Investigation of the Relations between Crude Oil Prices and Real Effective Exchange Rate (REER) in Iran using Phase-Angle Analysis

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Abstract:

This paper discusses two topics. At first, it uses continuous wavelet (Morlet) transform, coherency, and phase angle analysis to study the effect of mean volatility in OPEC Crude Oil prices, WTI crude oil prices, Brent Crude oil prices and Iran's crude oil prices on The Iran's REER. To this end, the monthly data of the variables for years 2003 to 2012 is used. Coherency analysis revealed areas where there are behavioral similarities between the two time series (The Oils Prices and The Iran's REER). These areas are displayed in spectral graphs. The results demonstrate that there is high coherency between the two variables (The Oils Prices and The Iran's REER). Then, to have a better understanding of type and depth of the relations between The Iran's Oil prices and The Iran's REER, cross wavelet transform and phase difference analysis are used. The final result demonstrates that if the government does not take countercyclical policies, The Iran's crude oil price variable has the potential to affect Iran's REER variable and be the lead operator.

Keywords: Coherency, Oil Price, Phase-Angle, REER, Time Series, Wavelet.

JEL Classification: B23, C22, E3.

1. Introduction

Since there are many factors that can be a source of uncertainties and volatility in markets and prices, it is necessary to conduct extensive research or employ advanced mathematics and physics tools to find the origin of volatility and changes and their impact on macroeconomics' important variables.

In this regard, an important factor that can affect effective exchange rate in

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oil-dependent countries is crude oil price which plays a key role in global economy. Therefore, different policies are applied to control the effect of crude oil price on effective exchange rate and to the volatility caused by oil shocks.

As an oil exporting country, Iran is not an exception. Many economists in recent years studied topics related to crude oil price and its impact on other macroeconomic variables, especially in oil-exporting countries. What makes these studies different is how to use various tools for more accurate analysis. With the increasing development of mathematics, physics and statistics as well as the increasing need for more accurate economic analysis, it is necessary to use 3D graphs and most recent transforms introduced by mathematicians and physicists for time series analysis in combination with statistical analysis and economics in order to have a more comprehensive analysis of economic events and the information contained in time series. Economic time series usually follow complex systems that are constantly studied by many researchers. Predictable behavior of economic time series can be a set of trends and cycles which is the focus of many researchers. By analyzing time-series, researchers seek to find more information about them. Studying long memory of such systems allows us to have a more comprehensive understanding of variables and their behavior over time or against different policies which are applied to control those variables.

Todays, wavelet transform is employed as an effective tool to study the relationship between financial variables and macroeconomic variables, especially when the objective is studying mutual effects of these variables on each other in time-frequency domain. Masset (2008), Ranta (2010), Gherman et al. (2012), Vacha and Barunik (2012), Fan et al. (2013), and Kriechbaumer (2014).

The other applications of wavelet transform are studying the interaction between oil prices, inflation, and other macroeconomics' important variables. Since 1970's, the impact of oil prices variations on macroeconomics' indexes has been widely considered. Researchers such as Arouri (2011), and Basher et al. (2012) examined the relationship between oil prices and stock prices. Hassan and Zaman (2012) also examined the relationship between oil prices and balance of payments. Other researchers in this field are: Dawson (2007), Huang and Guo (2007), Crowley and Mayes (2008), Chen (2009), Baubeau and Cazelles (2009), Rua and Nunes (2009), Ghosh (2011), Caraiani (2012), Fernandez (2012), Selmi et al. (2012), Shahbaz et al. (2013), Dar et al. (2014), Ftiti et al. (2014).

According to studies conducted by Bénassy-Quéré et al. (2007), Huang and Tseng (2010), and Lizardo and Mollick (2010), there is a relation between crude oil prices and effective exchange rates. Ding and Vo (2012)

showed that as crude oil price increase, exchange rate growth in oil-exporting countries is more than the oil-importing countries. In fact, investigating the relations between crude oil price and effective exchange rate lets us know which shocks in oil prices and exchange rates, as important factors affecting the economy of oil-exporting countries, cause changes in each variable. To this end, the role of oil price on exchange rate movements was studied by researchers such as Golub (1983), Krugman (1983), Reboredo (2012), and Turhan et al. (2013).

Since Iran is an oil-exporting country and a member of OPEC where oil revenues has a significant impact on economic growth, and according to previous studies conducted in other countries, it has to be investigated that is there any relation between Iran's oil price and effective exchange rate or not? If yes, when its impact is the maximum and what policies are applied in this regard? How are uncertainties and volatility in these variables in time-frequency domain? Which time horizon and which frequency depth represents the relations between the two variables more pronounced? Which oil shock has the greatest impact on effective exchange rate changes and how deep this impact is in time domain?

