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

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Abstract

This paper studies the lead–lag relationship between oil prices and trade balance for India by using monthly data covering the period from January 1980 to December 2011 and the post current account convertibility era (from August 1994 to December 2011). To analyse the issue, we adopt the approach proposed by Breitung and Candelon (2006) along with the traditional VAR-based conditional Granger causality. The results of VAR-based conditional Granger causality provide evidence of a bidirectional causal relationship in both study periods. Impulse response analysis shows a positive response of the oil price to one standard deviation shock in the trade balance, whereas the trade balance shows a negative response to one standard deviation shock in the oil price. However, frequency domain analysis also provides evidence of a bidirectional causal relationship, which holds for dissimilar frequencies in the short and medium run in the full sample. Moreover, greater strength and a high degree of cyclicality are found when causality runs from the oil price to the trade balance. Interestingly, the results of the post current account convertibility era provide evidence of frequency domain causality running from the oil price to the trade balance in the short, medium and long run, not otherwise. Hence, our study shows that the oil price has become a leading indicator of the Indian trade balance for the short, medium and long horizons.

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1. Introduction

Trade serves as a key engine for economic growth, particularly in the fastest-growing countries like India, and oil is the most traded commodity in the world. On the one hand, high dependence on trade benefits economies by improving their 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 its exports, reached 10.3 per cent 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 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 per cent of the GDP at market prices in 2010–11 to almost 10.3 per cent 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. However, this has not been the case for India. The merchandise exports grew by 38 per cent in 2011–12, which was higher than their growth of 22 per cent in 2010–11, but the import growth of 79 per cent in 2011–12 was far higher than the 17 per cent growth in the previous year. Hence, the rise in the trade deficit can be attributed to a much faster rise in imports than in exports. Therefore, the following question arises: what are the reasons behind the rapid rise in imports? 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 amounted to 4822.817 rupees (in billions). This represented an increase of about 54 per cent 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 per cent in 2011–12 compared with 26.2 per cent in 2010–11, showed a much lower rate of growth than oil imports. There is no doubt that the high growth in oil imports has been the main factor behind the sharp rise in the imports bill.

Additionally, global crude oil prices are rising at an unprecedented rate, which has substantially inflated India's imports bill. India's crude oil 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 is not affected to the same extent. However, during the last year, all 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 US$62.5 per barrel in 2006–07. Interestingly, the volume of oil imports experienced lower growth of 8.9 per cent in 2007–08 vis-à-vis 13.13 per cent in 2006–07. This further decreased to 4.3 per cent in 2011–12. Thus, the increase in oil imports was primarily value-driven and not volume-driven.

[1] The year-on-year growth in petroleum, oil and lubricants imports in 2007–08 was 35.3 per cent, which was higher than the growth of 30.76 per cent in 2006–07.

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 imports bill and trade balance will continue to remain sensitive to movements in the world oil prices. With global crude prices inching close to US$150 per barrel, the imports 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 per cent of GDP in 2010–11, the current account deficit increased to 4.3 per cent 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 policy discussions that oil price shocks would have large and negative effects on the trade balance. When there is a surge in oil prices, countries are forced to borrow from abroad to offset the 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 examine the lead–lag relationship between the oil price and the trade balance in India using the frequency domain approach.

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

2. Theoretical background and a brief review of the literature

Oil price shocks may have an impact on the external accounts of an economy through two different channels, namely the trade channel and the financial channel (Le and Chang, 2013). Transmission through the trade channel works through changes in the quantities and prices of tradable goods. Transmission through the financial channel works through changes in external portfolio positions and asset prices. However, given the aim of our study, we will focus on transmission through the trade channel and review the related literature. Oil prices 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. Kim and Loungani (1992) and Backus and Crucini (2000) 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 its effects on production decisions. The process can be explained as follows: in net oil-importing economies, imported oil may be considered as an intermediate input in the domestic production and thus an increase in oil prices leads to a direct increase in the input cost, which in turn forces firms and households to curtail their expenditure and investment plans, thus causing a decrease in the total output. A lower total output and hence fewer exports, but not correspondingly less consumption of oil, will lead to an overall negative trade balance and a further increase in the oil price will further increase the negative balance of the overall trade balance (with other things remaining constant).[2]

