



OIL PRICE AND EXCHANGE RATE IN MALAYSIA: A TIME-FREQUENCY ANALYSIS

Aviral Kumar Tiwari¹

¹Faculty of Management, IBS Hyderabad, IFHE University, India

ABSTRACT

The study analyzed the Granger-causal relationship in the time-frequency framework between return series of real oil price (ROP) and real effective exchange rate (REER) for Malaysia. In doing so, study relied on time-frequency framework of the Granger-causality, which is based on continuous wavelet approach. We found that the causal and reverse causal relations between oil price and real exchange rate vary across scale and period viz., during late 1989, in the time scale of 8~10 months, both variables were in phase and ROP was leading and both variables were out of phase and ROP was leading (a) in 1990-1991, in the time scale of 12~16 months, (b) in 1997-1998 in the time scale of 10~16 months, (c) in 2001-2003, in time scale of 9~15 months, and (d) in 2005 and early 2006, in the time scale of 2~7 months. Further, evidence shows that during 1989-1998, in 32~48 months scales, variable were in phase and ROP was lagging and throughout the study period, in 60~64 months scale, variables were in phase and ROP was leading. Hence, our evidence show that there is evidence of both cyclical and anti-cyclical relationship between ROP and REER at shorter time scales however, throughout study for higher scales REER was lagging and receiving cyclical effects of ROP shocks. Findings obtained in the study have implications for central monetary authority of Malaysia in the formulations of appropriate monetary and exchange rate policies and for traders in the formulations of effective risk management.

© 2015 AESS Publications. All Rights Reserved.

Keywords: Cyclical and anti-cyclical effects, Wavelet coherency, Real oil price, Real effective exchange rate, Malaysia.

JEL Classification: C40, E32.

Contribution/ Originality

This is the first study for the Malaysian economy in the context studied using the wavelet approach. Hence, results obtained may offer more insights for central monetary authority as well as risk managers from the policy perspectives.

1. INTRODUCTION

In the economic system the traders are categorized according to their characteristic time horizons or dealing frequencies, following upon the heterogeneous market hypothesis. To this end, study focus on the Granger-causality analysis in time-frequency framework between the variables of our interest by utilizing the continuous wavelet approach. This is because the market participants [1] differ in various aspects such as in their beliefs, their expectations, informational sets, risk profiles, and so on and so forth. As the market operates with different dealing frequencies (i.e., because of the presence of market heterogeneity) market responds differently at the same time for same news in the market. Further, each market component has varying reaction time to the news related to its time-frequency horizons (Dacorogna *et al.*, 2001).

The Granger-causality between exchange rate and oil price has been widely debated and comprehensively studied topic in the literature but results are inconclusive so far because of the type of exchange rate (i.e., real or real effective exchange rate) used, econometric method employed, period and country studied. Sadorsky (2000) and Zhang and Wei (2010), among others, argue that movements in the exchange rates may Granger-cause the change of the crude oil price and contribute to the oil price movements, whereas Chaudhuri and Daniel (1998), Bénassy-Quéré *et al.* (2007), Chen and Chen (2007), Coudert *et al.* (2008), Lizardo and Mollick (2010) have provided an empirical evidence that oil price Granger-cause exchange rate.

There are outstanding studies which suggest that oil price should not be studied as a gross variable as a lot of information content is lost by doing so. Various approaches have been used by researchers to overcome such issues for example, Mork (1989) decomposition of the oil price into two components, increase and decrease, Lee *et al.* (1995) “surprise effect” measure, and Kilian (2006) decomposition of the oil price shocks into 3 shocks such as:- supply shocks, aggregate demand shocks (that also affect other commodities) and oil specific demand shocks (that only affect the oil demand). These “transformations” of the oil price, proves that the oil price should not be studied as an aggregate series.

