spectrum, Torrence and Compo (1998) gave the theoretical distribution of the cross wavelet power of two time series, X_n and Y_n, have red noise with power spectra P_{ε}^X and P_{ε}^Y, respectively, connected with Fourier frequency ε as:

$$D\left(\frac{\left|W_n^X(s) W_n^{Y*}(s)\right|}{\sigma_X \sigma_Y} < p\right) = \frac{C_v(p)}{v} \sqrt{P_{\varepsilon}^X P_{\varepsilon}^Y} \tag{6}$$

Where, σ_X and σ_Y are the standard deviations associated with X and Y and $C_v(p)$ is the confidence level associated with the probability p where v is 1 for real and 2 for complex wavelets. For the 95% confidence interval is calculated as $Z_2(95\%) = 3.999$ (Grinsted et al., 2004; Torrence and Compo, 1998).

4.3. Wavelet Coherence

Wavelet coherence is a useful tool to distinguish possible relationships between two time series by searching frequency space and time intervals. In other words, wavelet coherence may enhance correlation analysis to help reveal intermittent correlations between two time series and their significant correlation relationship, if real, should thus represent how coherent the cross wavelet of two time series in time frequency space. It is, therefore, able to efficiently compute the wavelet coherence for the exchange rate returns and oil price returns relationship in the OPEC. Unlike cross wavelet power which shows areas with high common power, wavelet coherence is always helpful to implement the wavelet coherence analysis for relationship studies, even at intervals where high coherence exists but only minimal power is shown in the wavelet power spectrum of the two time series (Uddin et al., 2013; Ng and Chan, 2012; Aguiar-Conraria and Soares, 2011; Grinsted et al., 2004). Based on the cross wavelet spectra and the auto-wavelet power, the wavelet coherence is defined as the cross spectra normalized by the two related auto-spectra. The wavelet coherence of the exchange rates returns and oil price returns differential in the OPEC is given by Torrence and Webster (1999) as:

$$R_n^2(s) = \frac{\left|\forall(s^{-1} W_n^{XY}(s))\right|^2}{\forall\left(s^{-1}\left|W_n^X(s)\right|^2\right) \forall(s^{-1}\left|W_n^Y(s)\right|^2)} \tag{7}$$

Where, $R_n^2(s)$ is the squared wavelet coherency value and $\forall$ is a smoothing operator defined as $\forall(W) = \forall_{scale}(\forall_{time}(W_n(s)))$, where $\forall_{scale}$ represents smoothing along the wavelet scale axis and $\forall_{time}$ donates smoothing in time. The value of wavelet coherence ranges between 0 and 1 which describes all properties of the correlation, in wave function, between two non-stationary time series at a specific scale or over a specific period, i.e., showing a strong dependence between two time series and *viz*. (Tonn et al., 2010; Akoum et al., 2012). The arrow's angle, ϑ_{XY} of the wavelet coherence is called phase-difference, i.e., phase lead of X over Y. Zero phase-difference refers that the two time series move together at the particular time frequency. If $\vartheta_{XY} \in (0, \pi/2)$, then the two time series move in phase led by Y, however if $\vartheta_{XY} \in (-\pi/2, 0)$, then X leads Y. π or $-\pi$ explains an anti-phase relation in which $\vartheta_{XY} \in (\pi/2, \pi)$ then X is leading while Y is leading if $\vartheta_{XY} \in (-\pi, -\pi/2)$.

In phase and anti-phase represent direction whereby movement in the same direction is called in phase while anti-phase means it moves in the reverse direction. The arrows in the graph show us which variable is leading whereby the first variable would be leading if the arrows point to right-down or left up. On the flip side, the second variable would be leading if the arrows are pointing opposite to the first variable. Figure 1 illustrates these phase-differences among two time series (Aguiar-Conraria and Soares, 2011).

The horizontal axis in the wavelet coherence plot represents time/period while the vertical axis denotes frequency/scale. Within those axes, analysis will be conducted to observe the regions that indicate wavelet coherence. We notice that graphs are colorful whereby the regions with warmer colors indicate significant interrelation while regions with colder colors show lower dependency and interrelation among time and frequency.

