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Oil prices and trade balance: A wavelet based analysis for India

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Abstract

The study examinations lead-lag relationship between real oil price (ROP) and real trade balance (RTB) for India using monthly data and covering period from January 1980 to December 2011. To in depth examine the issue, study decomposes the time-frequency relationship between ROP and RTB utilising continuous wavelet approach. Result of the Rua's (2010) measure of wavelet cohesion show that there was high degree of positive correlation in the 0.25-0.5 years-scale corresponding to 1983-1984 and 1986-1989; and in the 0.75-2 years-scale corresponding to 2008-2010. However, evidence of high negative correlation was found in 0.5-1 years-scale corresponding to 1987-1990, 1994-1996 and 2001-2005 and evidence of strong negative correlation was found in 1.75-2.25 years-scale corresponding to 1990-1997. Further, results of wavelet coherence analysis show that in the significant region of coherency and corresponding year-scales, real oil price was leading over India's trade balance indicating that an increase in the oil price will increase India's trade balance. These results corroborate the findings in Le and Chang (2013) and contrary to the findings in Hassan and Zaman (2012).

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1. Introduction

Trade is a crucial engine of economic growth particularly in the fastest growing countries like India, while oil is one of the highly traded commodities in the world. On the one hand, high dependence on trade benefits the economies by improving economic efficiency – including efficient allocation of resources and efficient utilization of resources, among other benefits. On the other hand, high dependence on trade is likely to raise the trade deficit which, however, hinders the economic growth. The India's trade deficit, which reflects the excess of its merchandise imports over exports, has reached 10.2 percent of its gross domestic product (GDP at market prices). According to the Balance of Payments (BOP) statistics for the year 2009-10 released by the Reserve Bank of India, the deficit has increased from Rs. 368532 Crore[1] in 2007-08 to Rs. 542113 Crore in 2008-09. This increase of Rs. 174 Crore has resulted in the deficit swelling from 8.5 percent of GDP at market prices in 2007-08 to almost 11 percent in 2008-09. One of the possible reasons behind a progressively-widening trade deficit could be a decline in the exports accompanied by an increase in imports (keeping other things constant). The merchandise exports grew by 19.65 percent in 2008-09, which was higher than their growth of 14.56 percent in 2007-08. But the imports growth of 29.41 percent in 2008-09 was far higher than the 20.10 percent growth in the previous year. So, the rise in trade deficit can be attributed to a much faster rise in imports compared with the exports. So, we naturally ask: what are the reasons behind the rapid rise in imports? The imports can be divided into two broad groups: oil and non-oil commodities. According to the data made available by the Directorate General of Commercial Intelligence and Statistics of the Ministry of Commerce, India's crude oil imports during 2007-08 were US$77.04 billion (122 million ton crude oil was imported by India in 2007-08 while in 2006-07 the imported volume was only 112 million ton). This represents an increase of about 9 percent increase in the import volume of crude oil over the previous year. Further, the year-on-year growth in petroleum, oil and lubricants imports in 2007-08 was 35.3 percentages which was higher than the growth of 30.76 percent in 2006-07. In sharp contrast, the non-oil imports, despite growing at a higher rate of 23.5 percent in 2007-08, compared with 22.2 percent in 2006-07, show a much lower rate of growth than the oil imports. In the Figure-1 below, we plot in panel-A the India's total imports, oil imports and non-oil imports and in panel-B the India's oil imports as percentage of total imports, which make much clearer our arguments aforesaid.

Insert Figure 1 about here

There is no doubt that the high growth in the oil imports has been the main factor behind the sharp rise in the imports. Furthermore, a rise in the global crude oil prices at an unprecedented rate has substantially inflated India's import bill. India's crude imports comprise a basket of three varieties – U.K. Brent, Dubai, and West Texas Intermediate. Given the composition, sharp increases in any one of these varieties do not suggest that the overall price would be affected by the same extent. During 2006-07, however, all the three crude varieties saw their prices rise fast. The average price of the Indian basket varied between US$65.5 and US$99.8 per barrel, yielding an average price of US$79.5 per barrel for the year. This was a steep jump vis-à-vis US$62.5 per barrel in 2006-07. Interestingly, the volume of oil imports experienced a lower growth of 8.9 percent in 2007-08 vis-à-vis 13.13 percent in 2006-07. Thus,

[1] One Crore is equal 10 million in Indian currencies.

the increase in oil imports was primarily value-driven and not volume-driven. High crude prices, therefore, have been the main determinant of India's rising trade deficit. Given India's chronic dependence on oil imports, with the latter accounting for almost one third of the country's total imports, the Indian economy's import bill and trade balance will remain sensitive to the movements in the world oil prices. This has been verified in Tiwari (2012) which documents that foreign trade deficit is sustainable in the Indian context for non-oil commodities but not for oil commodities. With the global crude oil prices inching close to US$150 per barrel, the import bill and trade deficit are likely to increase further. Assuming that the oil prices will continue to rise in the near future, can we be so sure that the trade deficit will become unsustainable? This depends on the Indian economy's capacity to finance the deficit. Moreover, the high trade deficit has resulted in an increase in the current account deficit. From the 1.46 percent of GDP in 2007-08, the current account deficit increased to the 2.5 percent of GDP in 2008-09. However, the balance of payments is yet to come under stress, due to a healthy capital account surplus. Below in Figure-2 we plot the month by month percentage growth of oil price and trade deficit.

