Oil prices and trade balance: a frequency domain analysis for India

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Abstract
We study lead-lag relationships between oil price and trade balance for India by using monthly data covering the period from January 1980 to December 2011 and post current account convertibility era (from August 1994 to December 2011). We adopt the approach proposed by Breitung and Candelon (2006) along-with the traditional VAR based conditional Granger-causality. Results of VAR based conditional Granger-causality provide evidence of bidirectional causal relationship in both study periods. Impulse response analysis shows positive response of oil price to one innovation shock in trade balance whereas trade balance shows negative response to one innovation shock in oil price. Though, frequency domain analysis also provides evidence of bidirectional causal relationship but that hold for dissimilar frequencies of short and medium run in the full sample. Moreover, more strength and high degree of cyclicalty are found when causality is running from oil price to trade balance. Interestingly, results of the post current account convertibility provide evidence of frequency domain causality running from oil price to trade balance at short, medium and long run not the otherwise. Hence, our study shows that the oil price has become a leading indicator for Indian trade balance in the short, medium and long horizons.

Keywords: Oil prices, trade balance, frequency domain, India
JEL Code : C22, F41
1. Introduction

Trade serves a key engine for economic growth particularly in the fastest growing countries like India and oil is the highly traded commodity in the world. In one side high dependence on trade benefits the economies by improving economic efficiency- i.e., efficient allocation 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 economic growth. India’s trade deficit, which reflects the excess of its merchandise imports over exports, has reached 10.3 percent of its gross domestic product (GDP at market prices) in 2011-12. According to the Balance of Payments (BOP) statistics for the year 2011-12 released by the Reserve Bank of India, the deficit has increased from Rs. 5956 Billion in 2010-11 to Rs. 9121 Billion in 2011-12. This increase of Rs. 3165 Billion has resulted in the deficit swelling from 7.8 percent of GDP at market prices in 2010-11 to almost 10.3 percent in 2011-12.

Is this increase a cause for worry? The answer depends on the determinants of the deficit. One of the possible reasons behind a progressively-widening trade deficit could be a decline in exports accompanied by an increase in imports. But it has not been so in India’s case. Merchandise exports grew by 38 percent in 2011-12, which was higher than their growth of 22 percent in 2010-11. But the import growth of 79 percent in 2011-12 was far higher than the 17 percent growth in the previous year. Hence, the rise in trade deficit can be attributed to a much faster rise in imports compared with exports. So, now question arises: what the reasons behind the rapid rise in imports are? 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 2011-12 were of Rupees 4822.817 (in Billion). This represented an increase of about 54 percent increase in the oil imports bill over the previous year.¹ In sharp contrast, non-oil imports, despite growing at a higher rate of 33.5 percent in 2011-12, compared with 26.2 percent in 2010-11, show a much lower rate of growth than oil imports. There is no doubt that high growth in oil imports has been the main factor behind the sharp rise in imports bill.

Additionally, global crude prices are rising at an unprecedented rate which have substantially inflated India’s import bill. India’s crude imports comprise a basket of three varieties: Brent, Dubai and Oman. Given the composition, even if one among the three experiences sharp increases in prices, the overall price of the basket does not get affected by the same extent. However, during the last year, all the three crude varieties saw their prices rising 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

¹ 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.
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. This has further decreased to 4.3 percent in 2011-12. Thus, the increase in oil imports was primarily value-driven and not volume-driven.

High crude prices, therefore, have been the main determinants 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 continue to remain sensitive to movements in world oil prices. With global crude prices inching close to US$150 per barrel, the import bill and trade deficit are likely to increase further. Assuming that oil prices will continue to rise in the near future, will the trade deficit become unsustainable? This depends on the Indian economy’s capacity to finance the deficit. The high trade deficit has resulted in an increase in the current account deficit as well. From 2.7 percent of GDP in 2010-11, the current account deficit has increased to 4.3 percent of GDP in 2011-12. However, the balance of payments is yet to come under stress, due to a healthy capital account surplus. 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 our study aims to explore such a possibility for India, which could render theoretical and policy implications. It is often argued in the policy discussions that oil price shocks would have large and negative effects on trade balance. When there is surge in the oil prices, countries are forced to borrow from 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). 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 contribute to the literature by investigating lead-lag relationships between oil price and trade balance in India using frequency domain approach.