The statistical level of significance of the wavelet coherence is estimated using Monte Carlo methods. This paper concentrates on wavelet coherence of the exchange rates returns and oil price returns differential in the OPEC rather than cross wavelet since the numerator in Equation (7) elucidated the absolute smoothed cross wavelet value squared and denominator explained the smoothed wavelet power spectra (Uddin et al., 2013; Aguiar-Conraria and Soares, 2011; Rua and Nunes, 2009; Torrence and Webster, 1999).

5. DATA AND EMPIRICAL FINDINGS

To assess the interlinkages between oil prices and exchange rates of the OPEC, daily data over a sample period from 1 February 1999 until 11 March 2016 were collected, as the wavelet methodology requires large data observation. This period is based on the availability of data in the DataStream. It used the change in log nominal WTI crude oil price expressed in USD for the oil price and the change in log nominal effective OPEC currencies to USD to express the exchange rate, specifically Emirati Dirham (AED) to USD, Angolan Kwanza (AOA) to USD, Indonesian Rupiah (IDR) to USD, KWD to USD, Libyan Dinar (LYD) to USD, Nigerian Naira (NGN) to USD, Qatari Riyal (QAR) to USD, Saudi Riyal (SAR) to USD, Algerian Dinar (DZD) to USD, Iranian Rial (IRR) to USD, weighted USD index of major currencies[1] represents Ecuador's currency. Iraq and Venezuela are excluded from this study due to lack of available data on their exchange rates. The list of variables is presented in Table 2.

Discussion is based on micro scoping each country and then extracting the summary across the countries. From Figure 2, wavelet coherency of the AED exchange rate and oil price shows that the variables are interrelation in 32 days in different periods while the interrelation was strong in low term frequency from 2005 to 2011. The arrows are anti-phase during that period, meaning oil price is leading the exchange rate in the long run. Figure 3 represents AOA exchange rate and oil price relationship whereby the variables mostly fell within blue regions with insignificant interrelation. There was in phase movement during 2009-2012 and

1 Major currencies index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden.

Figure 1: Phase-difference circle

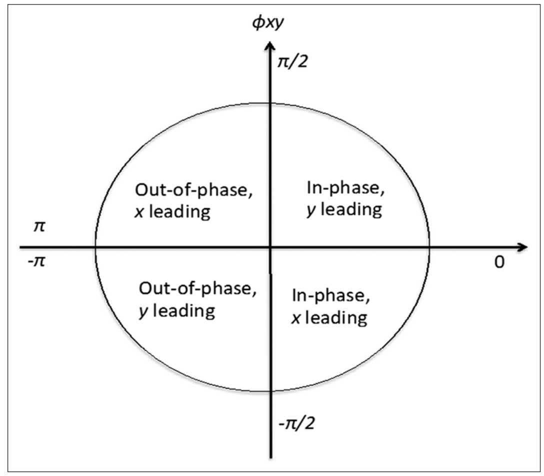


Figure 2: Wavelet coherence: Emirati Dirham exchange rate versus oil price

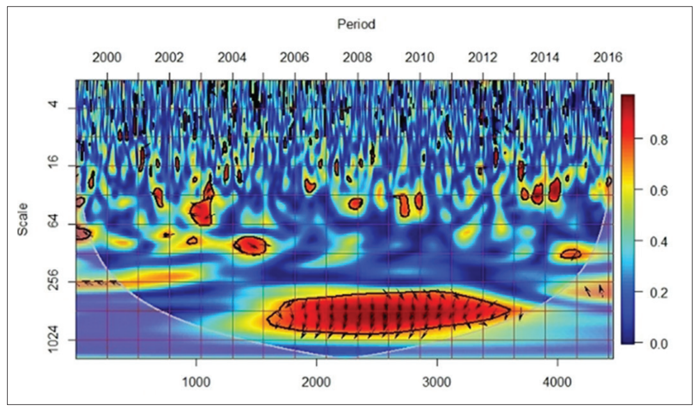


Table 2: Summary of OPEC members' currencies

Country	Currency	Exchange rate (lead/lag)
Emirate	Dirham	AED
Angola	Kwanza	AOA
Indonesia	Rupiah	IDR
Kuwait	Dinar	KWD
Libya	Dinar	LYD
Nigeria	Naira	NGN
Qatar	Riyal	QAR
Saudi Arabia	Riyal	SAR
Algeria	Dinar	DZD
Iran	Rial	IRR
Ecuador	US Dollar	USD

anti-phase after 2014. Since the significance is weak, we cannot form a clear judgement on the influence of the variables.