Despite the precious information the aforesaid transformation yield, they do not address an essential characteristic of the oil price i.e., they fail to deal with the heterogeneity market hypothesis. Furthermore, most of studies have used one-shot measure of Granger-causality and/or Fourier transformed series and/or spectral approach (when frequency domain is analyzed) and if any wavelet is used, discrete wavelet approach is utilized in those studies [2]. Whereas this paper aims to analyze the Granger-causality between the return series of oil price and exchange rate in the framework of continuous wavelets (please refer to section 2.2 for advances of this approach over

the discrete wavelet approach), which is able to detect the possible nonlinearities and complexities of such markets with reference to time. This is the first attempt for Malaysian economy to the best of our knowledge. This paper models the relationship between the return series of oil price and real effective exchange rate of Malaysia by using continuous wavelet approach. The results show the varying causal and reverse causal relationship between oil price and exchange rate across time and frequencies. Both cyclical and anti-cyclical relationship between oil price and exchange rate are found however, throughout the study period for higher time scale i.e., during study period and in 60~64 months scale, variables were in phase and ROP was lagging (that is ROP was lagging and receiving cyclical effects of REER shocks).

The study differs from the earlier works in many ways. Previous studies used Granger (1969) based linear Granger-causality methodology (those were based on time domain approach) to test the causal relationship between exchange rate and oil price. Normally used Granger causality tests, are based on unable to take in to account cyclical and anti-cyclical relationship between variables whereas approach used in the present study is useful to answer this question. Hence, we extend previous studies by testing the causality with wavelet approach. To analyse non-linear Granger-causal relationship some studies have used short-term Fourier, spectral or discrete wavelet based approaches so that causality can be evaluated in various frequency levels. However, in all the three approaches time content is lost. Therefore, even if we are able to analyse the Granger-causal relationship at various frequencies we are unable to identify in which year (or during which period) Granger-causal relationship was in existence and in which year (during which period) there was no Granger-causality. To this direction continuous wavelet has advantages. With this approach we are able to detect the Granger-causality between test variables and also able to keep time dimension of the data. Thus, we are able to capture both the time and frequency aspect in our analysis i.e., we are able to identify business cycle, their duration and also when they were detected and what was their strength. These are the major contribution of the study.

The remainder of the paper is organised as follows. Section 2 provides information about data and wavelet methodology used in the paper. In Section 3, the results of the analysis are discussed. Section 5 concludes.

2. DATA AND METHODOLOGY

2.1. Data

For the empirical estimation monthly data over the period 1986:01 to 2009:03 was collected in order to have enough observations. Exchange rate is measured by real effective exchange rate which is obtained from International Monetary Fund (IMF) CD-ROM of 2010 and the crude oil price variable is expressed in real terms, i.e., deflated by Malaysian consumer price index. Crude oil prices are the spot prices: West Texas Intermediate (WTI) - Cushing Oklahoma, (Source: U.S. Department of Energy: Energy Information Administration).

2.2. Methodology

The wavelet transform stretched and translates a time series with a flexible resolution in both frequency and time. The process is explained in very brief as follows:

Say, for example, the Morlet wavelet equation for a time series x_t at time n and scale τ with uniform time steps, in the continuous wavelet transform (CWT) $W_t^u(\tau)$ can be rewritten in the following expression:

$$W_t^u(\tau) = \sqrt{\frac{\delta t}{\tau}} \sum_{t=1}^n x_{n'} \Psi_{\theta} \left[(n' - n) \frac{\delta t}{\tau} \right] \quad (1)$$

Where, the wavelet power $|W_t^u(\tau)|^2$ is defined as the local phase. The edge effects are introduced by the Cone of Influence (COI). We followed the Monte-Carlo simulation process following the work of [Torrence and Compo \(1998\)](#) and computed the wavelet power spectrum¹ cross wavelet transform (XWT), wavelet coherency (WTC) and phase-differences following the work of [Grinsted et al. \(2004\)](#).