The rest of the paper is organized as follows. Section 2 presents in brief theoretical background and review of 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
The 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, given the aim of our study 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 as an intermediate input in the domestic production and thus an increase in oil prices kneads to a direct increase in the input cost which in turn forces firms and households to curtail their expenditure and investment plans and thus causes in the decrease of total output. Less total output and hence less export, but not correspondingly less consumption of oil will lead to overall negative trade balance and further increase in the oil prices will further increase the negative balance of overall trade balance (with other things constant). 

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 (Barsky and Kilian, 2004; Hamilton, 2005; Tiwari 2013). There are very few studies which address the issue on the trade channel of the transmission of oil price shocks to an economy. Noteworthy studied in this area are: Backus and Crucini (2000), Kilian et al. (2009), and Bodenstein et al. (2011); Hassan and Zaman (2012); and Le and Chang (2013).

Backus and Crucini (2000) conducted a study based on dynamic equilibrium model of international business cycles (which was based on properties of 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 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 so as for the non-oil trade balance whereas under incomplete markets, the former suffers from a depreciation that induces the latter to improve enough to correct the deficit.

Hassan and Zaman (2013) investigated the impact of rising oil prices on the trade balance of Pakistan by using ARDL approach and also explored the causality direction between trade balance and oil price shocks in the context of Pakistan over a period of 1975–2010. The result shows 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 infers that oil prices and exchange rate induces trade imbalance in Pakistan. In addition, there is a positive relationship between output gap and trade balance which infers inefficient resource allocation and utilization in production.

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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.
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 Toda and Yamamoto (1995) causality approach and 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) derived following conclusions: “First, oil exporters' improvements in trade balances 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 use monthly data of oil prices as average of U.K. Brent, Dubai, and West Texas Intermediate as in India oil is imported from these markets. As oil price is expressed in US $ we convert it into Indian Rupee using India-US exchange rate. Further, we use Index of Industrial Production (IIP), and Whole Sale Price Index (WPI) as conditional variables to remove the effect of these variables on trade balance. All series are obtained from data base of IMF. Our study period is 1980m1-2011m12. Further we analyze, in a second time, data beginning from 1994m8 as India adopted policy of full capital account convertibility in August 1994 to look into lead-lag relationship between variables in the post capital account convertibility era. All series are converted to natural logarithms (except trade balance) for analysis purpose in order to smoothen the series.

3.2 Methodology: Causality Analysis in the Frequency Domain
In statistics, frequency domain is a term used to describe the domain for analysis of mathematical functions or signals with respect to frequency, rather than time. In the frequency domain, a very similar definition holds for the Granger causality, as in the time domain. Put it in a non-technical
way, a time-domain graph shows how a signal changes over time but, a frequency-domain graph shows how much of the signal lies within each given frequency band over a range of frequencies. In very simple terms, “time” means the ability of indicating when a certain variation happens, whereas “frequency” is a component that measures the degree of a certain variation. Though there are other approaches, such as the Partial Directed Coherence (PDC) for testing of Ganger causality in the frequency domain however, we focus on a slightly different approach of Granger causality, due to Granger (1969) and later refined by Geweke (1982), which is adopted in Breitung and Candelon (2006). This approach provides an elegant interpretation of the frequency-domain Granger causality as a decomposition of the total spectral interdependence between the two series (based on the bivariate spectral density matrix, and directly related to the coherence) into a sum of “instantaneous”, “feedforward” and “feedback” causality terms. Breitung and Candelon (2006) approach can be explained as follows:

Let \( z_t = [x_t, y_t]^\prime \) be a two-dimensional vector of time series observed at \( t = 1, \ldots, T \) and it has a finite-order VAR representation of the form:

\[
z_t = \Theta(L)z_t
\]

where \( \Theta(L) = I - \Theta_1 L - \ldots - \Theta_p L^p \) is a \( 2 \times 2 \) lag polynomial with \( L^k z_t = z_{t-k} \). We assume that the error vector \( \varepsilon_t \) is white noise with \( E(\varepsilon_t) = 0 \) and \( E(\varepsilon_t \varepsilon_t') = \Sigma \); where \( \Sigma \) is positive definite. For ease of exposition we neglect any deterministic terms in equation (1).

Let \( G \) be the lower triangular matrix of the Cholesky decomposition \( G'G = \Sigma^{-1} \) such that \( E(\eta_t \eta_t') = I \) and \( \eta_t = G\varepsilon_t \). If the system is assumed to be stationary, the MA representation of the system is:

\[
z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}
\]

\[
= \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}
\]

where \( \Phi(L) = \Theta(L)^{-1} \) and \( \Psi(L) = \Phi(L)G^{-1} \).

Using this representation the spectral density of \( x_t \) can be expressed as:

\[
f_x(\omega) = \frac{1}{2\pi} \left\{ |\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2 \right\}.
\]
The measure of causality suggested by Geweke (1982) is defined as:

\[
M_{y\to x}(\omega) = \log \left[ \frac{2\pi f_y(\omega)}{|\Psi_{11}(e^{-i\omega})|^2} \right] = \log 1 + \left| \frac{\Psi_{12}(e^{-i\omega})}{\Psi_{11}(e^{-i\omega})} \right|.
\]  

(5)

(6)

If \( |\Psi_{12}(e^{-i\omega})|^2 = 0 \), then the Geweke’s measure will be zero, then \( y \) will not Granger cause \( x \) at frequency \( \omega \).

If the elements of \( z_t \) are \( I(1) \) and co-integrated, in that case in the frequency domain the measure of causality can be defined by using the orthogonalized MA representation:

\[
\Delta z_t = \tilde{\Phi}(L)e_t = \tilde{\Psi}(L)\eta_t,
\]

(7)

where \( \tilde{\Psi}(L) = \tilde{\Phi}(L)G^{-1}, \eta_t = G e_t, \) and \( G \) is a lower triangular matrix such that \( E(\eta_t\eta_t') = I \). Note that in a bivariate co-integrated system \( \beta' \tilde{\Psi}(1) = 0 \), where \( \beta \) is a co-integration vector such that \( \beta' z_t \) is stationary (Engle and Granger, 1987).

As in the stationary case the resulting causality measure is:

\[
M_{y\to x}(\omega) = \log 1 + \left| \frac{\tilde{\Psi}_{12}(e^{-i\omega})}{\tilde{\Psi}_{11}(e^{-i\omega})} \right|.
\]

(8)

To test the hypothesis that \( y \) does not cause \( x \) at frequency \( \omega \) we consider the null hypothesis:

\[
M_{y\to x}(\omega) = 0
\]

(9)

within a bivariate framework. Breitung and Candelon (2006) present this test by reformulating the relationship between \( x \) and \( y \) in VAR equation:
\[ x_t = a_0 x_{t-1} + ... + a_p x_{t-p} + \beta_0 y_{t-1} + ... + \beta_p y_{t-p} + \epsilon_{t} \] (10)

The null hypothesis tested by Geweke, \( M_{y \rightarrow x}(\omega) = 0 \), corresponds to the null hypothesis of

\[ H_0 : R(\omega) \beta = 0 \] (11)

where \( \beta \) is the vector of the coefficients of \( y \) and

\[ R(\omega) = \begin{bmatrix} \cos(\omega) \cos(2\omega) \ldots \cos(p\omega) \\ \sin(\omega) \sin(2\omega) \ldots \sin(p\omega) \end{bmatrix} \] (12)