Coherence of IDR exchange rate and oil price in Figure 4 shows that the variables are mostly anti-phase between 2000-2003 and 2006-2011. From 2000 to 2003, the scale interrelation fell in about 240 days-scale while from 2006 to 2011 the interrelation was significant in different frequencies. Anti-phase means if the oil price increased, the exchange rate of the Indonesian rupiah would appreciate. Figure 5 shows the KWD exchange rate and oil price are mostly anti-phase between 2001-2003 and 2005-2013. From the daily information at the long-term scale, the arrows are pointing left up, indicating that the KWD is controlled to oil price.

Figure 6 shows the LYD exchange rate and oil price coherency are mostly anti-phase between 2001-2003, 2006-2012, and 2014 onwards. This resulted from the decision made by Central Bank of Libya to adjust the exchange of LYD against USD by decreasing 50% of its value. Due to this change, we notice that oil price is leading exchange rate. Additionally, the coherence of NGN exchange rate and oil price can be observed in Figure 7 whereby the movement was predominantly anti-phase between 2006 and 2015. The arrows are pointing left up indicating that NGN has been controlled against the fluctuation of oil price.

According to Figure 8, the wavelet coherence of the QAR exchange rate with oil price is generally in the colder area, however the two variables are anti-phase between 2005 and 2009 then changed to in phase until 2011. The Qatari riyal was pegged with the USD in mid-2001 of which the graph shows in phase interrelation before the pegging at fixed rate indicating that when the oil price increased, the Qatari riyal depreciated. Similarly, in Figure 9, the SAR exchange