This paper investigates the discussed topic using the continuous wavelet (Morlet) transform. It also takes advantages of spectral analysis of signals and frequency analysis of time series to examine the prices of different oils and REER of Iran variables in details as univariate and bivariate. To this end, monthly data from January 2003 to January 2012 is used. Since continuous wavelet (Morlet) transform has the ability to decompose time series to real and imaginary parts, it provides information on both local amplitude and instantaneous phase at any time during the periodic processes. It allows us to investigate coherency and strong relationships between various time series based on comprehensive and accurate information. In other words, this is a powerful tool that enables us to accurately examine time series to find a variety of strong and mild shocks as well as the extent of the impact of these shocks on time series.

The paper is organized as follows. Section 2 discusses theoretical basics of methods used in this paper. Section 3 uses continuous wavelet transform for a univariate analysis, then examines the interaction between time series and finally employs continuous wavelet transform for a bivariate analysis. Section 4 provides conclusions and reviews findings.

2. Theoretical Basics

Here, first the CWT basic concepts, then cross-wavelet transform (XWT) and wavelet coherency (WTC) are defined.

2.1. Continuous Wavelet Transform (CWT)

Wavelet transform methods are usually divided into two categories: discrete wavelet transform which usually is used in de-noising and continuous wavelet transform which can be used in signal characteristics studies. Grinsted et al. (2004)[1].

Continuous Wavelet Transform (CWT) is a common tool for local analysis of volatility in time-frequency domain. To learn more about this tool, first some definitions about Fourier transform are mentioned.

The idea of wavelet analysis was first introduced by Joseph Fourier (1807). He showed that any periodic function can be simplified as weighted sum of trigonometric functions (sin and cos) at different frequencies. Even if the function is not periodic, under certain circumstances, it can be simplified. This allows investigating periods and cycles in time-frequency domain. Then, to determine which period plays the major role in explaining the variance of series, spectral Fourier analysis was introduced. Fourier transform is usually defined as:

$$X(\omega) = \int_{-\infty}^{\infty} x_t \left[e^{-i\omega t} \right] dt \qquad (1)$$

where χ_t denotes time series and $X(\omega)$ is its Fourier transform.

A limitation of the Fourier transform is that X is only a function of ω (frequency), and ignore information about time. To solve this problem, Gabor (1946) suggested a modified version of the Fourier transform as short-time Fourier transform in which the Fourier analysis is done in local sections. In fact, a window function is defined and the Fourier transform just applied to that part of the time series. So, that window is transformed along the time axis. In this case, two parameters τ (defining windows) and ω (defining frequency) are considered. Short-time Fourier transforms is written as:

$$G_{g,x}(\tau, \omega) = \int_{-\infty}^{\infty} x_t \left[\bar{g}(t - \tau) e^{-i\omega t} \right] dt \qquad (2)$$

where $\bar{g}$ represents the complex conjugation of g.

Gabor (1946) used Gaussian function to define the window functions. The main problem with this equation is that it considers a fixed resolution for the entire time-frequency plane.

To be able to investigate the relation between two time series, a tool is needed which is able to decompose time series into more components, then analyze the components. Also it is necessary to investigate different sections in time-space domain to find the maximum common power which includes

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1. We are grateful to Grinsted and co-authors for making the codes available, which are used in the present study.

relative phases between the two signals and indicates a strong relationship between them. CWT is also applicable for time series that are not normally distributed. Cross CWT can be applied on two signals to give XWT graphs that represent common power and relative phases in time-frequency domain.

2.2. Morlet Wavelet

After introduction of wavelet transform, many wavelets were introduced to filter out signals. Each wavelet has its specific characteristics. The important point to apply wavelet transform is that the researcher must know which wavelet is proper for which signal and objective.

When a wavelet is employed to extract characteristics of a time series, Morlet wavelet can be a good choice, because it can make a good local balance between time and frequency. In this regard, Morlet wavelet is presented as follows.

ψ represents the mother wavelet which is a zero-mean wavelet:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{3}$$

Morlet mother wavelet is defined as:

$$\psi_0(\eta) = \pi^{\frac{-1}{4}} e^{i\omega_0 \eta} e^{\frac{-1}{2}\eta^2} \tag{4}$$

where ω_0 is the dimensionless frequency, and η is the dimensionless time. In fact, ω is frequency angle (rotation degrees in radians per unit time).

The idea behind CWT is applying it as a bandpass filter (BPF) on time series. Wavelets can use a scale variable (s) over time to change the size, i.e. be expanded or compressed. Here, η = s.t.

Morlet wavelet transform of a time series (x_t) is the convolution of time series with a set of daughter wavelets generated by mother wavelet through time shifting (τ) and scaling (s):

$$W(\tau, s) = \sum_t x_t \frac{1}{\sqrt{s}} \overline{\psi}\left(\frac{t-\tau}{s}\right) dt \tag{5}$$

Here, $\overline{\psi}$ denotes the complex conjugation of ψ, x_t is the time series, and the scale is determined by s (note that scale and frequency are inversely related).

The location of a certain daughter is shifted in time by τ by small distances (*dt*). The scale set shows the depth of decomposition of time series in frequency domain. Morlet is a non-orthogonal wavelet, i.e. the number of convolutions at any scale is fixed and equal to the number of observations. Therefore it is highly powerful to decompose the wave and to identify volatility of time-series in time-frequency domain.