Insert Figure 2 about here

Given the significance of oil as an internationally traded commodity and the high volatility of its price, oil price shocks could explain the emergence of large trade imbalances in India. Thus the study aims to explore such a possibility for India, which could render theoretical and policy implications. It is often in the policy discussions that oil price shocks would have large and negative effects on trade balance. When there is a surge in the oil prices, countries are forced to borrow abroad to offset adverse terms-of-trade shocks. "There are some doubts that international risk sharing is not enough, implying that the ensuing imbalances may not be large enough to effectively cushion the domestic impact of oil price shocks" (Le and Chang, 2013, p. 78). Thus, the fundamental importance from both policy and conjectural points of view is to examine the impact of oil price shocks on trade balances. In our study, we examine the co-movement of oil price and trade balance in India using wavelet approach.

Rest of the paper is organized as follows. Section 2 presents a brief theoretical background and also reviews the literature. Section 3 describes data sources and the methodological framework. Section 4 reports the results, and conclusions are presented in Section 5.

2. Theoretical background and a brief review of literature

Oil price shocks may have impact on the external accounts of an economy through two different channels, namely, the trade channel and the financial channel (Le and Chang, 2013). The transmission in the trade channel works through changes in quantities and prices of tradable goods. The transmission in the financial channel works through changes in external portfolio positions and asset prices. However, we will focus on the transmission through the trade channel and review the related literature. The oil price may have direct and indirect economic impacts for both oil-importing and oil-exporting economies (Le and Chang, 2013). The indirect impact works through the transmission of the oil price shocks via international trade. Backus and Crucini (2000) and Kim and Loungani (1992) documented that for a net oil-importing economy, an exogenous increase in the price of imported crude oil is often regarded as a negative term-of-trade shock through their effects on production decisions. The process can be explained as follows: in the net oil importing economies imported oil may be considered an intermediate input in the domestic production and thus an increase in oil prices leads to a direct increase in the input cost. This, in turn, forces firms and households to curtail their expenditure and investment plans and thus causes a decrease in total output. With reduction in total output and hence exports and without corresponding reduction in consumption of oil, further increases in oil prices will worsen the overall trade balance (with other things constant). [2]

There is voluminous body of literature analyzing the macroeconomic impacts of oil price shocks with a focus on the responses of real economic growth and consumer price inflation (see Barsky and Kilian, 2004; Hamilton, 2005; Tiwari 2013, for recent reviews). There are very few studies which address the issue on the trade channel of the transmission of oil price shocks to an economy. Noteworthy studies in this area are: Backus and Crucini (2000), Kilian et al. (2009), Bodenstein et al. (2011); Hassan and Zaman (2012); and Le and Chang (2013)[3]. Backus and Crucini (2000) conducted a study based on dynamic equilibrium model depicting the properties of international business cycles in eight developed countries between 1955 and 1990. They found that oil accounts for much of the variation in the terms of trade over the period 1972–1987. Their results seem likely to hold regardless of the financial market structure. Bodenstein et al. (2011) generalized Backus and Crucini's (2000) model by allowing for the convex costs of adjusting the share of oil used in the production and consumption. Bodenstein et al. (2011) used a two country dynamic stochastic general equilibrium (DSGE) model (the US - as a home country - versus "rest of the world") to investigate how a rise in oil prices affects the trade balance and the non-oil terms of trade for the US case. Bodenstein et al. (2011) found that, under complete markets, the non-oil terms of trade remain unchanged, and therefore, the non-oil trade balance. However, under incomplete markets, Bodenstein et al. (2011) documented that the non-oil terms of trade suffers from a depreciation that induces the non-oil trade balance to improve enough to correct the deficit. Hassan and Zaman (2012) investigated the impact of rising oil prices on the trade balance of Pakistan by using autoregressive distributive lag model (ARDL) approach. They also explored the causality direction between trade balance and oil price shocks in the context of Pakistan over a period of 1975–2010. The results show that there is a significant negative relationship among oil prices, exchange rate and trade balance in Pakistan, i.e., if there is 1% increase in oil prices and exchange rate, the trade balance decreases by 0.382% and 0.342%, respectively. This implies that oil prices and exchange rate induce trade imbalance in Pakistan. In addition, there is a positive relationship between output gap and trade balance which indicates inefficient resource allocation and utilization in production. In the short run, there is a positive relationship among exchange rate, output gap and trade balance in Pakistan which shows that an increase in oil prices increases the net income flow in terms of huge cost payments for imports and increases the trade deficit in an economy. The result of Granger causality indicates that there is a unidirectional causality running from oil prices to trade imbalance. Le and Chang (2013) examined whether a large part of the variability of trade balances and their oil and non-oil components is associated with oil price fluctuations. They applied the Toda and Yamamoto (1995) causality approach and the generalized impulse response functions (IRFs) respectively to the monthly data spanning from January 1999 to November 2011 to examine the long-run causality from oil price to overall, oil and non-oil trade balances and their short-run dynamics. Le and Chang (2013) inferred as follows: "First, oil exporters' improvements in trade balances

[2] For more details on the theoretical part please refer to Kilian et al. (2009), Kilian (2010) and Bodenstein et al. (2011)

[3] There are some other studies in this area, for example, Bollino (2007), Rebucci and Spatafora (2006), and Setser (2007) but all these studied the subject for the US case.

seem associated with rising oil revenues. Second, for an oil refinery economy like Singapore, oil price shocks seem to have negligible long-run impact on trade balances and their oil and non-oil components. It may, however, have significant impacts in the short run. Third, for net oil importers, the impact of rising global oil prices on oil trade deficit depends on the unique nature of the demand for oil. If the economy is highly dependent on oil but has no ability to produce, its oil demand would be very inelastic. For net oil importing and major oil consuming economies associated with high oil dependency like Japan, rising oil prices seem to heavily dampen the oil trade deficit which likely to result in the overall trade deficit. However, the short run impact on the non-oil trade balance could be positive, which may eventually translate to a favorable effect on the overall trade balance, if the shock of the oil price rise to the economy stems from the demand side" (p. 95).

