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On the relationship between oil price and exchange rates: A wavelet analysis

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ABSTRACT

We may find numerous works in the existing literature regarding the cohesion between oil prices and exchange rates, yet an exact shape of the relationship remains undefined. By restoring to wavelet analysis and using a rich database from Japan, this study contributes to the literature by investigating the said relationship within the time–frequency space. Over the time horizon, it is being established that the strength of the relationship between oil price and exchange rate keeps changing. If the Bank of Japan needs to control the exchange rate, it should give proper importance to shocks on oil prices, while formulating exchange rate policy.

1. Introduction

From theoretical perspective, the concept regarding the relationship between oil market and currency market is firmly placed. The role of oil prices in explaining exchange rate movements was noted early on, by Golub (1983) and Krugman (1983): a country exporting oil may face exchange rate appreciation when oil price rises and exchange rate depreciation when oil price falls, whereas, the case is vice versa for an oil-importing country. Bloomberg and Harris (1995) tried to explain the same relationship from the perception of "law of one price for tradable goods". According to them, oil is a homogeneous and internationally traded commodity priced in US Dollar (USD). A depreciation of USD reduces the oil price to foreigners relative to the price of their commodities in foreign currencies and thus escalating their purchasing power and oil demand, consequently which pushes the USD-price of crude oil.

Recently the causality between these variables has become an interesting area to dig for researchers. Oil prices have a vital implication on both the real economy and financial markets. Huang and Tseng (2010) consider the price of crude oil as the primary variable that can explain the movements of foreign exchange rate. The earlier literatures were concentrated on the traditional methods of time series analysis, such as, different linear regressions, different approaches of co-integration techniques and variants of Granger-causality tests. Taking the empirical evidence, the relationship of the two variables in question, may possess, (a) a unidirectional aspect from the exchange rate to oil price (see, Zhang et al., 2008), (b) a unidirectional aspect from oil to exchange rate (see, Bénassy-Quéré et al., 2007 for china; Chen and Chen, 2007 for G7 countries; Chaudhuri and Daniel, 1998 for 16 OECD countries), and (c) a bi-directional aspect, having influences over each other for the variables (see, Chen et al., 2010 for Australia, Canada, Chile, New Zealand, and South Africa). Groen and Pesenti (2010) tried to explain the prediction of oil (and other commodities) by using exchange rate; interestingly, Amano and van Norden (1998) suggested that, if the model integrates oil price, prediction of exchange rate improves.

After US and china, Japan holds the world's third largest economy and is one of the major oil importing countries in the world (The World Factbook, 2012). As a key oil importing country, Japan's economy is intensively influenced by international oil price changes, explaining the movements in foreign exchange rates. This study is concentrated in understanding the co-movements between the change in real exchange rates and the real oil price differential using continuous wavelet analysis encompassing Japan. The scope of this study integrates both monthly and quarterly data between 1983M_{07}–2013 M_{05} and 1983Q_{03}–2013Q_{01}. To reproduce co-movements between changes in real exchange rates and oil prices in Japan, both time and frequency domains are considered.

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While explaining connection between changes in the real exchange rates and changes in the real oil prices in Japan, continuous wavelet transform possess several advantages over the other traditional time series techniques. In this procedure, we can interpret the change in real exchange rate and the real oil price differential with a flexible resolution in both frequency and time information that corresponds to leads and lags associated with variables that we are studying. The said approach strikes a balance between the time and frequency domain aspects of the monthly and quarterly data for Japan. Over the time horizons in Japan, it is also being observed that co-movements between changes in real exchange rates and real oil prices differs and takes various alternative shapes.

The paper is organized as follows. Section 2 presents a brief literature review on the association between oil price and exchange rates. The wavelet-based measure of co-movement is introduced in Section 3. Section 4 discusses the empirical findings; while Section 5 revolves around the concluding tones.