Figure 3: Wavelet coherence: Angolan Kwanza exchange rate versus oil price

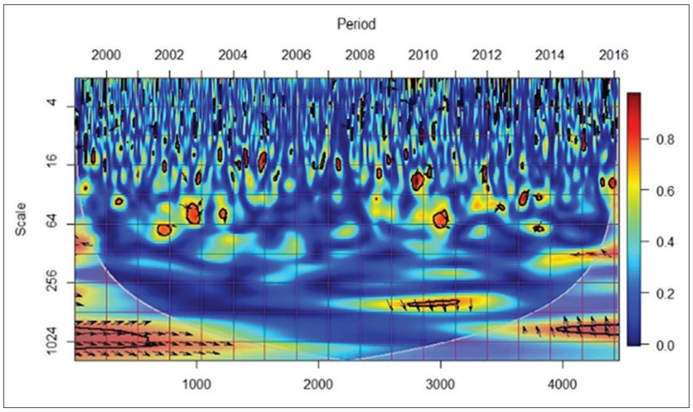


Figure 4: Wavelet coherence: Indonesian rupiah exchange rate versus oil price

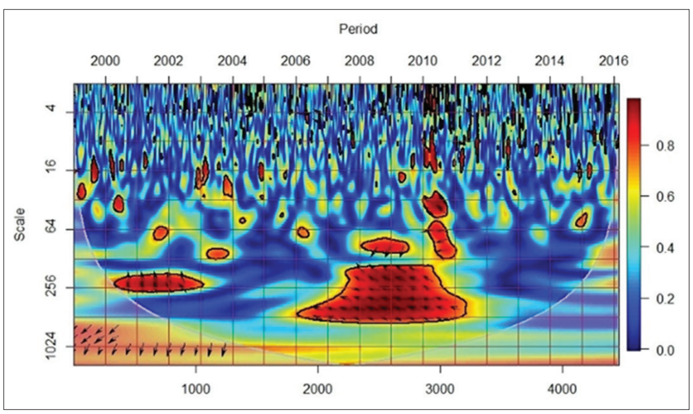


Figure 5: Wavelet coherence: Kuwait dinar exchange rate versus oil price

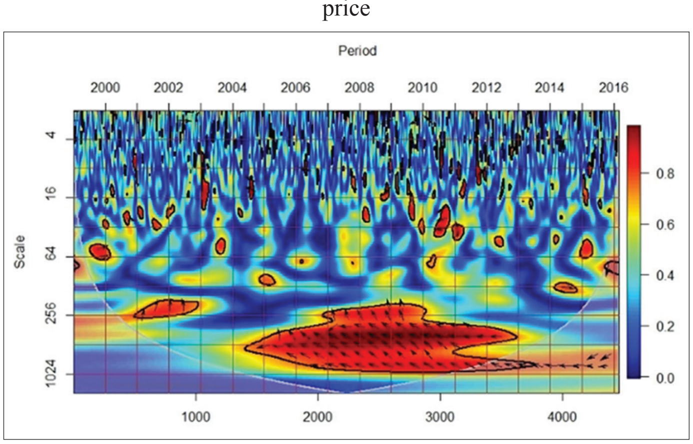


Figure 6: Wavelet coherence: Libyan Dinar exchange rate versus oil price

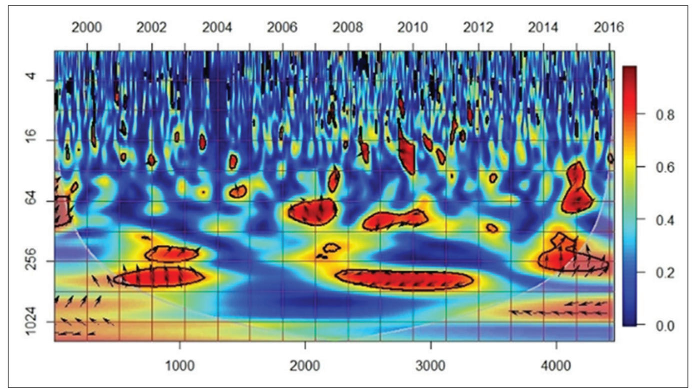


Figure 7: Wavelet coherence: Nigerian Naira exchange rate versus oil price

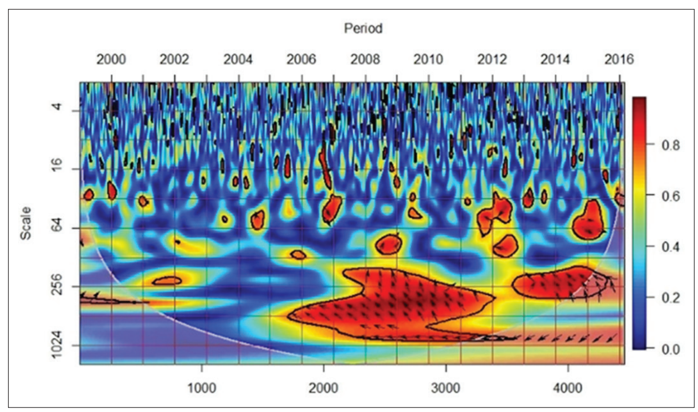
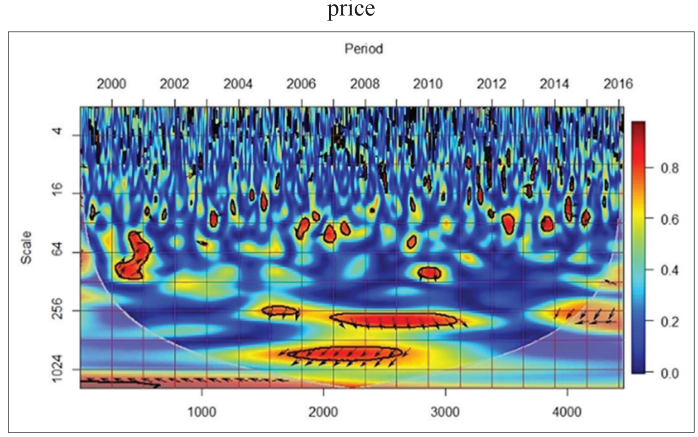


Figure 8: Wavelet coherence: Qatari Riyal exchange rate versus oil price



rate and oil price coherency is in the blue region meaning the relationship is of little significance except in the long-term scale, i.e. short-term frequency, within 2005-2013. The arrows are pointing left-down, indicating that oil price is leading the exchange rate. Additionally, the arrows are pointing on the left which means anti-phase and SAR appreciates with increase in oil prices. Interestingly, the arrows changed slightly from down to up, indicating the SAR has been controlled due to the decrease in oil price in mid-2014.