3. Data and methodology

3.1 Data

For our analysis we used data of oil prices as average of U.K. Brent, Dubai, and West Texas Intermediate since India imports oil from all these markets. As oil price was expressed in US $ therefore, we converted the oil price into the Indian Rupee using the Indian-US exchange rate and finally the obtained values were further deflated using whole sale price index (WPI). The WPI was also used to deflate the trade balance to obtain real trade balance. The data were obtained from the International Financial Statistics (IFS) database of International Monetary Fund (IMF). Our study period is 1980m1-2011m12. Bothe series were further converted in to percentage growth terms.

3.2 Methodology

Torrence and Compo (1998) developed the approaches to estimating the cross-wavelet power, the cross-wavelet coherency, and the phase difference which can be interpreted as local variance, covariance and the time lag in the time-frequency space respectively. The term "phase" implies the position in the pseudo-cycle of the series as a function of frequency. Consequently, the phase difference gives us information "on the delay, or synchronization, between oscillations of the two time series" (Aguiar-Conraria et al., 2008, p. 2867).

According to frequency and time spaces, the Continuous Wavelet Transform (CWT) $W_t^u(\tau)$ of a time series x_t at time n and scale τ with uniform time steps, the Morlet wavelet[4] equation (1) can be rewritten in the following expression:

$$W_m^x(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \cdot \psi^* \left((m-n) \frac{\delta t}{s} \right), \quad m = 1,2,\ldots,N-1 \qquad (1)$$

where, the wavelet power $\left|W_t^u(\tau)\right|^2$ is defined as the local phase. The Cone of Influence (COI) is important to introduce a as edge effects. The Monte-Carlo simulation process is used in this paper that is explained by Torrence and Compo (1998). We computed the wavelet power

[4] $\psi_\theta(\mu) = \pi^{-1/4} e^{i\omega_a \mu} e^{-\frac{1}{2}\mu^2}$, where ω_a and μ are dimensionless frequency spaces and time scales. Morlet wavelet with frequency parameter, $\omega_a = 6$.

spectrum[5] using the similar procedure used by Torrence and Compo (1998). The description of CWT, Cross Wavelet Transform (XWT) and Wavelet Coherency (WTC) presented is introduced from Grinsted et al. (2004).

The two financial time series such as the change in trade balance and the change in real oil price, u_t and v_t, with the wavelet transformation W^u and W^v, the XWT is defined as $W^{uv} = W^u W^{v*}$, where W^{v*} denotes complex conjugate of W^v. However, following Aguiar-Conraria and Soares (2011) WTC, instead of the XWT is preferable, since "(1) the wavelet coherency has the advantage of being normalized by the power spectrum of the two time-series, and (2) that the wavelets cross spectrum can show strong peaks even for the realization of independent processes suggesting the possibility of spurious significance tests".

According to Torrence and Compo (1998), theoretical distribution of the cross wavelet power of two time series P_k^u and P_k^v with background power spectra can be defined as:

$$D\left(\frac{W_t^u(\tau)W_t^{v*}(\tau)}{\sigma_u \sigma_v} < p\right) = \frac{z_\omega(p)}{\omega}\sqrt{P_k^u P_k^v} \qquad (2)$$

The confidence level $z_\omega(p)$ explained the square root of the product of two χ^2 distributions. Using the similar description of the XWT, the WTC (Torrence and Webster, 1999) between the change in oil price and the change in trade balance can be defined as:

$$R_t^2(\tau_S) = \frac{\left|\varepsilon(\tau_s^{-1}W_t^{uv}(\tau_s))\right|^2}{\varepsilon\left|(\tau_S^{-1}W_t^{uv}(\tau_S))\right| \cdot \varepsilon\left|(\tau_S^{-1}W_t^{uv}(\tau_S))\right|} \qquad (3)$$

where ε is considered as a smoothing operator (Rua and Nunes, 2009). In equation 3, 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; Rua and Nunes, 2009). The value of the wavelet squared coherency $R_t^2(\tau_S)$ gives a quantity between 0 and unity. In other words WTC can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time series. Thus, wavelet coherency near one shows a high similarity between the time series, while coherency near zero show no relationship. This present study will focus on the WTC, instead of the XWT pursuing the application by Aguiar-Conraria and Soares (2011). In this study, we follow Torrence and Compo (1998) for identifying the COI region and phase relationship.

Further we define the phase difference as follows, which shows any lag or lead relationships between components,

5 $D\left(\frac{\left|W_t^u(\tau)\right|^2}{\sigma_u^2} < p\right) = \frac{1}{2}P_k \chi_\nu^2(p)$, where ν is equal to 1 and 2 for real and complex wavelets respectively.

$$\phi_{u,v} = \tan^{-1} \frac{I\{W_n^{uv}\}}{R\{W_n^{uv}\}}, \phi_{u,v} \in [-\pi, \pi] \quad (4)$$

where, I and R are the imaginary and real parts, respectively, of the smooth power spectrum. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency; if $\phi_{u,v} \in [0, \pi/2]$, the series move in-phase, with the time-series *v* leading *u*; if $\phi_{u,v} \in [-\pi/2, 0]$, the series move in-phase, with the time-series *u* leading *v*. We have an anti-phase relation if we have a phase difference of π (or $-\pi$). If $\phi_{u,v} \in [\pi/2, \pi]$, there is anti-phase relation with *u* leading *v* and if $\phi_{u,v} \in [-\pi, -\pi/2]$, there is anti-phase relation with *v* leading *u*.[6]

4. Data analysis and empirical findings

We presented the descriptive statistics of monthly real oil price (ROP) and real trade balance (RTB) measured month by month percentage growth rate in Table 1. The sample mean of both variables is negative. The measure of skewness indicates that RTB is negatively skewed whereas ROP is positively skewed. Data series in percentage growth from demonstrate excess kurtosis which indicates that ROP and RTB are leptokurtic relative to a normal distribution. The Jarque-Bera normality test rejects normality of both series. In the next step, stationary property of the data series of all test variables has been tested through Augment Dickey-Fuller test (ADF test) and the Phillips-Perron test (PP test). We find that both variables are non-stationary in the level form while they are stationary at percentage growth form. Therefore, for further analysis we used our series in the percentage growth form.