2. Literature review

According to Iwayemi and Fowowe (2011), since the 1970s, the influence of oil price over the macroeconomic indicators such as GDP, industrial production, inflation and interest rates has drawn an attention with the introduction of oil shocks; as movement in demand and supply has brought out an exponential climb in oil prices. Thus, the investigation on these issues remains fundamentally important for both oil importing and exporting countries. The influence of oil price over the macroeconomic indicators happens to be a well investigated area. For an instance, research related to the influence of oil price over stock price (Arouri, 2011), over economic growth (Kilian, 2009), over inflation (Tiwari, 2012), over industrial (Tiwari, 2012); may be cited here. The role for the demand side association between oil price and exchange rates was highlighted in the earlier literature by Golub (1983) and Krugman (1983), and more recently, by Reboredo (2012) and Turhan et al. (2012). According to the studies conducted by them, an oil-exporting country may experience a currency appreciation when oil price rise and depreciation when oil prices fall; whereas, the fundamentals are reverse in the case of an oil-importing country. Both the supply and demand channels take part in the making of a transmission apparatus through which oil prices impact the real exchange rate (Oriavwote and Eriemo, 2012).

The stand of the supply side argument is that, oil is one of the primary inputs in the production process. So, if the oil price escalates, it has an amplified influence on the cost of product and sales price, consequently which reduces the consumption capability and the demand of non-tradable goods drops down that contributes to a fall in their prices. Additionally, the real exchange rate also depreciates. The expression in the demand side argument also state about the same phenomenon. Wang and Wu (2012), for an instance, converse about the fact, that exchange rate is being conquered by oil prices.

Non-stationary feature of time series poses some problems, which can be mitigated by wavelet transformation. The major benefit offered by the wavelet analysis is that it can decompose macroeconomic time-series into a set of time-scale components, where each of the time-scale components elucidates the time development of the signal at a particular observation scale. Lately, implementations of wavelet analysis in the field of economics and finance are being documented in various literature.[1] We can also refer to the ground breaking work of Ramsey and Zhang (1996, 1997) and Ramsey and Lampart (1998a, b) which explained the wavelet analysis representing in-depth understandings regarding several economic phenomena. According to our record, by using a wavelet framework and applying a non-linear causality test, only Benhmad (2012), Tiwari et al. (2013) and using continuous wavelet only Uddin and Tiwari (2013) have explored the relationship of oil prices–US dollar real exchange rate. To investigate the linear and non-linear Granger causality between the real oil price and real effective U.S. dollar exchange rate, Benhmad (2012) took the aid of a wavelet approach. Moreover, Tiwari et al. (2013), by following the same approach, has found both linear and non-linear causal relationships between the oil price and the real effective exchange rate of Indian rupee at higher time scales (lower frequency). The investigators did not find any causal relationship at the lower time scale, though they found evidence of causality only at the higher time scales. Recently, Uddin and Tiwari (2013) using the continuous wavelet procedure to investigate the change in the real exchange rate and the change in the oil price differential for Bangladesh. The author's find that cycle of 32 months and more, less convincing evidence of coherence are sustained between the change in real oil price and exchange rate in Bangladesh. Nevertheless, none of the said studies represented the continuous wavelets transform possessing bias-rectified power spectra. In this work, wavelet tools developed by Ng and Chan (2012) are being used, that has improved the bias in the wavelet power spectrum (WPS) and in the wavelet cross-spectrum (XWT).

We contribute to these studies by restoring to wavelet approach that has several advantages in depicting the results in a simple way and that demands less strict assumptions on data. A vivid enumeration regarding the wavelet approach is presented at the next section.

3. A wavelet-based measure of co-movement

The appealing feature of the Wavelet transform in analyzing macroeconomic data is a three dimensional diagram that demonstrates time series information at different frequencies (low and high), time (short term or long term scale) horizons and strength of association is measured by color coding. The wavelet is classified in two groups, such as; discrete and continuous. In this present study, the methodological discussion is based on the continuous wavelet transform in examining the macroeconomic series which is suitable or preferable for orthogonal wavelet bases. The framework of continuous wavelet transform (CWT), cross wavelet transform (XWT) and wavelet coherency (WTC) is being borrowed from Grinsted et al. (2004).