2.3. Polar Wavelet Transform

When $\psi(t)$ is a complex function, wavelet transform of W_x will also be complex. So we will have two parts: real part $R(W_x)$ and imaginary part $I(W_x)$. The polar form of the transform is as:

$$W_x = |W_x|e^{i\phi_x} , \phi_x \in (-\pi, \pi]$$ (6)

where ϕ_x is considered as the wavelet phase, for the wavelet functions which have the real part, the value of imaginary part is zero thus no phase is defined. So, to separate phase and amplitude information of a time series, it is necessary to use the complex form of the wavelet.

2.4. Coherency

Analysis using cross wavelet transforms make it possible to compare the frequency content of two time series. The results demonstrated the simultaneous occurrence of two time series at a certain frequency and a certain amplitude. For two time series, $x(t)$ and $y(t)$, the cross wavelet transform, denoted by W_{xy}, is defined as follows:

$$W_{xy} = W_x\overline{W_y}$$ (7)

where W_x and W_y are wavelet transforms for x and y, respectively. The absolute value of the cross wavelet transform, $|W_{xy}|$, indicates the cross wavelet power. In fact, wavelet spectral power examines the variance distribution of a time series at another time series in the time-frequency domain. In addition, W_{xy} indicated the local relative phase for the time series x_n and y_n in time-frequency domain.

The complex wavelet coherency of x and y is shown by ϱ_{xy} and calculated as:

$$\varrho_{xy} = \frac{S(W_{xy})}{\left[S(|W_x|^2)S\left(|W_y|^2\right)\right]^{\frac{1}{2}}}$$ (8)

where S is the smoothing operator of time and scale, smoothing operator is essential, because in the absence of this operator, the coherency severity will be 1 and we will be no longer able to recognize the severity.

Aguiar-Conraria et al. (2008), defined wavelet coherency as the ratio of the cross-spectrum to the product of the spectrum of each series which can be considered as local relation between the two time series in the time-frequency domain. The closer the coherency to 1, the higher the similarities between the two time series. In other words, if coherency is zero or close to zero, there is no relation between the two time series.

2.5. Cross Wavelet Transform

Cross wavelet transform is a tool used to test the adaptability of time series at different frequencies to evaluate them over time. In fact, the cross wavelet transform of two time series, x_t and y_t, decomposes both time series simultaneously in the time-frequency domain. Torrence and Compo (1998) defined the distribution of cross-wavelet power for two time-series with background power spectra, P^x_k and P^Y_k as:

$$D\left(\frac{\left|W^X_n(s)\overline{W^Y_n}(s)\right|}{\sigma_X \sigma_Y}\right) < p = \frac{Z_v(p)}{v}\sqrt{P^X_k P^Y_k} \tag{9}$$

where $\overline{W^Y_n}$ denotes the complex conjugation, $Z_v(p)$ is the confidence level with probability p for defining a probability density function (pdf) of the square root of the product of two Chi-square distribution.

A wavelet power spectrum represents the evolution of the variance of a time series at different frequencies.

Here, periods with large variances are considered as periods with high power at different scales. In fact, geometrically, cross wavelet transform is similar to covariance and depends on measurement unit of time series.

2.6. Cone of Influence (COI)

The CWT has edge artifacts because the wavelet is not completely localized in time. It is therefore useful to introduce a Cone of Influence (COI) in which edge effects cannot be ignored. However, COI here is defined as the area in which the wavelet power occurred due to actually discontinuities at the edge.

2.7. Cross Wavelet Phase Angle

Complex values of wavelet allow us to calculate the phases for both time series. The difference between the two phases gives us information about possible lags in volatility of time series as a function in time-frequency domain.

In order to calculate the phase difference between two time series the mean and the confidence interval of the phase difference need to be estimated. For calculating the mean phase and quantifying the phase relationship, circular mean of the phase over regions with higher than 5% statistical significance that are outside the COI is used.

Circular mean of an angle set (a_i, i = 1, ..., n) is defined as follows:

$$a_m = \arg(X,Y) \ , \ X = \sum_{i=1}^{n}\cos(a_i) \ , \ Y = \sum_{i=1}^{n}\sin(a_i) \tag{10}$$

The number of angles used in calculation can be set arbitrarily high simply by increasing the scale resolution. Distribution of angles around the mean can be calculated using standard deviation as follows:

$$s = \sqrt{-2\ln\left(\frac{R}{n}\right)} \quad , R = \sqrt{(X^2 + Y^2)} \tag{11}$$

In wavelets, phase indicates the lag/lead relation between the two time series which is defined as follows:

$$\emptyset_{x,y} = \tan^{-1}\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}} \quad , \quad \emptyset_{x,y} \in [-\pi \, , \pi] \tag{12}$$

I and R denote imaginary and real parts, respectively.