The ordinary \( F \) statistic for (11) is approximately distributed as \( F(2, T - 2p) \) for \( \omega \in (0, \pi) \). It is interesting to consider the frequency domain causality test within a co-integrating framework. To this end Breitung and Candelon (2006) suggested to replace \( x_t \) in regression (7) by \( \Delta x_t \), with the right-hand side of the equation remaining the same (see Breitung and Candelon, 2006, for more detailed discussion on this and for the case when one variable is \( I(1) \) and other is \( I(0) \)). Further, it is important to mention that in co-integrated systems the definition of causality at frequency zero is equivalent to the concept of “long-run causality” and in stationary framework there exists no long-run relationship between time series, a series may nevertheless explain future low frequency variation of another time series. Hence, in a stationary system, causality at low frequencies implies that the additional variable is able to forecast the low frequency component of the variable of interest on one period ahead.

4. Data analysis and empirical findings

First of all, the time series plots along with the distribution plots of the variables are presented in Figure-1, to show the nature of the variables over period and their distribution.
Figure 1: Plot of the variables
Note: OP, TB, WPI and IIP stands for, respectively, oil price, trade balance, whole sale price index and index of industrial production.
Time series plots show that OP has been declining till 1999 and afterwards it is again increasing rapidly albeit with fluctuations; trade balance has become worse after 2004 and continues more negative trend; WPI and IIP show a linear trend relationship but growth of IIP has been experiencing volatility. Quantile plots of the variables show that all variables are non-normal. This has been further confirmed by their kernel distribution plot relative to theoretical kernel distribution plot. Further to see the sample property we present results of descriptive statistics of variables in Table-1 below.

<table>
<thead>
<tr>
<th></th>
<th>OP</th>
<th>TB</th>
<th>WPI</th>
<th>IIP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.089122</td>
<td>-88.94065</td>
<td>4.017579</td>
<td>4.015641</td>
</tr>
<tr>
<td>Median</td>
<td>0.069654</td>
<td>-11.72350</td>
<td>4.143693</td>
<td>4.050071</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.662415</td>
<td>11.05500</td>
<td>5.010969</td>
<td>5.196196</td>
</tr>
<tr>
<td>Minimum</td>
<td>-1.408874</td>
<td>-907.8100</td>
<td>2.857493</td>
<td>2.916364</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.719755</td>
<td>164.3629</td>
<td>0.606661</td>
<td>0.609646</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.242859</td>
<td>-2.419240</td>
<td>-0.216328</td>
<td>0.013581</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.070577</td>
<td>8.546893</td>
<td>1.763672</td>
<td>1.910642</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>17.59600</td>
<td>866.8627</td>
<td>27.45118</td>
<td>18.99901</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000151</td>
<td>0.000000</td>
<td>0.000001</td>
<td>0.000075</td>
</tr>
</tbody>
</table>

Note: OP, TB, WPI and IIP stands for, respectively, oil price, trade balance, wholesale price index and index of industrial production.

It is evident from Table-1 that trade balance is the most volatile variable, followed by oil price, IIP, and WPI, respectively. Skewness statistics show that TB and WPI are negatively skewed whereas OP and IIP are positively skewed. The trade balance demonstrate high kurtosis indicating that trade balance series is Leptokurtic relative to the normal distribution whereas OP, WPI and IIP demonstrate less kurtosis which indicates that distribution of these three series are Platykurtic relative to a normal distribution. The normality test provides evidence that all variables are highly non-normal corroborating the findings of distribution plots.