Insert Table 1 about here

Firstly, we present results of continuous wavelet power spectrum of both ROP (in the top panel) and RTB (in the bottom panel) in Figure 3. However, it should be noted that some of the recent previous works have shown evidence of bias toward low-frequency oscillations in the wavelet power spectra (WPS) or in the CWT (Liu et al., 2007; Veleda et al., 2012). A bias problem towards low-frequency oscillations is found to be existed in the estimate of WPS. For example, a time series that comprises of sine waves with different periods but same amplitudes does not produce identical peaks (Liu et al., 2007). Similar problem exists in XWT (Veleda et al., 2012). To address this point we used wavelets tools developed by Ng and Chan (2012) that rectified the bias in the WPS or CWT and XWT.

Insert Figure 3 about here

It is evident from Figure 3 that there are some common islands. In particular, the common features in the wavelet power of the two time series are evident in the 0-3 years' scale that belongs to 1990-1995 and 2002-2003. In these different years' scale both series have the power above to the 5 percent significance level as marked by thick black contour. However, the similarity between the portrayed patterns in these periods is not very much clear and it is therefore hard to tell if it is merely a coincidence. The cross wavelet transform helps in this

[6] For discussion on the significance level and background noise of the distribution, refer to appendix 1.

regard. We further, analyzed the nature of data through XWT and presented results in Figure-2A in the appendix. Our results of cross wavelet power show that during 1991-1994 and 2002-2003 in the 0.25 to 2 years scale arrows are left and down indicating that real oil price is lagging and there is anti-cyclical relationship between real oil price and real trade balance.

Further, it is worthy to mention that wavelet cross-spectrum (i.e., cross wavelet) describes the common power of two processes without normalization to the single wavelet power spectrum. This can produce misleading results, because one essentially multiplies the continuous wavelet transform of two time series. For example, if one of the spectra is locally and the other exhibits strong peaks, peaks in the cross spectrum can be produced that may have nothing to do with any relation of the two series. This leads us to conclude that wavelet cross spectrum is not suitable to test the significance of relationship between two time series. Therefore, in our conclusion, we relied on the wavelet coherency (as it is able to detect a significant interrelation between two time series). However, one can still use wavelet cross-spectrum to estimate the phase spectrum. The wavelet coherency is used to identify both frequency bands and time intervals within which pairs of indices are co-varying. Therefore, first we presented results of wavelet cohesion, a measure to show the comovement of two series proposed by Rua (2010) in Figure-4 below. This measure is very much similar to the correlation and ranges from +1 to -1.

Insert Figure 4 about here

It is evident from Figure-4 that there is high degree of positive correlation in 1983-1984 and during 1986 to 1989 in the 0.25-0.5 years scale. Another evidence for high degree of positive correlation is found during 2008-2010 in 0.75-2 years of scale. However, we also have evidence of high negative correlation in 0.5-1 years of scale during 1987-1990, 1994-1996 and 2001-2005. Further evidence of strong negative correlation is found during 1990-1997 in 1.75-2.25 years scale. This finding is pointing to the fact that economic agents are responding to policies and incentives differently at the same time. In other words, policy changes mean different things to different people depending on whether economic agents are having long or short run perspectives on the relationship between oil price and trade balance. It simply reinforces the need to evaluate the degree of correlation over scale and time. Concentrating on the time domain alone would not have yielded such a result.

Further, to analyze the lead-lag relationship between real oil price and real trade balance we used phase relationship and presented results along with the wavelet coherency in Figure-5. The squared WTC of series ROP and RTB is shown in Figure 5. The interpretation of our econometric results for WTC proceeds as follows. First, we check the time frequency regions in which the coherency between the variables is statistically significant, meaning that, in those episodes, we may confidently say that there has been a significant co-movement of the variables for cycles of the indicated period. Then, for the statistically significant time frequency locations, we analyze the phase differences, to detect whether the co-movement has been positive or negative, and which variables were leading and lagging. However, note that, we will not mention often results about the coherency and phase differences at the higher frequencies i.e., cycles of 1 month to 1 year as they are typically noisy and, as such, rather uninformative.

Insert Figure 5 about here

From Figure-5, significant coherency is evident in three instances; first during 1985-1990 in the 4~8 years scale, during 1990-1995 around 2 years scale and during 2001-2004 in the 1~2 years of scale. Now we will present results of phase difference for these noticed periods as well as year scales. First, during 1985-1990 in the 4~8 years of scale phase difference is between $[-\pi/2,0]$ indicating that both series are in phase and real oil price is leading India's trade balance. This was the period when there was lot of political uncertainty. In the second instance, that is during 1990-1995 around 2~4 years of phase difference is between $[-\pi/2,0]$ indicating that both series are in phase and real oil price is leading India's trade balance. This was the period when India opted for major economic reforms in 1990-91 and obtained current account convertibility in August 1994 (around start of 1995).[7] Similarly real oil price was found to be leading variable with both variables are in the phase during 2000-2005 for phase difference of 1~2 years of scale. Now with the application of WTC analysis we have very clear evidence on lead-lag relationship between ROP and RTB. 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.