Which actually represents the phase difference between the local signal obtained from x and y time series in time-frequency domain (when studying the angle unit) at amplitude $[-\pi, \pi]$.

To identify the relative phase, it is necessary to calculate the phase difference between the two time series as follows:

A phase-difference of zero indicates that the time series move together at the specified frequency (analogous to positive covariance). If $\emptyset_{x,y} \in [0, \pi/2]$, the two time-series are so-called "in-phase". In this case, Y is introduced as lead operator for X.

A relation is called "anti-phase" when the phase difference is π or $-\pi$, that is:

$\emptyset_{x,y} \in [-\pi/2 \, , \, \pi] \cup [-\pi, \pi/2]$ (Analogous to negative covariance).

If $\emptyset_{x,y} \in [\pi/2, \pi]$, X is considered as the lead operator, and if $\emptyset_{x,y} \in [-\pi, -\pi/2]$, Y is introduced as the lead operator.

3. Data

This study employs monthly data, from January 2003 to January 2012, to study the relation between The Oils Prices and The Iran's REER and Also the relation between The Iran's Oil prices and The Iran's REER. Figure 1 represents the studied time series and their growth. To study the time series' details more precisely, wavelet-based spectral graphs are used which are discussed later.
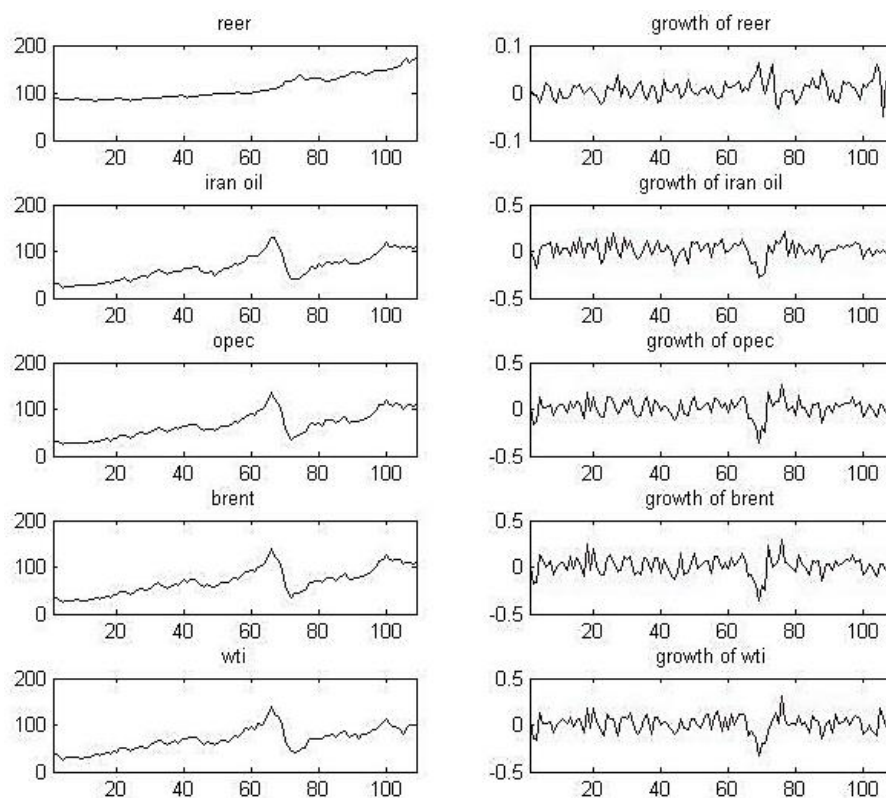
Fig. 1. Left figure shows the time series of Iran's REER, Iran's crude oil prices, OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices. The right figure represents the growth of them.

3.1. Continuous Wavelet Analysis

Since the influence depth of a shock in the frequency domain is a key factor when studying the impact of the shock on the target signal in the time domain, this section first analyzes the time series by Morlet Wavelet transform. Two time series from 2003 to 2012 are accurately analyzed in the time-frequency domain. The following section reveals the relations between the two series.

Analysis of time series using Morlet wavelet in the time-frequency domain reveals the time interval of different shocks and the severity of the impact and influence of shocks and volatility on time series. Figure 2 shows the contour obtained by decomposition of time series of Iran's REER, Iran's crude oil prices, OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices in three dimensions of time, frequency, and color codes indicating the severity of occurred shocks (red color represents the most severe shocks occurring in mentioned time series.

At such points, if shocks continue in time and not be controlled, the

possibility of structural breaks sharply increases. It is also possible for shocks to have permanent effect and their effects last longer time).

Figure 2 properly shows that different time series, particularly different in nature, show different features and behaviors in the time-frequency domain. As obvious, the highest contour belongs to Iran's REER after decomposing which is showing a behavior partially different from results obtained for other oil-related variables. However, the behavior of 4 lower contour, which corresponds to the different oils prices, show similar results with minor differences. This may be due to the conformity of policies applied for these variables (Iran's crude oil prices, OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices) and the similar nature of the four variables.