Further, to test for the unit root among the variables we use Zivot and Andrews (1992) test. To examine the unit roots of a series, the Augmented Dickey-Fuller (1979) test and Phillips and Perron (1988) test were widely used. Nevertheless, Perron (1989) showed that failure to allow for an existing break leads to a bias that reduces the ability to reject a false unit root null hypothesis and to overcome this, Perron (1989) proposed a test that allows for a single exogenous or known structural break. However, Perron’s (1989) known assumption of the break date was criticized, most notably by Christiano (1992) as ‘data mining’. Since then, several studies have developed unit root test using different methodologies and accounting for endogenously determining the break date such as: Zivot and Andrews (1992), Perron and Vogelsang (1992), Perron (1997) and Lumsdaine and Papell (1998). However, in this paper we have applied Zivot and Andrews (1992) unit root test. Zivot and Andrews (1992) endogenous structural break test is a sequential test which utilizes the full sample and uses a different dummy
variable for each possible break date. The break date is selected where the t-statistic from the ADF test of unit root is at a minimum (most negative). Results of unit root test based on Zivot and Andrews (1992) are presented in Table-2 below.

<table>
<thead>
<tr>
<th>Test</th>
<th>IIP</th>
<th>OP</th>
<th>WPI</th>
<th>TB</th>
</tr>
</thead>
<tbody>
<tr>
<td>(10% critical value)</td>
<td>[-4.82]</td>
<td>[-4.82]</td>
<td>[-4.82]</td>
<td></td>
</tr>
</tbody>
</table>

Note: OP, TB, WPI and IIP stands for, respectively, oil price, trade balance, whole sale price index and index of industrial production. [k] denotes the lag-length chosen based on AIC.

Table-2 shows that null hypothesis of unit root is rejected for all variables in the level form at 10% level of significance. This implies that all variables are integrated of order zero i.e., I(0). Further to analyse the Granger-causality in the frequency domain we utilise all variables in level form and chose AR(p) based on AIC, LR and FPE. However, to compare findings of our frequency domain with the traditional VAR based Granger-causality we also analyse conditional VAR Granger-causality model and report results in Table-3 below.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Trade Balance</th>
<th>Oil Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excluded Chi-sq</td>
<td>43.50702</td>
<td>14.5856</td>
</tr>
<tr>
<td>df</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>Prob.</td>
<td>0.0000</td>
<td>0.0417</td>
</tr>
</tbody>
</table>

Table-3 shows that there is strong evidence of bidirectional causal relation between the tested variable after conditioning the VAR model for both time periods (that when India current account become full convertible and period before). Further, we examined the impulse response analysis and presented results in Figure-2 below. Prior to this we confirm that our VAR model is stable and do not suffer from the problem of serial correlation (all results are presented in Table -1A and Figure-1A in the appendix).

Figure 2: Conditional Impulse-Response functions analysis
Figure-2 demonstrates that results are almost same for both periods i.e., for 1980-2011 and 1994-2011. It is very clear that response of OP, due to one standard deviation shock to TB is positive throughout study period (indicating that fluctuations in the Indian trade balance could increase the oil prices). However, response of TB due to one standard deviation shock to OP is negative throughout period (indicating that increase in the prices of oil may worsen the trade balance of India).

Finally, we present the results of frequency domain analysis. Here, we have also adopted two approaches. In the first case, a bi-variate model is estimated, i.e., without conditioning the model and, in the second case, a bi-variate model is estimated with conditioning the model. We present the results of both models in the following Figures, in two panels-A and -B, for without and with conditioning the model, respectively. In Figure-3 we present results of frequency domain analysis when study period starts from 1980.