The two financial time series such as the change in real exchange rate and the change in real oil price, u_t and v_t , with the wavelet transformation W^u and W^v , the cross wavelet transform (XWT) is defined as $W^{uv} = W^u W^{v*}$, where W^u and W^v are the wavelet transforms of u and v , respectively, denoting complex conjugation. Using the similar description of the XWT, the Wavelet Coherence (WTC) ([Torrence and Webster, 1999](#)) between the change in real exchange rate and the change in real oil price of two time series can be defined as:

$$R_t^2(\tau_s) = \frac{|\varepsilon(\tau_s^{-1} W_t^{uv}(\tau_s))|^2}{\varepsilon[|\tau_s^{-1} W_t^u(\tau_s)|^2] \varepsilon[|\tau_s^{-1} W_t^v(\tau_s)|^2]} \quad (2)$$

where, ε is considered as a smoothing operator. In equation 2, the numerator is the absolute value squared of the smoothed cross-wavelet spectrum and denominator represents the smoothed wavelet power spectra ([Torrence and Webster, 1999](#)). The value of the wavelet squared coherency $R_t^2(\tau_s)$ gives a quantity between 0 and unity. This present study will focus on the Wavelet Coherency, instead of the Wavelet Cross Spectrum pursuing the application by [Aguilar-Conraria and Soares \(2011\)](#).

3. DATA ANALYSIS AND EMPIRICAL FINDINGS

Before, we move for estimation both series are transformed to their natural logarithms. Time series plot of both the series (in log-level and log-first difference form) are presented in Figure 1. We presented the descriptive statistics of monthly oil and real effective exchange rate, measured in log level as well as in returns in Table 1. The sample means of exchange rate (in level) and oil price (in first difference) is positive whereas the sample mean of oil price (in level) and exchange rate (in first difference) is negative. The measure of skewness indicates that in level form both series are positively skewed whereas return series are negatively skewed. The return series (and also level series of oil prices) have demonstrated excess kurtosis which indicates that distributions of those

¹ $D \left(\frac{|W_t^u(\tau)|^2}{\sigma_u^2} < p \right) = \frac{1}{2} P_{k\lambda}^2(p)$, where ν is equal to 1 and 2 for real and complex wavelets respectively.

series are leptokurtic relative to a normal distribution. The Jarque-Bera normality test rejects normality of all series, at any level of statistical significance. In the next step stationary property of the data series of all test variables has been tested through ADF and PP test [4]. We find that both variables are non-stationary in the log level form while they are stationary at their first differenced form. Therefore, for further analysis we transformed our series into first difference from hence, both the series represents the monthly returns:- which were calculated as the differences of the two variables natural logarithms of successive months.

Table-1. Descriptive statistics of level and returns series

	LnROP	LnREER	D(LnROP)	D(LnREER)
Mean	-1.135080	4.765124	0.000395	-0.001636
Median	-1.219038	4.787595	0.009463	-0.000700
Maximum	0.165776	5.079558	0.392189	0.129947
Minimum	-2.062262	4.517996	-0.394981	-0.116364
Std. Dev.	0.417518	0.129520	0.089487	0.019394
Skewness	0.917189	0.090951	-0.378604	-0.001593
Kurtosis	3.773273	1.750571	5.960100	16.73864
Jarque-Bera	45.90351	18.46572	108.1369	2186.357
Probability	0.000000	0.000098	0.000000	0.000000

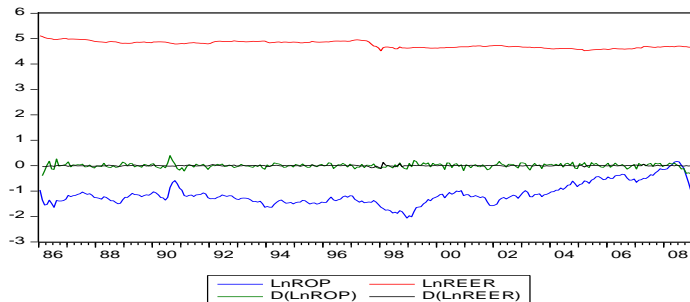


Figure-1. Plot of the real effective rupee exchange returns and oil returns

Firstly, in Fig. 2 we present results of continuous wavelet power spectrum of both real effective exchange rate (in the top) and real oil price (in the bottom).