The most severe shocks in the studied interval for different oils prices happened in data interval 63 to 77 (from early 2008 to late 2009). This is due the effect of global financial crisis occurred in year interval 2008 to 2009 which caused sharp fluctuations in exchange rate and consequently in different oils prices. Crude oil price increase can have direct and indirect effects on other macroeconomics' indicators and the extent of the effect depends on the dependency of those indicators on oil price. Within this interval, the global macroeconomic consequences of that increased oil price is so severe that it is expected the volatility of this variable has a significant impact on other international market variables such as REER of oil-exporting countries.

In addition, from the data 65 to latest data in Iran's REER time series (2008 to 2012), sharp volatility is observed for scale 1 to 35. This means that shocks affecting these variables has permanently continued from year 2008 to 2012. Therefore, the effects of these shocks passed as permanent effect to lower frequency (longer-term) intervals. However, from 97th data (early 2011) to latest data in time series, the severity of volatility was reduced; yet, the volatility permanently continued with no convergence even at higher frequencies.
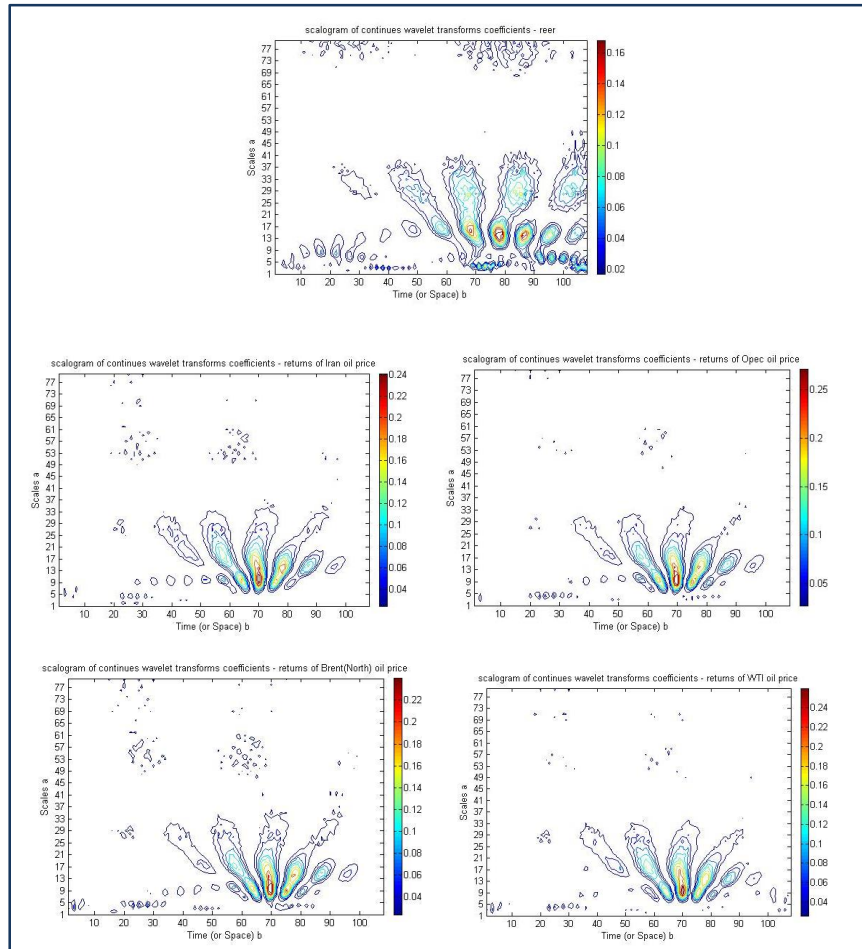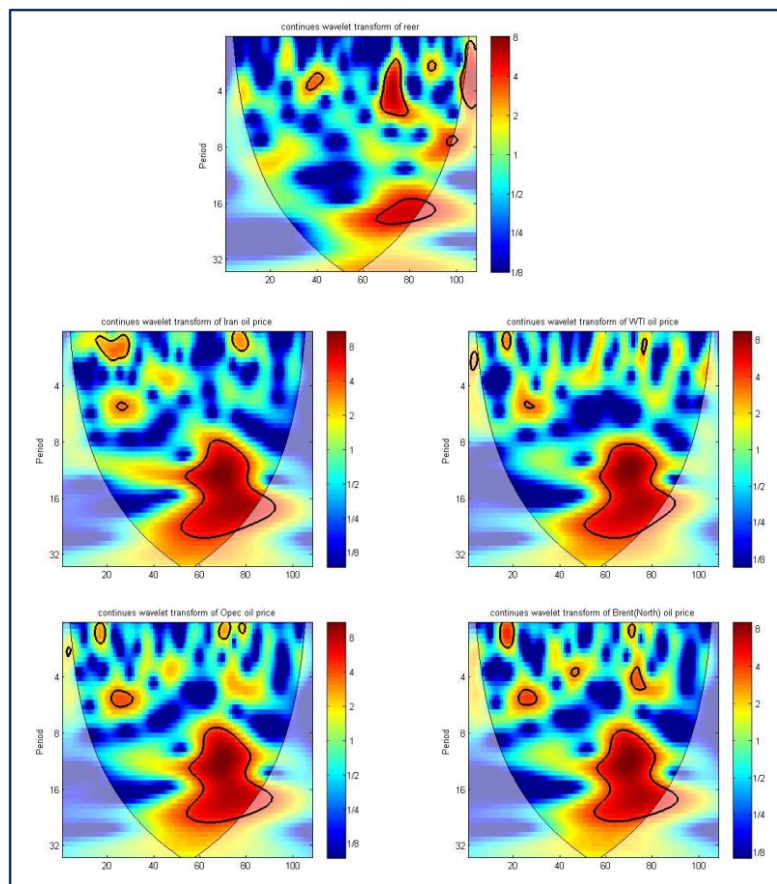
Fig. 2. The contour for decomposition of the time series of Iran's REER, Iran's crude oil prices, OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices using Morlet Continues wavelet transform