5. Conclusions

The study examined the lead-lag relationship between ROP and RTB for India using the monthly data covering period from January 1980 to December 2011. To analyze the issue in depth, study decomposes the time-frequency relationship between ROP and RTB through continuous wavelet approach. To the best of our knowledge, this is first ever study in this direction with the present approach to any economy. We found from the continuous power spectrum figure that the common features in the wavelet power of the two time series are evident in the 0-3 years' scale that belongs to 1990-1995 and 2002-2003. Results of Rua's (2010) measure of wavelet cohesion show that there is high degree of positive correlation during 1983-1984 and 1986-1989 in the 0.25-0.5 years scale. Another evidence for high degree of positive correlation is found during 2008-2010 in 0.75-2 years of scale. And evidence of high negative correlation in 0.5-1 years of scale during 1987-1990, 1994-1996 and 2001-2005. Further evidence of strong negative correlation is found during 1990-1997 in 1.75-2.25 years scale. However, results of wavelet coherence analysis show that in the significant region of coherency and associate time scale in all situations real oil price is leading over the India's trade balance indicating that an increase in the oil price will increase India's trade balance. These results are corroborates to the findings of Le

[7] India initiated process of trade liberalization in 1990 which were not fully effective till 1997 even after India adopted current account convertibility in August 1994 by adopting Article VIII of the IMF. In 1997, Tarapore Committee on Capital Account Convertibility was appointed by the Reserve Bank of India which has recommended a number of measures while inviting attention to several preconditions. Among the various liberalisation measures undertaken in the light of these recommendations are those relating to foreign direct investment, portfolio investment, investment in Joint Ventures/wholly owned subsidiaries abroad, project exports, opening of Indian corporate offices abroad, raising of Exchange Earners Foreign Currency (EEFC) entitlement to 50 per cent, for allowing acceptance credit for exports, allowing FIIs to cover forward a part of their exposures in debt and equity market, etc.

and Chang (2013) who mentions that for net oil importing and major oil consuming economies associated with high oil dependency like Japan, rising oil prices seem to heavily dampen the oil trade deficit which likely to result in the overall trade deficit. But our results are contrary to Hassan and Zaman (2012) who documented negative relationship between oil and trade balance for Pakistan using time series analysis. The present study can be extended by analyzing the trivariate/multivariate wavelet based approach which might include different other theoretically possible variables.

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Figure 1: Oil Imports, Non-Oil Imports and Total Imports

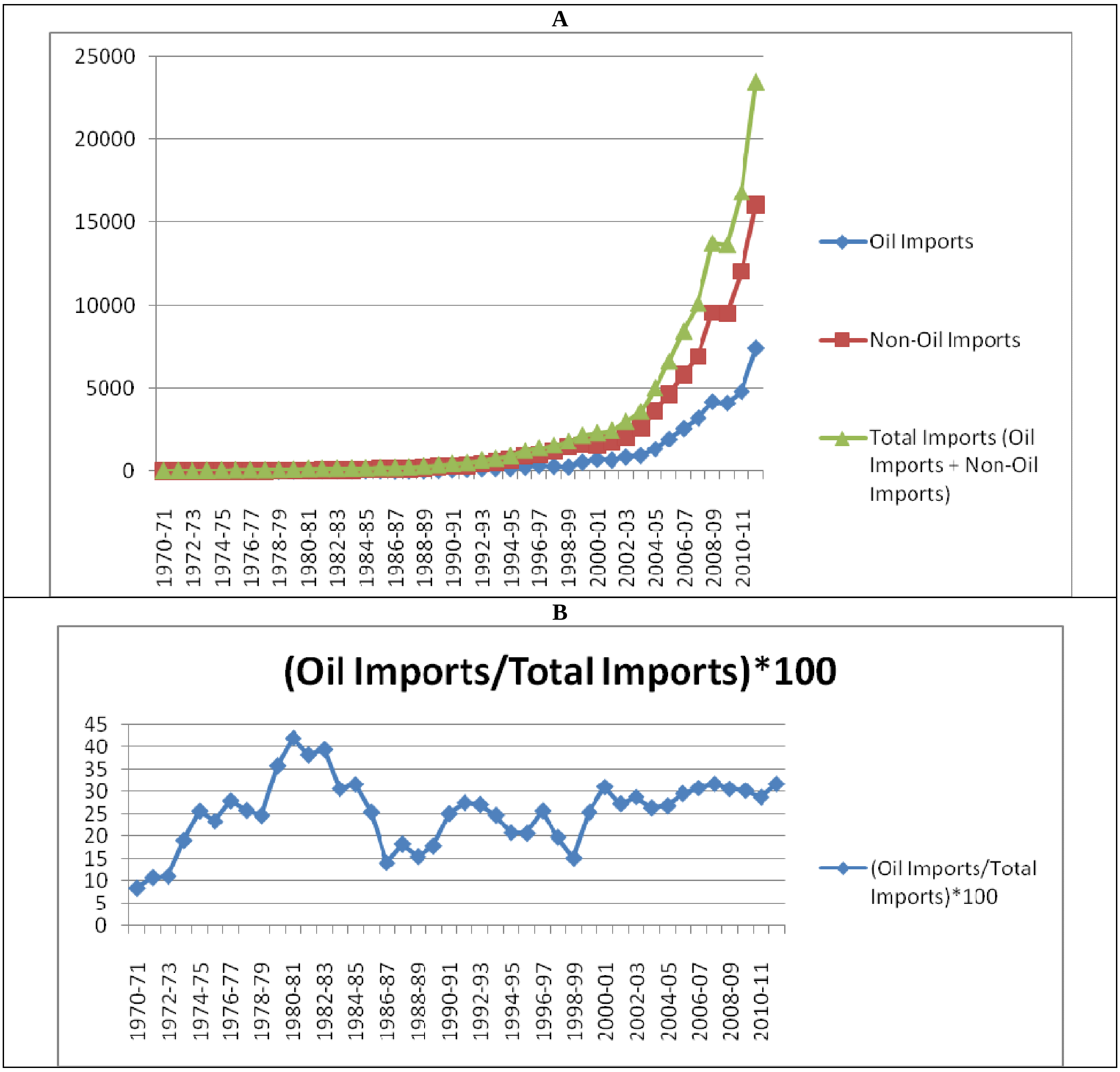


Figure 2: Plot of the real oil price (ROP) and real trade balance (RTB) (in percentage growth)