Figure 10 shows that the DZD exchange rate and oil price relationship are anti-phase between 2006 and 2013 within different scales. The arrows pointing left up indicate that the Algerian dinar has been controlled. The relationship of IRR exchange rate and oil price has been seen in different periods in Figure 11 whereby the variables are mostly in phase during the 1999 – mi-2000 and 2002 to 2004, anti-phase from 2007 to 2010, and returned to in phase in 2015. Interestingly in low term frequency above 1 year, we do not observe any significant relationship between the variables. Figure 12 shows the USD exchange rate and oil price coherency are mostly anti-phase between 2005-2013 and 2013-2016. The arrows are pointing left-down, from 2005 to 2013, indicating that oil price is leading the exchange rate. From 2013 to 2016, the arrows changed slightly from down to up.

To summarize, over the time horizon, the strength of the relationship between oil price and exchange rate divides into three main categories, namely oil price leads exchange rate, exchange rate leads oil prices, and the relationship keeps changing. Countries with currencies pegged to USD (i.e., Emirate, Qatar and Saudi Arabia), are lagging against oil price changes, while countries with floating exchange rates (i.e., Algeria, Angola, Indonesia, Iran and Nigeria), and countries with an undisclosed weighted basket of international currencies (i.e., Kuwait), lead changes in oil price. Finally, in countries with currencies pegged to SDR (i.e. Libya), the relationship between oil prices and exchange rate changes. Table 3 summarizes the relationships between oil price and exchange rate for OPEC.

6. CONCLUSION

Oil is vital revenue for oil exporting countries. Fluctuations of oil price are leading concerns in the OPEC which holds a major share in the market with around 41.7% in 2015. A country's currency also plays a crucial role maintaining its economy. This paper studied the correlation between changes of oil price with changes in exchange rate of OPEC members from February 1999 to March 2016. Wavelet coherence was used to distinguish possible relationships between changes in oil prices and changes in exchange rate of OPEC member currencies by searching frequency space and time intervals.

The paper found that the strength of the relationship between oil price and exchange rate divides into three main categories, namely