3.1. The continuous wavelet transform (CWT)

In general, the time series application on a wavelet function is defined by $\psi_\Theta(\mu)$ with zero mean. In particular, the continuous wavelet transform $W_t^\varepsilon(\Omega)$ of a time series $x_{t,}$ at time $n_.$ and scale Ω with uniform time steps, can be written in the following expression:

$$W_t^\varepsilon(\Omega) = \sqrt{\frac{\Phi t}{\Omega}} \sum_{t=1}^{n} x_{n\ddot{E}} \psi_\Theta \left[(n\ddot{E} - n) \frac{\Phi t}{\Omega} \right] \tag{1}$$

where, n = 1,…, N, s is the set of scales used, and Φt is the time step (Grinsted et al., 2004). Through Fourier transform, the transform process would be faster. The wavelet power $|W_t^\varepsilon(\Omega)|^2$ is defined as the local phase. The cone of influence (COI) is introduces the edge effects. This study applied the similar procedure that Torrence and Compo (1998) used for Monte-Carlo simulation process for data generation. According to Torrence and Compo (1998), regarding the white noise and red noise wavelet power spectra, under the null, the corresponding distribution for the local wavelet power spectrum at each time n and scale Ω is as follows[2]:

$$D\left(\frac{|W_t^\varepsilon(\Omega)|^2}{\sigma_\varepsilon^2} < p \right) = \frac{1}{2} P_\varepsilon \chi_o^2(p). \tag{2}$$

[1] In and Kim (2006), Naccache (2011), Nachane and Dubey (2011), Gallegati et al. (2011), Jammazi (2012).

[2] Where o is equal to 1 for real and 2 for complex wavelets.

3.2. The cross wavelet transform (XWT) and phase angle

By identifying the common power of the change in real exchange rate and the real oil price differential in Japan, cross-wavelet transform provides for a criterion of comparison. However, without normalizing to the single WPS, wavelet cross spectrum cannot completely reflect the possible link between the change in real exchange rate and the real oil price differential in Japan, and is thus, no longer useful for relationship identification. Yet, it still remains good enough for phase estimation.

Taking the change in real exchange rate and the real oil price differential series, e_t and o_t with the wavelet transformation W^e and W^o, the cross wavelet transform (XWT) is defined as $W^{eo} = W^e W^{o*}$, where W^e and W^o are the wavelet transforms of e and o respectively, denoting complex conjugation. In the light of Torrence and Compo (1998), theoretical distribution of the cross wavelet power of two time series P_k^e and P_k^o with background power spectra, can be defined as:

$$D\left(\frac{\left|W_t^e \Omega W_t^{o*}(\Omega)\right|}{\sigma_e \sigma_o} < p\right) = \frac{Z_\omega(p)}{\omega}\sqrt{P_k^e P_k^o}. \tag{3}$$

In the Eq. (3), $Z_\omega(p)$ is the confidence level.[3]

It is worthy to mention that recent literature on the wavelet power spectra (WPS) has found the evidence of bias on the way to low-frequency oscillations (Liu et al., 2007; Veleda et al., 2012). This transformation process is found to be obvious in the estimation of WPS. Liu et al. (2007) worked with times series including the combination of frequency and time horizon, yet failed to produce identical peaks at the same amplitudes. To Veleda et al. (2012), this shortcoming also existed in the wavelet cross spectrum (XWT). In order to overcome this limitation in the wavelet cross spectrum(XWT), we applied wavelets tools developed by Ng and Chan (2012) that improved on the bias attached to wavelet power spectrum (WPS) and wavelet cross-spectrum (XWT).

3.3. Wavelet coherence (WTC)

We can use the Wavelet coherence (WTC) as a tool for analyzing to represent the relationships between two processes by searching frequency bands and time intervals. Specifically this procedure associated with linear correlation analysis that helps revealing intermittent correlations between two phenomena (Gurley and Kareem, 1999; Gurley et al., 2003), and their significant linear cohesion relationship. It is thus possible to efficiently calculate WTC analysis for relationship between the change in real exchange rate and the real oil price differential in Japan, even at intervals where high coherence exists having minimal power in the WPS of the two processes. Following Torrence and Webster (1999), the Wavelet Coherence of the change in real exchange rate and the real oil price differential in Japan series can be defined as:

$$R_t^2(\Omega_s) = \frac{\left|\varepsilon\left(\Omega_s^{-1} W_t^{eo}(\Omega_s)\right)\right|^2}{\varepsilon\left|\left(\Omega_s^{-1}|W_t^e(\Omega_s)|^2\right)\right| . \varepsilon\left|\left(\Omega_s^{-1}|W_t^o(\Omega_s)|^2\right)\right|}. \tag{4}$$