**Figure 3: Frequency domain Granger-causality (Period= 1980-2011)**
Note: OP and TB, stands for, respectively, oil price and trade balance.

\[ Frequency \ (\omega) = \frac{2\pi}{cycle \ length \ (T)} \]

The panel-A and panel-B of Figure-3 show that both variables Granger-cause each other at short and long frequency horizons. Specifically, in panel-A, TB Granger-causes OP in the frequency range of 0.01 to 0.77, and 2.28 to 3 indicating business cycles of 8 to 629 months, and 2 to 2.7 months, respectively. In panel-A, OP Granger-causes the TB in the frequency range of 0.01 to 0.77, and 2.49 to 3 indicating business cycles of 8 to 629 months, and 2 to 2.5 months, respectively. In panel-B, TB Granger-causes OP in the frequency range of 0.01 to 0.55, and 2.6 to 3 indicating business cycle of 11 to 629, and 2 to 2.4 months, respectively. In panel-B, OP Granger-causes the TB in the frequency range of 0.01 to 0.34, and 2.49 to 2.8 indicating business cycles of 18.5 to 629, and 2 to 2.2 months, respectively. Finally, we analyze model for the period of post capital account liberalization and presented results in Figure-4 below.
We find from panel-A and panel-B of Figure-3 that both variables Granger-cause each other at short and long frequency horizons. Specifically, in panel-A, TB Granger-causes OP in the frequency range of 0.01 to 0.87, and 1.63 to 3 indicating business cycles of 7.2 to 629, and 3.9 to 2 months, respectively. In panel-A, OP Granger-causes TB in the frequency range of 0.01 to 0.77, 1.3 to 1.5, and 2.38 to 3 indicating business cycles of 8.1 to 369, 4.1 to 4.8, and 2.6 to 2
months, respectively. In panel-B, TB Granger-causes OP in the frequency range of 0.01 to 0.44, and 1.84 to 2.38 indicating business cycle of 14.3 to 629, and 2.6 to 3.4 months cycle, respectively. In panel-B, OP Granger-causes TB in the frequency range of 0.01 to 0.334, 1.31 to 1.73, and 2.5 to 3 indicating business cycles of 18.8 to 629, 3.63 to 4.8, and 2.5 to 2 months, respectively.

5. Conclusions and policy implications

The study analyzed the lead-lag relationship between oil price and trade balance for India by using monthly data covering the period from January 1980 to December 2011 and also for the post current account convertibility era i.e., August 1994 to December 2011. To analyze the issue in depth, study decomposes the causal relationship into frequency components using Breitung and Candelon’s (2006) approach. To the best of our knowledge, this is first ever study in this direction with the present approach to any economy. VAR based conditional Granger-causality provide evidence of bidirectional causality. However, impulse response analysis shows that oil price has negative impact on trade balance whereas impact of trade balance on oil price is positive. Results of VAR based conditional Granger-causality analysis are robust as there is no difference in the findings of both samples of period. Further, frequency domain analysis throws more lights in the strength of direction of causality and its cyclical nature. Evidence of bivariate model as well as bivariate conditional model for period 1980 show that there is significant bidirectional long-run as well as short-run business cycle causality between TB and OP. Evidence of bivariate model as well as bivariate conditional model for period 1994 show that there is bidirectional long-run as well as short-run business causality between TB and OP, however, there is unidirectional medium-run business cycle causality running from OP to TB.

In conclusion, our finding provides evidence of a bidirectional frequency domain causal relationship between oil price and trade balance at short and long frequencies. However, frequencies of bidirectional causal relationship are not same for both variables. Moreover, more strength is found when causality is running from oil price to trade balance. Also, high degree of cyclical nature is found when causality is running from oil price to trade balance. Interestingly, results of the post current account convertibility provide evidence of significant frequency domain causality running from oil price to trade balance at short, medium and long run not the otherwise. Hence, our study shows that the oil price has become a leading indicator for Indian trade balance in the short-medium- and long horizons. These findings have important policy implications for Indian government and policy formulations as India is experiencing a growing trade deficit. We recommend that dependence on oil should be reduced as it is the main factor responsible for the short-run, medium-run and long-run trade imbalance in the Indian economy. Another possible alternative is to diversify further oil import basket which may be to some extent helpful to minimise the negative consequences of growing oil prices on trade balance.
References


Appendix

Figure 1A: VAR stability analysis

Table 1A: VAR residual serial correlation test

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Probs from chi-square with 4 df.