Figure 9: Wavelet coherence: Saudi Riyal exchange rate versus oil price

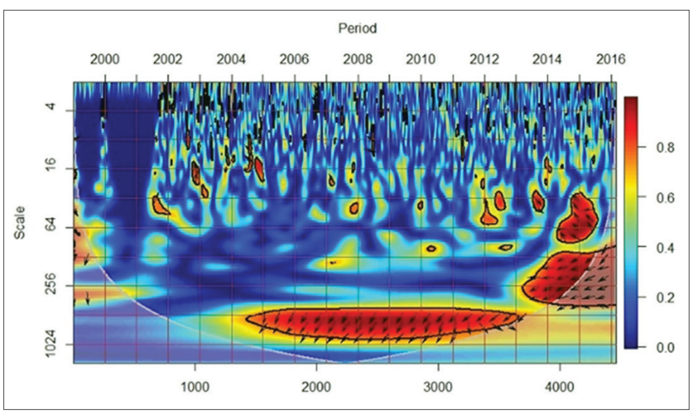


Figure 10: Wavelet coherence: Algerian Dinar versus oil price

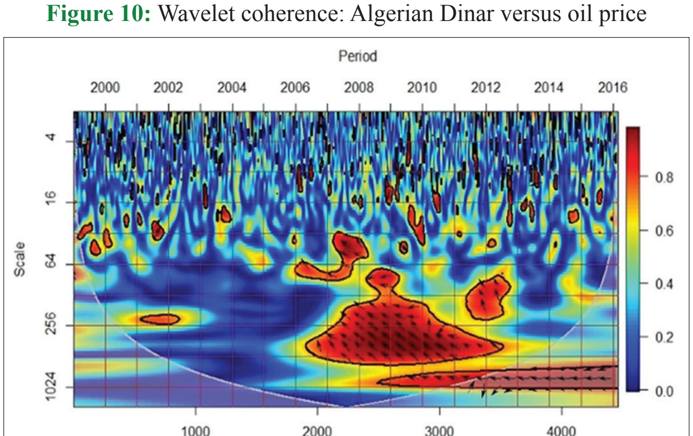


Figure 11: Wavelet coherence: Iranian Rial exchange rate versus oil price

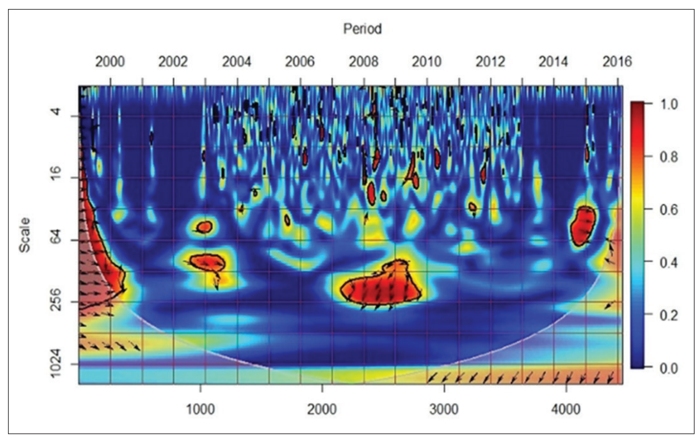


Figure 12: Wavelet coherence: US Dollar exchange rate versus oil price

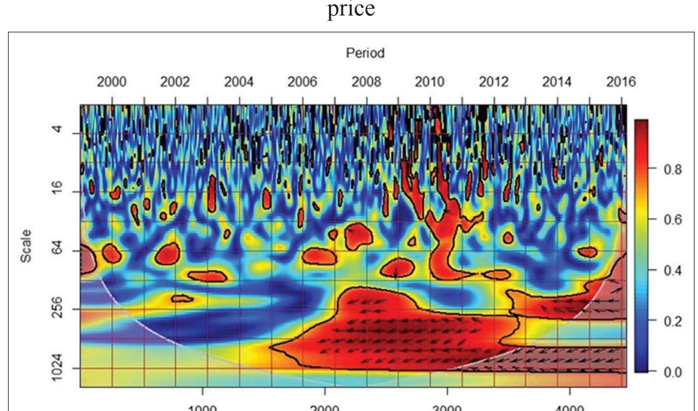


Table 3: Summery of wavelet coherence: OPEC currencies' exchange rate versus oil price

Country	Pegged exchange rate	High coherency (period)	High coherency (scale)	Phase-difference	Exchange rate (lead/lag)
Emirate	USD	2005-2011	260-1024	Anti-phase	Lagging
Angola	Floating	2009-2012	350-500	In phase	Leading
		2014-2016	128	Anti-phase	
Indonesia	Floating	2000-2003	240	Anti-phase	Leading
		2006-2001	128-512		
Kuwait	Basket	2001-2003	150-256	Anti-phase	Leading
		2005-2013	150-1024		
Libya	SDR	Different periods	Different scales	Mixed	Mixed
Nigeria	Floating	2005-2015	128-1024	Anti-phase	Leading
Qatar	USD	2007-2011	260	In phase	Leading
		2005-2009	700	Anti-phase	Lagging
Saudi Arabia	USD	2005-2013	512-1024	Anti-phase	Lagging
		2013-2016	128-500		Lagging
		2014-2015	32-100		Leading
Algeria	Floating	2006-2013	32-1024	Anti-phase	Leading
Iran	Floating	1999-2000	32-256	In phase	Leading
		2002-2004	32-128	In phase	Leading
		2007-2010	128-256	Anti-phase	Lagging
		2015	32-64	In phase	Leading
Ecuador	Floating	2005-2013	128-1024	Anti-phase	Lagging
		2013-2016	128-156		Leading

OPEC: Organization of Oil Exporting Countries

oil price leads exchange rate, exchange rate leads oil prices, and the relationship keeps changing. Countries with currencies pegged to USD are lagging against oil price changes, while countries with a floating exchange rate and countries with undisclosed weighted basket of international currencies lead changes in oil price. Finally, countries which currencies pegged to SDR have a changing relationship between oil prices and exchange rate.

The results of this study have interesting implications for policy makers and market players. It can optimize monetary policies to control inflationary pressures originated from oil or exchange rate fluctuation. It can help formulate currency policies of the oil producing and exporting countries, help in the pricing method of oil-related assets, and in the formulation of appropriate fiscal measures for OPEC members. Moreover, the implications of heterogeneity of market players are found in wavelet coherence by decomposing the causal relationship of oil prices and exchange rate into different time scales or investment horizons to match the heterogeneity of investment among market players.

Strong evidence of coherency is found between the change in oil price and exchange rate differential for high frequency and medium frequency corresponding to speculators and portfolio managers respectively. For the fundamentalists, pension and insurance fund managers and institutional investors for a business cycle of 1024 days and more, there is little evidence of coherency between oil price and real exchange rates.

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