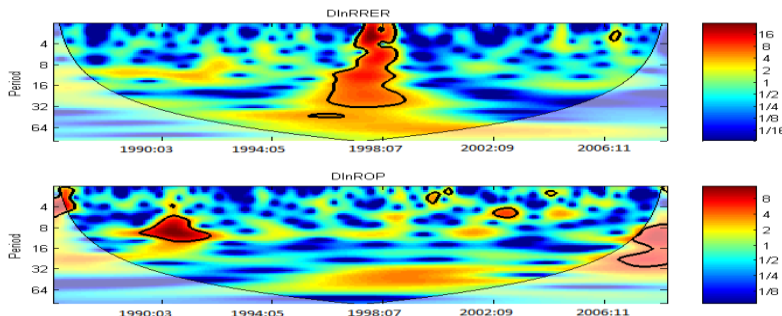


Figure-2. The continuous wavelet power spectrum of DlnREER and DlnROP

Note: The thick black contour designates the 5% significance level against red noise and the cone of influence (COI) where edge effects might distort the picture is shown as a lighter shade. The color code for power ranges from blue (low power) to red (high power). Y-axis measures frequencies or scale and X-axis represent the time period studied.

It is evident from Fig.2 that there are some common islands i.e., there are some common areas where wavelet power is high in both the signals. In particular, the common features in the wavelet power of the two time series (signals) are evident in 9~12 months scale corresponding to 1990-1991 and around 32~64 months scale corresponding to 1997-2002. Some close relation between oil price and exchange rate is also observed in the post 2002 however, the wavelet power is not so high. Noteworthy to mention that the portrayed patterns depicting the similarity between the time series in these periods is vague and it may be just a coincidence. Thus we analyzed the cross wavelet transform in order to get more insights. The results obtained through cross wavelet analysis are presented in Fig.3.

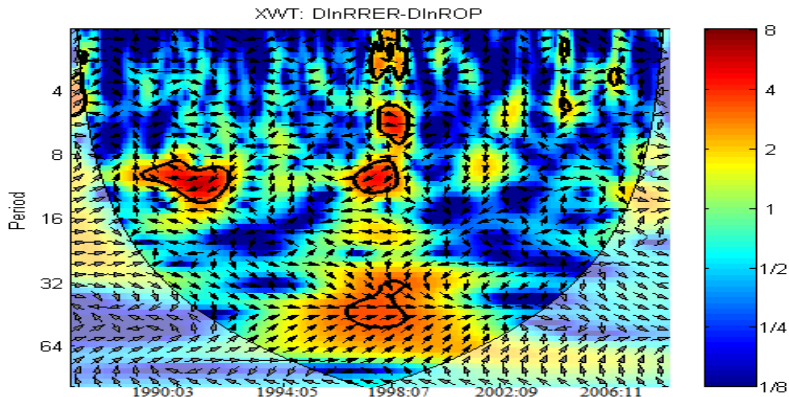


Figure-3. Cross wavelet transform of the DlnREER and DlnROP time series

Note: The thick black contour designates the 5% significance level against red noise which estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is shown with a lighter shade black line. The color code for power ranges from blue (low power) to red (high power). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, with real oil price (ROP) is leading. To the right and down, with ROP is lagging. Arrows pointing to the left mean that the variables are out of phase. To the left and up, with ROP is lagging. To the left and down, with ROP is leading. In phase indicate that variables will be having cyclical effect on each other and out of phase or anti-phase shows that variable will be having anti-cyclical effect on each other.

We find from the close observation of Fig.3 that there is difference in the direction of arrows across time-frequency. In 1990-1991, in the significant region (marked by thick black contour), arrows are left up and left down in the 9~12 months scale, indicating that variables are out of phase in this period and real oil price (ROP) is leading and lagging, respectively. This provides evidence of bi-directional causal relationship between the ROP and REER during 1990-1991 i.e., in 1990-1991 anti-cyclical effect are observed on each other. However, during 1994-2002 we observe that (a) arrows are right up in the scale of 48~96 months, indicating that variables are in phase and ROP is leading; (b) arrows are right down in the scale of 32~48 months indicating that variables are in phase and ROP is lagging. During 1997-1998 arrows are left down in the scale of 10~13 months scale indicating that variables are out of phase and ROP is leading and in 1998 arrows are right down in the scale of 5~7 months indicating that variables are in phase and ROP is lagging. Hence, in 1998 we observe the cyclical and anti-cyclical relationship between real oil price and exchange rate in Malaysia wherein ROP was leading in anti-cyclical situation and lagging variable when cyclical effects were observed. Broadly we observe that in the shorter months scale arrows are left