Considering the above discussion, Figure 2 shows a relatively similar effect in changes in the different oils prices and Iran's REER trends. The question is that whether volatility in oil price in these years (2008-2009) could induce volatility in Iran's REER? We note that the objective of this paper is to investigate the possible effect of oil price on Iran's REER and not the cause volatility in oil prices.

Thus, for a closer look, spectrometry graphs are used to study each of the time series. To ensure the accuracy of the results and to eliminate edge effects, COI region in graphs is considered. Here, the red color represents the most severe occurred shocks, and the depth of influence of these shocks (i.e. the power of shocks to pass volatility to longer-term periods) can be seen easily. As Figure 3 shows, the similarity of shocks generated between the different oil

prices and the Iran's REER and relative similarity of amplitudes of these shocks in the time-frequency domain suggest that the probability of that oil price has an effect on REER is increasing and the results are significant considering the defined confidence region and COI. The hyperbolic black line isolates the COI region where edge effects are not negligible (below the hyperbolic). Regions surrounded with solid black lines experienced the most severe effects of shocks in the interval in time-scale domain. For a closer look at this issue, the next section examines coherency and cross wavelet graphs.
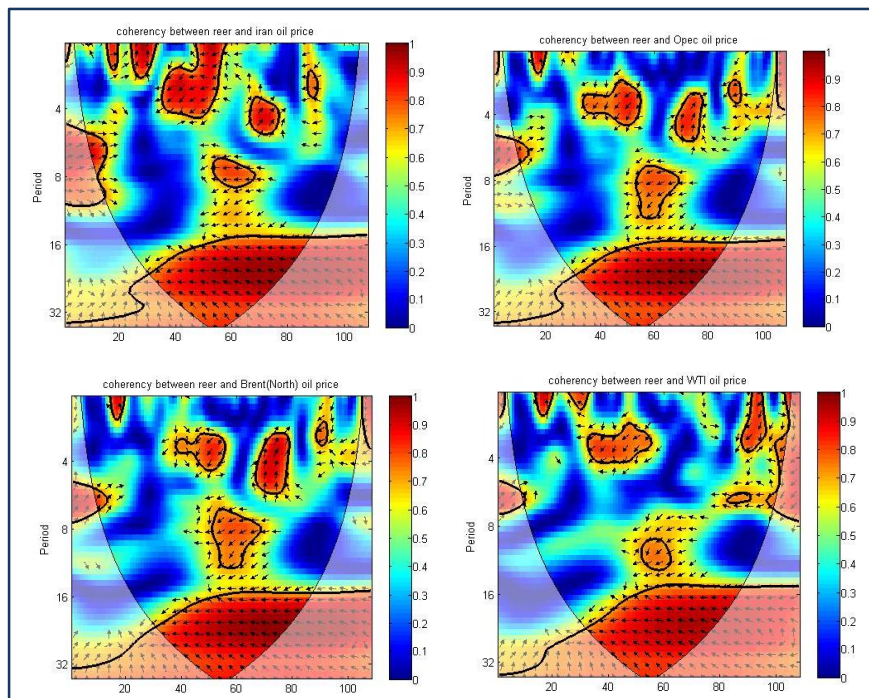

Fig. 3. Spectrometry graphs for the analysis of the time series of Iran's REER, Iran's crude oil prices, OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices

3.2. Coherency Analysis

Coherency analysis reveals areas where there are similarities between the behavior of the two time series (in time-frequency domain), which can be shown as spectral graphs. In such graphs, dark red color represents a coherency equal to one (maximum behavioral similarity) and dark blue

represents a coherency equal to zero (minimum behavioral similarity). In fact, the coordinate with maximum coherency in time-scale (time-frequency) domain shows the most similarity in characteristics between the two variables. In this analysis, COI region is also considered to prevent any similarity arising from edge effects.