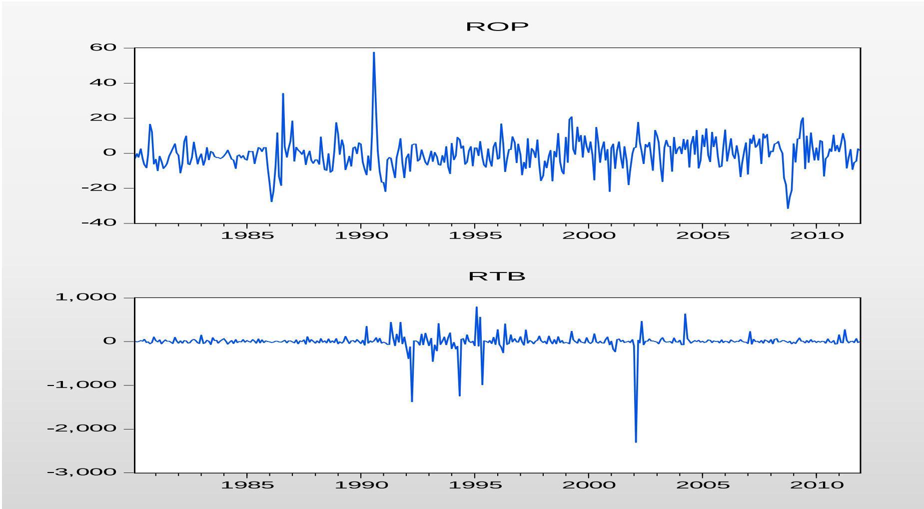
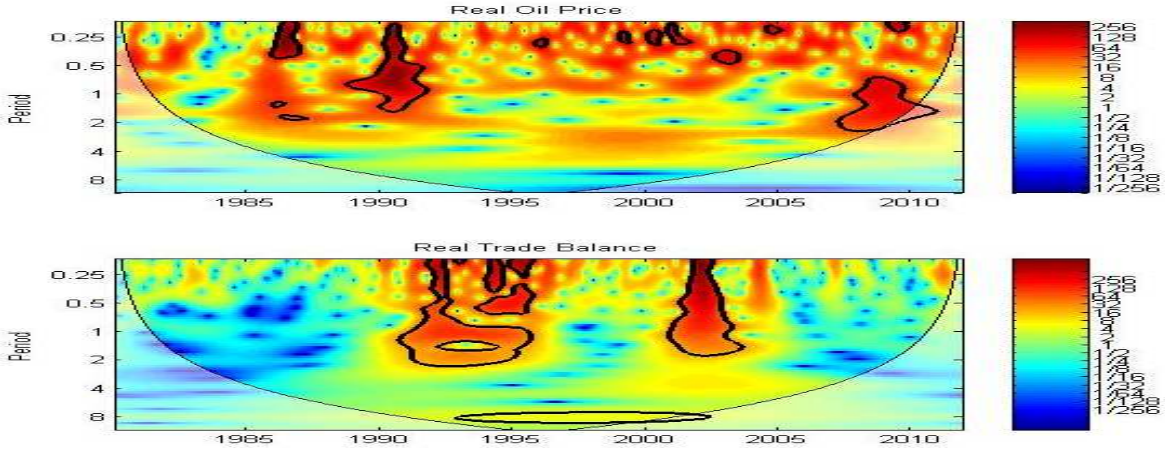


Table 1: Descriptive statistics of series (in month by month percentage growth)

	ROP	RTB
Mean	-0.380301	-1.059584
Median	-0.664608	1.612642
Maximum	57.68593	790.1693
Minimum	-31.54311	-2302.629
Std. Dev.	8.709615	191.2905
Skewness	0.676912	-6.124348
Kurtosis	8.635023	70.42162
Jarque-Bera	535.9817	74935.63
Probability	0.000000	0.000000
Source: Authors calculation		

Figure 3: Wavelet power spectrum for ROP and RTB



Note: The continuous wavelet power spectrum of both Real Oil Price (ROP) (in the top) and Real Trade Balance (RTB) (in the bottom) series are shown here. The thick black contour designates the 5 percent 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 scales and X-axis represent the time period studied.