Here, ε is considered as a smoothing operator (Rua and Nunes, 2009) and $R_t^2(\Omega_s)$ s the value of the wavelet squared coherency.[4] In Eq. (4), the numerator is explained the absolute value squared of the smoothed cross-wavelet spectrum and denominator represents the smoothed wavelet power spectra (Rua and Nunes, 2009; Torrence and Webster, 1999). This present study will focus on the Wavelet Coherency, instead of the Wavelet Cross Spectrum, pursuing the study by Aguiar-Conraria and Soares (2011). The circular mean of the phase over regions is being used in this study, with higher than 5% statistical significance that is outside the COI, to quantify the phase relationship by following Grinsted et al. (2004).

4. Data and empirical findings

For empirical purpose, we have collected both monthly and quarterly frequency data on real oil price and real exchange rate over the period of 1983 M_{07}–2013 M_{05} and 1983Q_{03}–2013Q_{01}, as wavelet methodology requires a large data observation. This scope of the period is based on the availability of data in the Datastream. For reliable and consistent results, data span as such, is large and sufficient enough. Real exchange rate is constructed aligning with the changes in exchange rates of two currencies—Japan and US—which is determined by the relative prices of the countries in question. The WTI (West Texas Intermediate) based crude oil price (a variable) is expressed in real terms. The first difference of the logarithmic transformation of the concerned variables; "RER" is represents for the change in real exchange rate and "ROP" is represents for the change in real oil price. Fig. 1 we present the WPS of concerned variables, in Fig. 2 we present XWT and in Fig. 3 we present WTC.

In this section, we present the results of the changes in real exchange rate (RER) and the real oil price (ROP), obtained by using three dimensional graphs namely, continuous, cross and Squared Wavelet (Coherence) approach. Fig. 1 represents the continuous wavelets transform having bias-rectified power spectra[5] of monthly and quarterly series regarding the change on the real exchange rate and the return on real oil price between 1983 M_{06}–2013 M_{05} and 1983Q_{02}–2013Q_{01}. The information on the change in the real exchange rate and on the change in the real oil price has demonstrated higher power in different frequency and also in different time scale.

From the analysis of the result obtained from Fig. 1, the change in the real exchange rate has higher power in the 8–15 months of scale (frequency) which corresponds to 1995s, 1999 to 2000s and 2008s respectively, during the period 1983 M_{06}–2013 M_{05}; whereas in the 0–4 quarters of scale (frequency), which corresponds to 1987s, 1988s and 1991s respectively has high power during the period 1983Q_{02}–2013$Q_{01.}$ On the other hand, the increasing trend in the real oil price has higher power in the 4–8 months of scale (frequency) which corresponds to 1985s; in the 06–12 months of scale (frequency) which corresponds to 1991s; and in the 8–32 months of scale (frequency) which corresponds to the year 2006 to 2009 respectively, during the period 1983 M_{06}–2013 M_{05}. Contrasting with the quarterly data, it has higher power in the 0–12 quarters of scale (frequency) which corresponds to 2008s, and in the 0–5 quarters of scale (frequency) which corresponds to 1990s. The results claim that both the changes in real exchange rate and in the real oil price have high power in the short-term time scale or in long-term frequency band. It is evident that for both series, the high power region is above the 5% significant level.

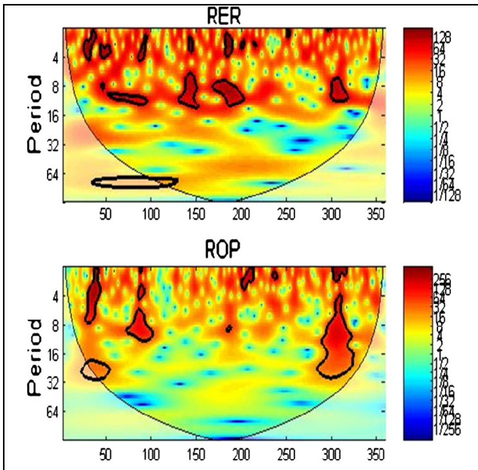
In order to understand the relations between the two variables in a better form, the cross-wavelet transform may be helpful; since referring to the continuous wavelet transform poses several difficulties while explaining the coincidence of the variables.