According to Figure 4, results obtained from the coherency between different oils prices and Iran's REER are relatively similar which can be due to similar international policies taken about the global oil prices. Although coherency results are relatively similar, the similarities between Iran's oil price and Iran's REER in short term are more pronounced than the similarities between the other oils prices and Iran's REER. In general, the results obtained from Figure 4 suggest that the two variables (Iran's oil price and Iran's REER) are associated with each other. About the oils prices and Iran's REER, we can conclude that changes occurred as a result of various shocks show a high coherency. To know the type and intensity of this relation and the mechanisms passing the effects of changes through these two variables (Iran's oil price and Iran's REER), we must employ cross wavelet transform and phase difference analysis, which are discussed in the following section.

Fig. 4. The coherency of each oil price variables (Iran's crude oil prices, OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices) with Iran's REER variable

3.3. Analysis of High-Power Relations Points

The previous section investigated the similarities of volatility in the Oils price variables and Iran's REER based on patterns plotted in coherency analysis. This section first studies the high-power relations points between these two variables (the Oils price variables and Iran's REER), and then for investigating the type of the relations between the Oils price variables and Iran's REER, phase angle analysis, and phase differences are applied.

According to the wavelet power spectrum representing simultaneous and joint movements of the two time series, Figure 5 shows the XWT of two variables (the Oils price variables and Iran's REER) in the three dimensions of time, frequency, and color codes. In Figure 5, in some time points, especially data 60 to 80 (about year 2008 to 2009), changes in volatility are most similar in 8 to 25 months scales. In lower-scale areas (high frequency), there are also intervals where the relation power for these two variables is the most.

In Figure 5, both intervals with highest relation power (common features) between the two time series and the relative phases are observable and provide a simple image of the cause-effect relation between the occurring phenomena in the studied variables. Finally, the type of movement (in-phase or anti-phase) is examined.

In interval data 60 to 80 and scale 8 to 30, which was recognized as a region with highest relation power for the two variables, it is observed that most arrows turn left indicating that the relation between the two variables is an anti-phase one. In other words, the Oils price variables and Iran's REER are inversely related. In the same interval and scale from 15 to 30 arrows are directly towards the left which shows the government takes counter-cyclical policies to control the impact of the 'oils price volatility on Iran's REER. The output of these policies is obvious in longer-term periods (15 to 30 months). However, in smaller scales (less than 15 month), the relative direction of arrows is downward suggesting that oil price variable can be introduced as the lead operator for Iran's REER in this period.

Thus, it can be concluded that if government doesn't take counter-cyclical policies, oil price variable has an effect on Iran's REER variable and acts as lead operator.
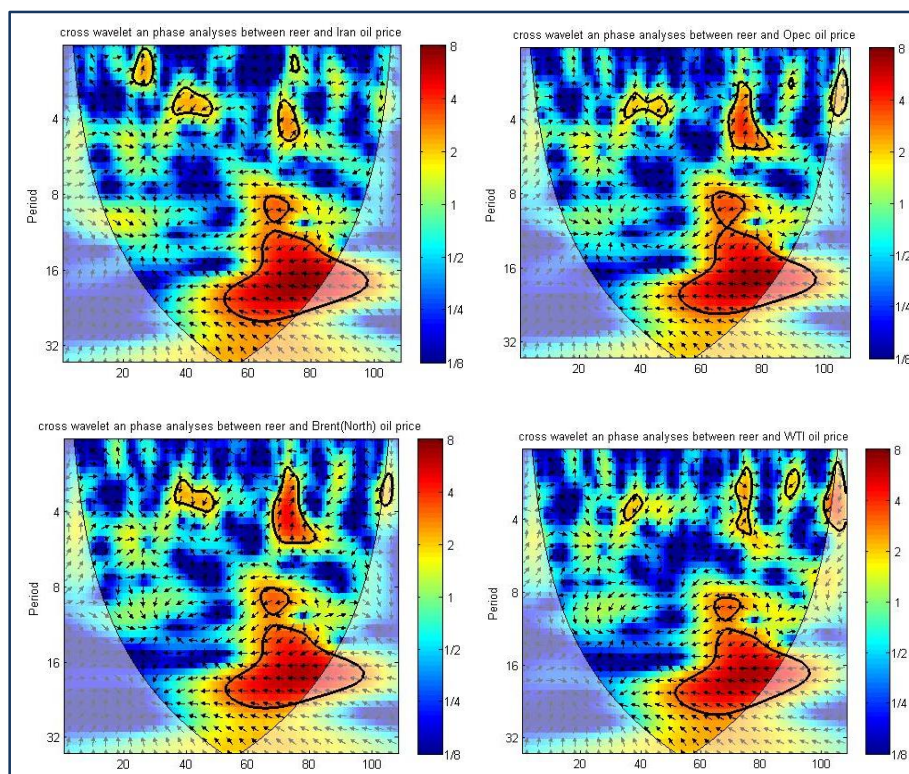
Fig. 5. Wavelet transforms for each the different oils variable with Iran's REER

4. Conclusion

Wavelet-based methods are practical approaches for studying cyclic phenomena in time series (especially in studies about the potential changes of time-series in frequency over time). Wavelets allow decomposition of time series in time-frequency domain. For the purpose of this paper which is to investigate the effects of global oils prices (OPEC Crude Oil prices, Brent Crude oil prices and WTI crude oil prices) and Iran's oil prices on Iran's REER, Morlet continues wavelet transform and the concepts of coherency, cross wavelet analysis, and phase angle analysis were employed. Coherency analysis revealed areas where there are similarities between the behaviors of the two time series (the different Oils prices and Iran's REER) shown as spectral graphs.