Figure-4: Wavelet cohesion analysis

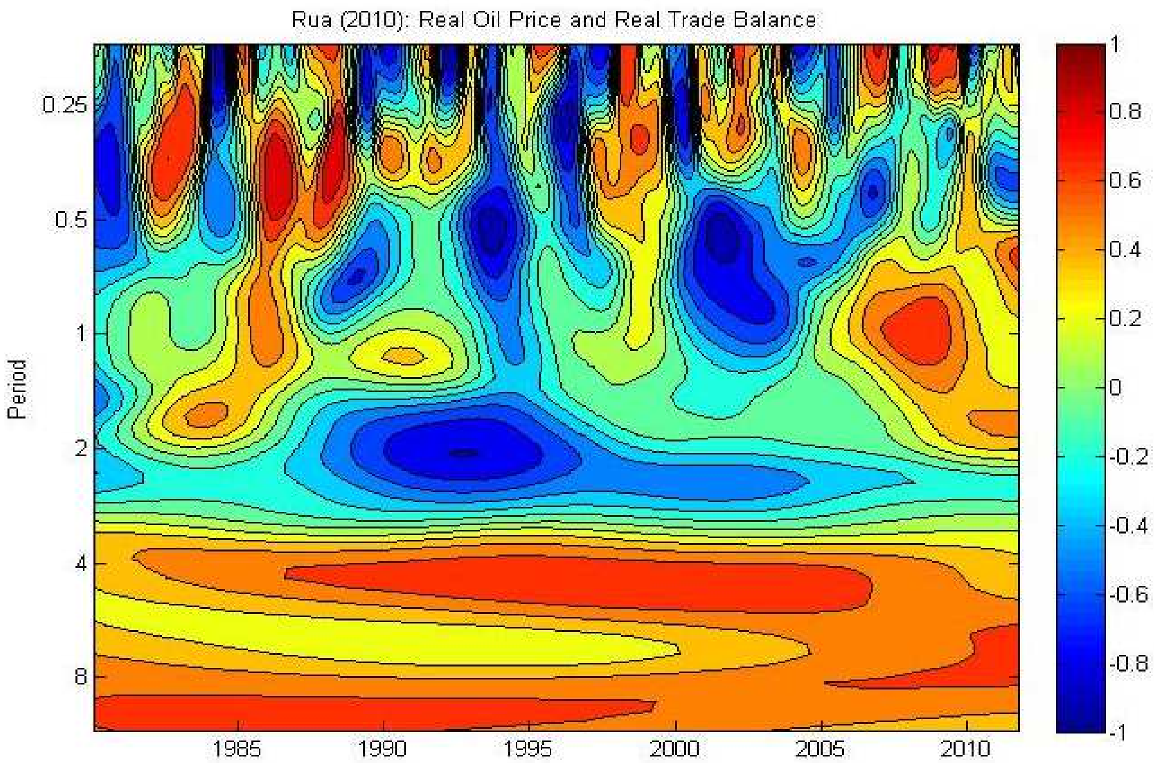
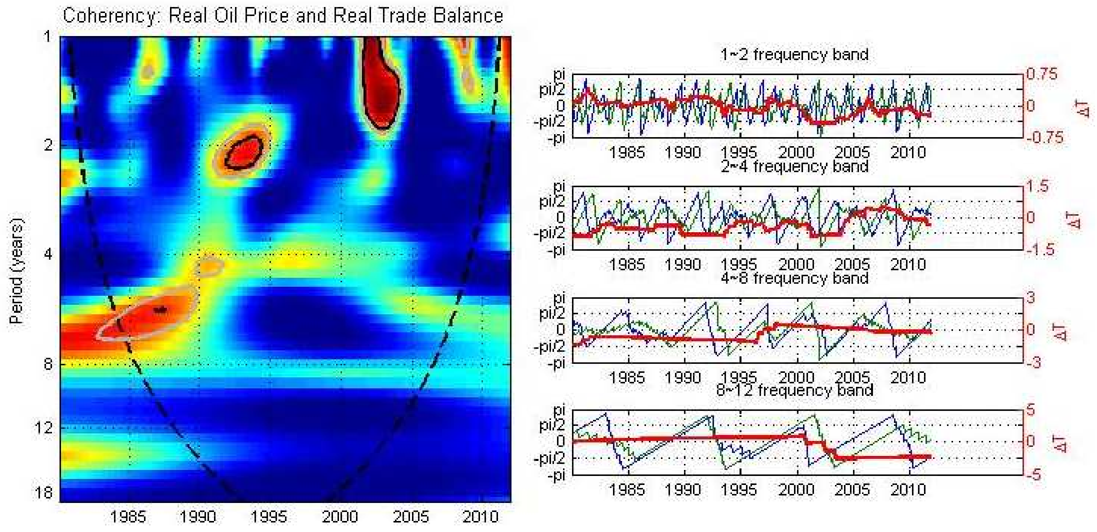


Figure 5: Wavelet coherency between real oil price and real trade balance



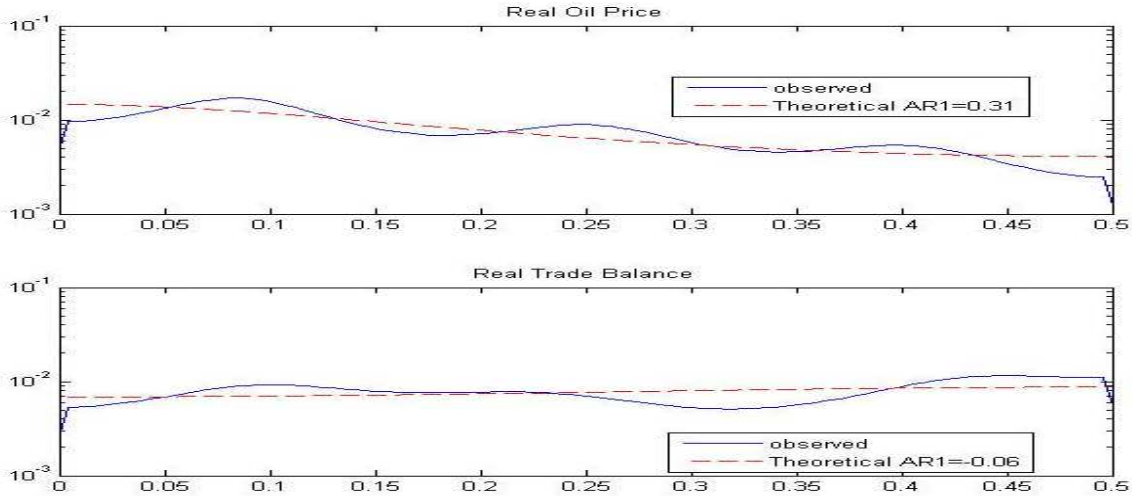
Note: The thick contours designate the 5 and 10 percent significance level against red noise which is estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line. The color code for coherency ranges from blue (low coherency-close to zero) to red (high coherency-close to one). The phase-difference is represented by a thick red line. The green line represents the phase of real oil price, and the blue line represents the phase of the real trade balance.