down throughout the period of high common power indicating that variables are out of phase and ROP is leading and for higher months scale we observe that arrows are right up and right down indicating that variables are in the phase and both are causing each-other. The situation, when arrows are right-up, indicates that REER is accommodating cyclical effect from ROP. Similarly, right-down arrows indicates that ROP is accommodating cyclical effect REER. Even if, now, we do not have very clear results but this type of results one analyst would have not got if he/she would have utilized either time series or spectral or frequency analysis based methods. Overall we, therefore, speculate that there is a stronger link between return series of ROP and REER than that implied by the cross wavelet power.

Finally, we relied on the wavelet coherency as the wavelet cross-spectrum (i.e., cross wavelet) does not normalizes the single wavelet power spectrum and thus results obtained can be misleading whereas the wavelet coherency is used to identify both frequency bands and time intervals within which pairs of indices are co-varying. In Fig. 4 we present results obtained from the cross-wavelet coherency analysis.

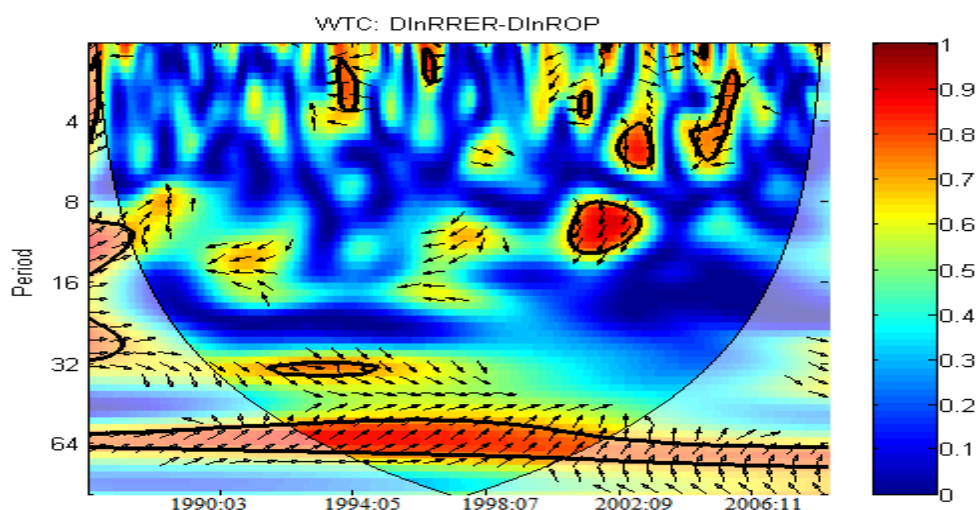


Figure-4. Cross-wavelet coherency or squared wavelet coherence between DlnREER and DlnROP

Note: The thick black contour designates the 5% significance level against red noise which is estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line. The color code for coherency ranges from blue (low coherency-close to zero) to red (high coherency-close to one). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, with ROP is leading. To the right and down, with ROP is lagging. Arrows pointing to the left mean that the variables are out of phase. To the left and up, with ROP is lagging. To the left and down, with ROP is leading. In phase indicate that variables will be having cyclical effect on each other and out of phase or anti-phase shows that variable will be having anti-cyclical effect on each other.