The results demonstrated that the coherency of the different Oils prices and Iran's REER are relatively similar and this can be due to similar international policies taken about global oil price. In general, the results suggested that these two variables (the different Oils prices and Iran's REER) are associated with each other. About the different Oils prices and

Iran's REER, it is concluded that changes induced by various shocks showed a great coherency.

To have a better understanding of type and depth of the relation between Iran's oil price and Iran's REER, cross wavelet transform and phase differences analysis were conducted. The results show that Iran's oil price had dramatic effects on Iran's REER in short-term scales (1 to 7 months), but with taking counter-cyclical policies, the government attempted to control volatility of Iran's REER caused by oil prices shocks. The applied policies were successful to preserve the relative stability of Iran's REER (as shown in Fig. 5), and the severity of volatility was reduced. In addition, governments establish policies to maintain the stability of Iran's REER, to reduce volatility, and to prevent the transmission of short-term volatility of shocks occurred in Iran's REER time series to longer-term periods. In fact, the focus was on preventing a significant impact of shocks occurred in the different oils prices on Iran's REER. Thus, if counter-cyclical policies are not applied, Oil price can be introduced as a lead operator for Iran's REER.

References

Aguiar-Conraria, L., Azevedo N., & Soares, M. J. (2008). Using Wavelets to Decompose the Time-Frequency Effects of Monetary Policy. *Phys A, 387*: 2863–2878.

Baubeau, P., & Cazelles, B. (2009). French Economic Cycles: a Wavelet Analysis of French Retrospective GNP Series. *Cliometrica, 3:* 275–300.

Caraiani, P. (2012). Stylized Facts of Business Cycles in a Transition Economy in Time and Frequency. *Econ Model, 29(6):* 2163–2173.

Crowley, P., Mayes, D. (2008). How Fused Is the Euro Area Core?: an Evaluation of Growth Cycle Co-Movement and Synchronization Using Wavelet Analysis. J. *Bus Cycle Meas Anal, 4:* 63–95.

Dar A. B., Bhanja, N., & Tiwari, A.K. (2014). Inflation-Industrial Growth Nexus in India– a Revisit through Continuous Wavelet Transform. *Central Bank Review, 14*, 1-11.

Fan, Shuangrui, Ji, Tingyun, Gordon, Wilmsmeier, & Rickard, Bergqvist (2013). Forecasting Baltic Dirty Tanker Index by Applying Wavelet Neural Networks. *Journal of Transportation Technologies, 3*, 68-87.

Ftiti, Z., Tiwari, A., Belanès, A., & Guesmi, K. (2014). Tests of Financial Market Contagion: Evolutionary Co-spectral Analysis Versus Wavelet Analysis. *Compute Econ, Springer*.

Gabor, D. (1946). Theory of communication. *Inst. of Electr. Eng., 93*: 429–457.

Gherman, Mircea, Terebes, Romulus, & Borda, Monica (2012). Time Series Analysis Using Wavelets and Gjr-Garch Models. *20th European Signal Processing Conference (Eusipco), Romania.*

Grinsted, A., Moore, J. C., & Jevrejeva, S. (2004). Application of the Cross Wavelet Transform and Wavelet Coherence to Geophysical Time Series. *Nonlinear Process Geophys., 11:* 561–566.

Kriechbaumer, T., Angus, A., Parsons, D. J., & Rivas, Casado, M. (2014). An Improved Wavelet-Arima Approach for Forecasting Metal Prices. *Resources Policy, 39*, 32-41.

Ranta, Mike (2010). Wavelet Multiresolution Analysis of Financial Time Series. Acta Wasaensia, 223.

Rua, A., & Nunes, L. C. (2009). International Co-Movement of Stock Market Returns: a Wavelet Analysis. *Journal of Empir Finance, 16*: 632–639.

Masset, Philippe, (2008). Analysis of Financial Time-Series Using Fourier and Wavelet Methods. Working Papers Series.

Shahbaz, M., Tiwari, A. K., Tahir. M. I. (2013). Analyzing Time-Frequency Relationship between Oil Price and Exchange Rate in Pakistan through Wavelets. MPRA Paper, 48086.

Vacha, Lukas, & Barunik, Jozef (2012). Co-Movement of Energy Commodities Revisited: Evidence from Wavelet Coherence Analysis. *Energy Economics, 34*, 241–247.