Fig. 2 represents the cross-wavelet transform regarding the co-movement between the changes in the real exchange rate and the changes in the real oil price. The variables are mostly in the phase, in the significant region. Considering the typical co-movement pattern, the co-movement between the changes in the real exchange rate and the changes in real oil price is concentrated on the short term frequency scale.

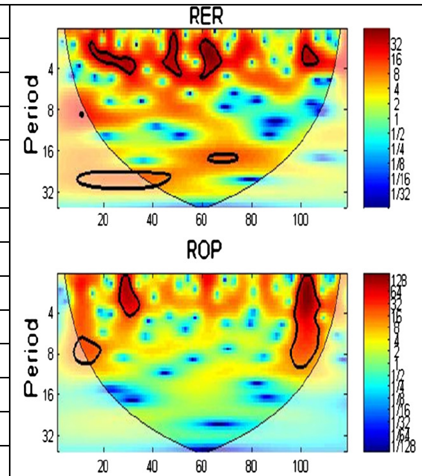
[3] $Z_\omega(p)$ is attached with the probability p for a pdf defined by the square root of the product of two χ^2 distributions. In this paper, phase angles pointing left and right represent anti-phase and in-phase relationships, respectively.

[4] The range between 0 and 1.

[5] The software for the bias-rectified wavelet power spectrum, partial wavelet coherence and multiple wavelet coherence was provided by E.K.W. Ng and T.W. Kwok, which is available at: http://www.cityu.edu.hk/gcacic/wavelet.



Monthly	
50	1987M08
100	1991M10
150	1995M12
200	2000M02
250	2004M04
300	2008M06
350	2012M08
Quarterly	
20	1988Q02
40	1993Q02
60	1998Q02
80	2003Q02
100	2008Q02



Notes:

1. The continuous wavelet power spectra of both real exchange rate RER (top) and real oil price ROP (bottom) are shown here.
2. The thick black contour designates the 5% significance level estimated from Monte Carlo simulations using phase randomized surrogate series.
3. The cone of influence, which indicates the region affected by edge effects, is depicted with a lighter shade black line.
4. The color code for power ranges from Blue (low power) to Red (high power).
5. Y-axis measures frequencies or scale and X-axis represents the time period studied. The left and right side present the monthly and quarterly data, respectively.
6. Data Range: $1983M_{07}$ -$2013M_{05}$ and $1983Q_{03}$ – $2013Q_{01}$
7. Data Source: Datastream

Fig. 1. Continuous wavelet power spectra of RER and ROP. Notes: 1. The continuous wavelet power spectra of both real exchange rate RER (top) and real oil price ROP (bottom) are shown here. 2. The thick black contour designates the 5% significance level estimated from Monte Carlo simulations using phase randomized surrogate series. 3. The cone of influence, which indicates the region affected by edge effects, is depicted with a lighter shade black line. 4. The color code for power ranges from blue (low power) to red (high power). 5. Y-axis measures frequencies or scale and X-axis represents the time period studied. The left and right side present the monthly and quarterly data, respectively. 6. Data range: 1983 M_{07}–2013 M_{05} and $1983Q_{03}$–$2013Q_{01}$ 7. Data Source: Datastream. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In particular, at the long-term frequency band (or short term time scales), in the 8–12 and 4–16 months of scale, the arrows are pointing right, indicating that variables are in the phase corresponding to the 2000s and 2008–2009s. However, during 1991s observation, in the 8–12 months of scale, arrows are pointing left-down, slightly; indicating that ROP is lagging to the RER in Japan.

Referring to the co-movements in the quarterly time interval, during the cycles of 1990s and 2008s, in the 2–5 and 2–6 quarters of scale, it is found that arrows are right-up and left-down, slightly; indicating that ROP is lagging to RER. The shown graphical analysis illustrates that, the arrows in the 2–4 quarters of scale corresponding to 1998s are pointing to right; which indicates that the variables are in the phase. On top of it, outside the area that has significant power, the variables are in the phase, invariably.