The squared WTC of return series of real oil price and real exchange rate is shown in Fig.4. If we compare results of WTC and XWT i.e., if we compare Fig.3 and Fig.4 we find very clear results of phase difference of lead-lag relationship between return series of real oil price and real exchange rate in Fig.4. We find that variables are in phase and ROP is leading in 1989, in the time scale of 8~10 months, as arrows are right up; variables are out of phase and ROP is leading (as arrows are left down) (a) in 1990-1991, in the time scale of 12~16 months, (b) in 1997 -1998 in the time scale

of 10~16 months, (c) in 2001-2003, in time scale of 9~15 months, and (d) in 2005 and early 2006, in the time scale of 2~7 months. However, in 32~48 months scale we observe that arrows are right down before 1998 indicating that variable are in phase and ROP is lagging and in 60~64 months scale throughout the period studied we observe that arrows are right up indicating that variables are in phase ROP is leading. The most interesting part which comes now in existence (which did not appear in XWT analysis) is the evidence of bidirectional causal relationship between the return series of oil price and exchange rate during 1986 to 1998 (but note that there is difference in time scale). Now with the application of WTC analysis we have very clear evidence on lead-lag relationship between return series of oil price and exchange rate. Further, we also come to know whether one variable influence or influenced by the other through anti-cyclical or cyclical shocks. Definitely these results would have not been drawn through the application of time series or Fourier transformation analysis if one could have attempted.

4. CONCLUSIONS

The study analyzed Granger-causality in the wavelet transform framework between the return series of real oil price (ROP) and real effective exchange rate (REER) for Malaysia. The ADF and PP unit root tests show that that both variables are nonstationary in log level form and stationary in log first difference form. The continuous power spectrum figure shows that the common features in the wavelet power of the two time series are evident in 9~12 months scale corresponding to 1990-1991 and around 32~64 months scale corresponding to 1997-2002. Results of XWT are unable to give clear-cut results but indicate that both variables have been in phase and out phase (i.e., they are anti-cyclical and cyclical in nature) in some or other durations. However, the WTC results, which can be interpreted as correlation, reveal that both variables were in phase and ROP was leading during the late 1989 in the time scale of 8~10 months, and both variables were out of phase and ROP was leading (a) in 1990-1991, in the time scale of 12~16 months, (b) in 1997 -1998 in the time scale of 10~16 months, (c) in 2001-2003, in time scale of 9~15 months, and (d) in 2005 and early 2006, in the time scale of 2~7 months. Further, evidence shows that during 1989-1998, in 32~48 months scales, variable were in phase and ROP was lagging and throughout the study period, in 60~64 months scale, variables were in phase ROP was leading. Hence, we find for the Malaysian economy that there is varying nature of causal and reverse causal relations between oil price and real exchange rate vary across time and frequencies. There are evidence of both cyclical and anti-cyclical relationship between oil price and exchange rate however, for throughout the period and for higher scales real exchange rate was lagging and receiving cyclical effects emanating from real oil price shocks.

These findings have commanding implications for government policy making and monetary authority of Malaysia. These findings will also guard traders for effectively management of risk. Further, as a major player on the global stage, performance of the Malaysian economy depends on the consumption of oil. Oil is a major factor of production and when prices are non-sticky, oil price

shocks can lead to reduced output, increased inflation, and real exchange rate depreciation. However, the deepness of negative consequences of oil shocks such as output losses, inflation etc., will depend on the sensitivity of the consumer durables (where oil is a factor of production) to the oil prices.

For the fundamentalists e.g. fund-managers and institutional investors, for time horizons more than 32 months, strong bidirectional causal relationships between ROP and REER are found. Further, as a major player on the global stage, performance of the Malaysian economy depends on the consumption of oil. Oil is a major factor of production and when prices are non-sticky, oil price shocks can lead to reduced output, increased inflation, and real exchange rate depreciation. However, the deepness of negative consequences of oil shocks such as output losses, inflation etc., will depend on the sensitivity of the consumer durables (where oil is a factor of production) to the oil prices.

The present study can be extended by analyzing the multivariate wavelet based approach which might include different interest rates, money supply inflation, and stock market return as other explanatory variables.