Appendix

Significance level and background noise of the distribution

The statistical significance of wavelet power spectrum of the observed time series can be assessed relative to the null hypothesis that the signal generating the process is stationary. Since the series in this study cannot be said to be stationary at level, stationarity is induced for analysis. This transformation ensures that the observed time series is normal and can be modelled as a Gaussian AR(1) process. We assume that null hypothesis for power spectrum is normally distributed as AR(1) process. This assumption affects the acceptance of null hypothesis for the power spectrum of each time series or for the co-spectrum of any two time series as well as their coherence. The colour of the noise on the other hand is important for both the spectrum and the co-spectrum while the wavelet coherence is insensitive to the choice of the color. Figure-1A shows that red noise is an appropriate background to test against, the theoretical AR1 spectrum for the power decay closely matching the observed spectrum.

Figure 1A: Plots of observed and theoretical AR1 spectrum for real oil price and real trade balance



In what follows, we choose to work with red noise process given that the observed data were stationarity, but also investigate the implication of red noise for the null hypothesis. The following simple AR(1) model will serve to illustrate the difference between white and red noise

$$y_t = m + \alpha y_{t-1} + \varepsilon_t \qquad (1)$$

where $y_0 = 0$, m is a constant, α is the autocorrelation coefficient and $\varepsilon_t \sim N(0,\sigma^2)$. The white noise model is implied by setting $m = 0$ and $\alpha = 0$ (that is, $y_t = \varepsilon_t$) while the red noise results by setting $m = 0$ and $\alpha \to 1$. For the red noise, the Fourier power spectrum is given by

$$P_k = \frac{1-\alpha^2}{1+\alpha^2 - 2\alpha\cos\left(\frac{2\pi k}{N}\right)} \qquad (2)$$

where we see that $P_k = 1$ for white noise. Although Torrence and Compo (1998) have shown how the statistical significance of wavelet power can be assessed against the null hypothesis that the data generating process is given by an AR(0) or AR(1) stationary process with a certain background Fourier power spectrum, for more general processes one has to rely on Monte-Carlo simulations. Torrence and Compo (1998) computed the white noise and red noise wavelet power spectra, from which they derived, under the null, the corresponding distribution for the local wavelet power spectrum at each time *m* and scale *s* as follows:

$$\frac{\left|W_m^x(s)\right|^2}{\sigma_X^2} \sim \frac{1}{2} P_k \chi_v^2 \tag{3}$$

where v is equal to 1 for real and 2 for complex wavelets. According to Torrrence and Compo (1998), if two time-series have theoretical Fourier spectra P_k^X and P_k^Y as defined in equation (3), and are both χ^2 distributed then the cross-wavelet distribution is given by (Torrence and Compo, 1998, p. 76)

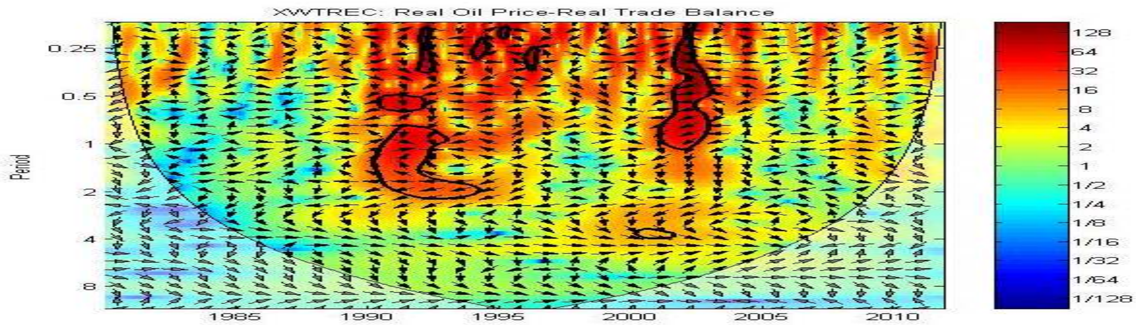
$$\frac{\left|W_m^x(s)\tilde{W}_m^y(s)\right|}{\sigma_X \sigma_Y} \sim \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y}, \tag{4}$$

where $Z_v(p)$ is the confidence level associated with the probability *p* for a probability density function defined by the square root of the product of two χ^2 distributions. In another context, Priestley (1981, p. 703) derives the asymptotic distribution of the *estimated* cross-amplitude power and shows that the asymptotic distribution depends on the coherence. In particular, he shows the variance of the estimated cross-amplitude power at frequency ω is

$$\operatorname{var}\{\hat{\alpha}_{xy}(\omega)\} \sim \frac{C_W}{2N} \alpha_{xy}^2(\omega) \left\{ 1 + \frac{1}{\left|C_{xy}(\omega)\right|^2} \right\} \tag{5}$$

This result is an important demonstration of the relationship between the variability of the cross-amplitude estimate and the coherence of the series. It shows that at all frequencies where coherence is low, the estimate of the cross-amplitude may have an extremely large variance (Priestley, 1981, p. 703). We observe that this analogy may well be true of wavelet cross spectrum as well. Aside from this insight into the noted relationship, this conclusion has no damaging implication for the distribution in Equation (4) or for our results. For testing the statistical significance of results we make use of Monte Carlo simulation approach. We specifically make use of ARMA(1,0) background noise to imitate the red noise. Again, we must mention that wavelet coherence is insensitive to the noise colour and the choice of background colour may not affect the result reported for coherence.

Figure 2A: Cross-wavelet power between real effective rupee exchange returns and real oil price returns



Note: The thick black contour designates the 5 percent 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 is lagging. To the right and down, with real oil price is leading. Arrows pointing to the left mean that the variables are out of phase. To the left and up, with real oil price is leading. To the left and down, with real oil price is lagging. 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.