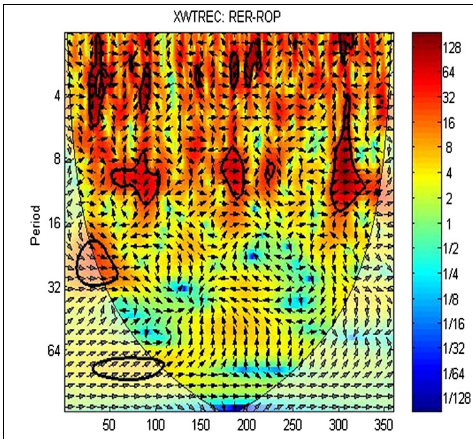
If, we adhere our attention at the Wavelet coherency and refer to the analysis of the results of Fig. 3, we will find that for two variables, more portions of the data stand out as being significant. The area of the time frequency plots below the 95% confidence level and it is not a reliable sign of causality. An interesting scenario is being identified regarding the causality between the change in exchange rate and the return on oil price in Japan, considering the co-movement between these two variables.

Wavelet coherency gives us a transparent impression that the variables are mostly in the phase during the periods between 1986–1989s and 2007–2010s. Referring to the monthly information at the short term scale of 8–16 months, arrows are pointing right-down, indicating that the ROP is leading to RER that corresponds to the 2000s. In the long-term frequency or short-term scale of 8–16 months, within the period of 2002s, arrows are also pointing right-down, signifying that the ROP is leading RER. In the cycle between 2007 and 2010, the arrows are indicating that variables are out of the phase in 6–12 months' scale. Looking at the 64–68 months' scale, it is being found that, in the long-term scale or short-term frequency, arrows are directing towards right-up, which gives an impression that the ROP is lagging to RER; corresponding to the 1991–2000s cycles.

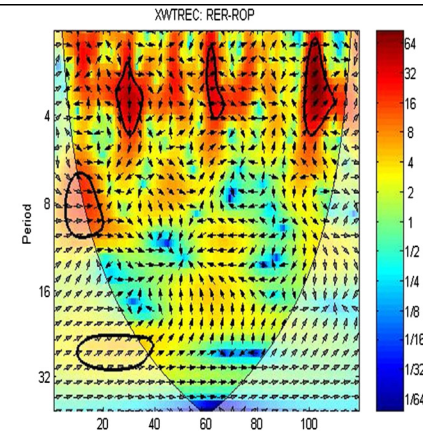
In the 0–6 and 6–12 quarters of scale, on the contrary side of the quarterly observation, the arrows are pointing to right, indicating that the series are in the phase, corresponding to the 1985–1990s and 1998–2003s cycles. Additionally, in the time horizon of 2007–2010s, in the scale of 0–8 quarters, arrows are pointing right-up, signifying that the ROP is lagging. In the long-term scale or in the short-term frequency band, within the cycle between 1993 and 2003s, in the 24–30 quarters of scale, arrows are directed (again) towards right-up, demonstrating that the ROP is lagging to RER in Japan.

5. Conclusion

This study, restoring to wavelet analysis, tries to sort out the relationship between exchange rate and oil price within both the time and frequency space, by using the data of Japan (over the period of 1983 M_6–2013 M_{05}). To strike a balance between the time and frequency domain aspects of data, a wavelet-based measure of co-movement is being used, which, ultimately fine-tunes the previous approaches practiced in analyzing time series. It is being found that,



Monthly	
50	1987M$_{08}$
100	1991M$_{10}$
150	1995M$_{12}$
200	2000M$_{02}$
250	2004M$_{04}$
300	2008M$_{06}$
350	2012M$_{08}$
Quarterly	
20	1988Q$_{02}$
40	1993Q$_{02}$
60	1998Q$_{02}$
80	2003Q$_{02}$
100	2008Q$_{02}$



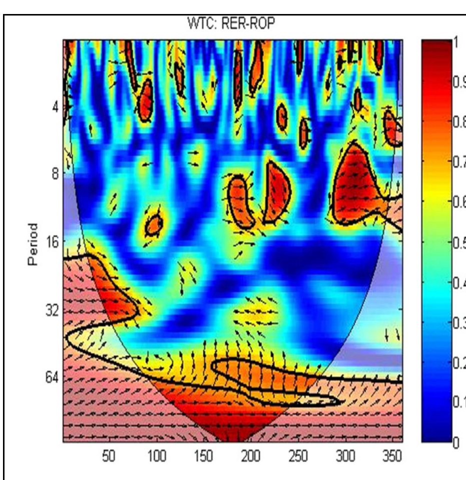
Notes:

1. The phase difference between the real exchange rate RER and real oil price ROP is indicated by arrows.
2. Arrows pointing to the right mean that the variables are in the phase; to the right and up, with ROP is lagging and to the right and down, with ROP is leading.
3. Arrows pointing to the left mean that the variables are out of the phase; to the left and up, with ROP is leading and to the left and down, with ROP is lagging.
4. "In the phase" indicates that variables will be having cyclical effect on each other and "out of the phase" or "anti-phase" shows that variable will be having anti-cyclical effect on each other.
5. Data range and source same as figure 1.

Fig. 2. Cross wavelet transform of RER and ROP. Notes: 1. The phase difference between the real exchange rate RER and real oil price ROP is indicated by arrows. 2. Arrows pointing to the right mean that the variables are in the phase; to the right and up, with ROP is lagging and to the right and down, with ROP is leading. 3. Arrows pointing to the left mean that the variables are out of the phase; to the left and up, with ROP is leading and to the left and down, with ROP is lagging. 4. "In the phase" indicates that variables will be having cyclical effect on each other and "out of the phase" or "anti-phase" shows that variable will be having anti-cyclical effect on each other. 5. Data range and source same as Fig. 1.

the strength of co-movement regarding the return on the real effective exchange rate and oil price growth, differ and deviates over the time horizon. From the said findings, it can be suggested that, Japan should emphasize on the shocks of oil price, at a greater scale, while establishing a steady state of exchange rate.

On top of it, results found and conclusion drawn in this study have interesting implications for the policy makers and traders in the areas of effective risk management, in the optimization of monetary policies to control inflationary pressures originated from oil or exchange rate fluctuations in the formulation of the yen–dollar-pegging policies for



Monthly	
50	1987M08
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200	2000M02
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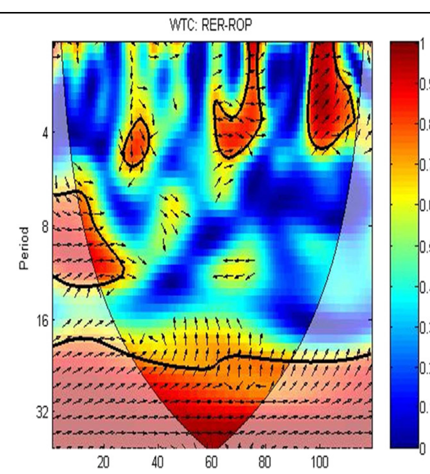
300	2008M06
350	2012M08
Quarterly	
20	1988Q02
40	1993Q02
60	1998Q02
80	2003Q02
100	2008Q02



Notes:

1. The color code for coherency ranges from blue (low coherency-close to zero) to red (high coherency-close to one).
2. The arrow and phase have the same note as figure 2.
3. Data range and source same as figure 1.

Fig. 3. Wavelet coherency of RER and ROP. Notes: 1. The color code for coherency ranges from blue (low coherency—close to zero) to red (high coherency—close to one). 2. The arrow and phase have the same note as Fig. 2. 3. Data range and source same as Fig. 1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Japan (a major petrol-importing country), in the pricing method of petrol-related assets and/or products, and also in the formulation of an appropriate fiscal policy measures for Japan.

Strong evidence of coherency is being found between the change in real oil price and real exchange rate differential for short and medium month cycles corresponding to speculative trading (high frequency or noise trading i.e., for time horizons less than 34 months). Nonetheless, for the fund-managers and institutional investors (known as fundamentalists), for business cycle of 34 months and more, less strong evidence of coherency between real oil price and real exchange rate is being noticed.

Additionally, Japan[6] is the third largest industrialized advanced economy based on 2012 nominal GDP and is amongst the top major oil importing counties after U.S. and China. Hence, as oil is one of the primary inputs in the production process, the pacey adjustment of the Japanese economy depends on the consumption or availability of oil. Fundamental discussion in the monetary transmission mechanism ascertains that the fluctuation of the oil price shock can harm industrial output that will influence inflation through the exchange rate depreciation. Consequently, the negative oil shock is sensitive to the industrial output in Japan.

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[6] Source: CIA World Factbook January 1, 2012.