5. FOOTNOTES

1. Among the different frequency traders central banks and institutional investors constitute low frequency traders whereas, speculators and market makers are categorised into high frequency traders.
2. To the best of our knowledge the only study which utilizes (discrete) wavelets and non-linear causality tests is Benhmad (2012).
3. The description of CWT, XWT and WTC is heavily drawn from Grinsted *et al.* (2004). I am grateful to Grinsted and co-authors for making codes available at: <http://www.pol.ac.uk/home/research/waveletcoherence/>, which was utilized in the present study.
4. ADF and PP unit root test are not presented to save space, however, can be obtained from the author upon request.

REFERENCES

- Aguiar-Conraria, L. and M.J. Soares, 2011. Oil and the macroeconomy: Using wavelets to analyze old issues. *Empirical Economics*, 40(3): 645-655.
- Bénassy-Quéré, A., V. Mignon and A. Penot, 2007. China and the relationship between the oil price and the dollar. *Energy Policy*, 35(11): 5795-5805.
- Benhmad, F., 2012. Modeling nonlinear granger causality between the oil price and U.S. dollar: A wavelet based approach. *Economic Modelling*, 29(4): 1505-1514.
- Chaudhuri, K. and B.C. Daniel, 1998. Long run equilibrium real exchange rates and oil price. *Economics Letters*, 58(2): 231-238.
- Chen, S.S. and H.C. Chen, 2007. Oil price and real exchange rates. *Energy Economics*, 29(3): 390-404.

- Coudert, V., V. Mignon and A. Penot, 2008. Oil price and the dollar. *Energy Studies Review*, 18(2), Article 3.
- Dacorogna, M., R. Gençay, U. Müller, R. Olsen and V. Pictet, 2001. *An introduction to high-frequency finance*. San Diego, California: Academic Press.
- Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3): 424–438.
- Grinsted, A., J.C. Moore and S. Jevrejeva, 2004. Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Processes in Geophysics*, 11(5/6): 561-566.
- Kilian, L., 2006. Not all oil prices shocks are alike: Disentangling demand and supply shocks on the crude oil market. Discussion Paper, International Economics, Center for Economic Policy Research.
- Lee, K., S. Ni and R.A. Ratti, 1995. Oil shocks and the macroeconomy: The role of price variability. *The Energy Journal*, 16(4): 39-56.
- Lizardo, R.A. and A.V. Mollick, 2010. Oil price fluctuations and U.S. dollar exchange rates. *Energy Economics*, 32(2): 399-408.
- Mork, K.A., 1989. Oil and the macroeconomy when prices go up and down: An extension of hamilton's results. *Journal of Political Economy*, 97(3): 740-744.
- Sadorsky, P., 2000. The empirical relationship between energy futures prices and exchange rates. *Energy Economics*, 22(2): 253-266.
- Torrence, C. and G.P. Compo, 1998. A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, 79(1): 605-618.
- Torrence, C. and P. Webster, 1999. Interdecadal changes in the esno monsoon system. *Journal of Climate*, 12(8): 2679-2690.
- Zhang, Y.J. and Y.M. Wei, 2010. The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. *Resources Policy*, 35(3): 168-177.

BIBLIOGRAPHY

- Aguiar-Conraria, L., N. Azevedo and M.J. Soares, 2008. Using wavelets to decompose the time-frequency effects of monetary policy. *Physica A: Statistical Mechanics and its Applications*, 387(12): 2863-2878.
- Faria, J.R., A.V. Mollick, P.H. Albuquerque and M.A. Leon-Ledesma, 2009. The effect of oil price on China's exports. *China Economic Review*, 20(4): 793-805.
- Gabor, D., 1946. Theory of communication. *Journal of the Institute of Electrical Engineers*, 93: 429-457.
- Hudgins, L., C. Friehe and M. Mayer, 1993. Wavelet transforms and atmospheric turbulence. *Physical Review Letters*, 71(20): 3279-3282.
- Raihan, S., Y. Wen and B. Zeng, 2005. Wavelet: A new tool for business cycle analysis. Working Paper, Federal Reserve Bank of St. Louis, 2005-050A.

Views and opinions expressed in this article are the views and opinions of the authors, Asian Economic and Financial Review shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content.