There is a voluminous body of literature analysing 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). However, very few studies have addressed the trade channel of the transmission of oil price shocks to an economy. Noteworthy exceptions 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 the 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 production and consumption. Bodenstein et al. (2011) used a two-country DSGE model (the US – as the home country – versus the "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, in complete markets, the non-oil terms of trade remain unchanged, as does the non-oil trade balance, whereas in incomplete markets, the former suffers from 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 the ARDL approach and also explored the causality direction between the trade balance and the oil price shocks over a period from 1975 to 2010. The result shows that there is a significant negative relationship among the oil prices, the exchange rate and the trade balance, i.e., if there is a 1 per cent increase in oil prices and the exchange rate, the trade balance decreases by 0.382 per cent and 0.342 per cent, respectively. This implies that the oil prices and the exchange rate induce a trade imbalance in Pakistan. In addition, there is a positive relationship between the output gap and the trade balance, which implies inefficient resource allocation and utilization in production. In the short run, there is a positive relationship among the exchange rate, the output gap and the 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

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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, Rebucci and Spatafora (2006), Bollino (2007) and Setser (2007), but all these studied the subject for the US case.

increases the trade deficit. The results of Granger causality tests indicate that there is unidirectional causality running from oil prices to the 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 generalized impulse response functions (IRFs), respectively, to monthly data spanning from January 1999 to November 2011 to examine the long-run causality from oil prices to overall, oil and non-oil trade balances and their short-run dynamics. Le and Chang (2013) derived the 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. They 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 is 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

We use data on oil prices as the average of U.K. Brent, Dubai and Oman, as in India oil is imported from these markets. As the oil prices are expressed in US dollars, we convert them into Indian rupees using the India–US exchange rate. Further, we use the Index of Industrial Production (IIP) and Whole Sale Price Index (WPI) as conditional variables to remove the effects of these variables on the trade balance. All the series are obtained from the database of the IMF. Our study period is 1980m1–2011m12. Further, we analyse, in a second time period, data beginning from 1994m8 as India adopted the policy of full capital account convertibility in August 1994 to look into the lead–lag relationship between variables in the post capital account convertibility era. All the series are converted to natural logarithms (except the trade balance) for analysis purposes in order to smooth 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 Granger causality to that in the time domain. To 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 to indicate 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 partial directed coherence (PDC), for testing Granger causality in the frequency domain, we focus on a slightly different approach to Granger causality, following a method by Granger (1969) and later refined by Geweke (1982), which is adopted by 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 the sum of “instantaneous”, “feedforward” and “feedback” causality terms. The Breitung and Candelon (2006) approach can be explained as follows:

Let $z_t = [x_t, y_t]'$ be a two-dimensional vector of time series observed at $t = 1,...,T$ that has a finite-order VAR representation of the form:

$$\Theta(L) z_t = \varepsilon_t, \tag{1}$$

where $\Theta(L) = I - \Theta_1 L - ... - \Theta_p L^p$ is a 2×2 lag polynomial with $L^k z_t = z_{t-k}$. We assume that the error vector ε_t is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t^{'}) = \Sigma,$ where Σ 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:

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

$$= \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \tag{3}$$

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:

$$f_x(\omega) = \frac{1}{2\pi} \{ | \Psi_{11}(e^{-i\omega}) |^2 + | \Psi_{12}(e^{-i\omega}) |^2 \}. \tag{4}$$

The measure of causality suggested by Geweke (1982) is defined as:

$$M_{y\to x}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{\left|\Psi_{11}(e^{-i\omega})\right|^2}\right] \tag{5}$$

$$= \log\left|1 + \frac{\left|\Psi_{12}(e^{-i\omega})\right|}{\left|\Psi_{11}(e^{-i\omega})\right|}\right|. \tag{6}$$

If $\left|\psi_{12}(e^{-i\omega})\right|^2 = 0,$ then Geweke's measure will be zero, then y will not Granger cause x at frequency ω.

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:

$$\Delta z_t = \tilde{\Phi}(L)\varepsilon_t = \tilde{\Psi}(L)\eta_t, \tag{7}$$

where $\tilde{\Psi}(L) = \tilde{\Phi}(L)G^{-1}, \eta_t = G\varepsilon_t,$ 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 β 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:

$$M_{y\to x}(\omega) = \log\left|1 + \frac{\left|\tilde{\Psi}_{12}(e^{-i\omega})\right|}{\left|\tilde{\Psi}_{11}(e^{-i\omega})\right|}\right|. \tag{8}$$

To test the hypothesis that y does not cause x at frequency ω, we consider the null hypothesis:

$$M_{y\to x}(\omega) = 0 \tag{9}$$

within a bivariate framework. Breitung and Candelon (2006) presented this test by reformulating the relationship between x and y in the VAR equation:

$$x_t = a_1 x_{t-1} + ... + a_p x_{t-p} + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + \varepsilon_{1t} \tag{10}$$

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

$$H_0 : R(\omega)\beta = 0 \tag{11}$$

where β is the vector of the coefficients of y and

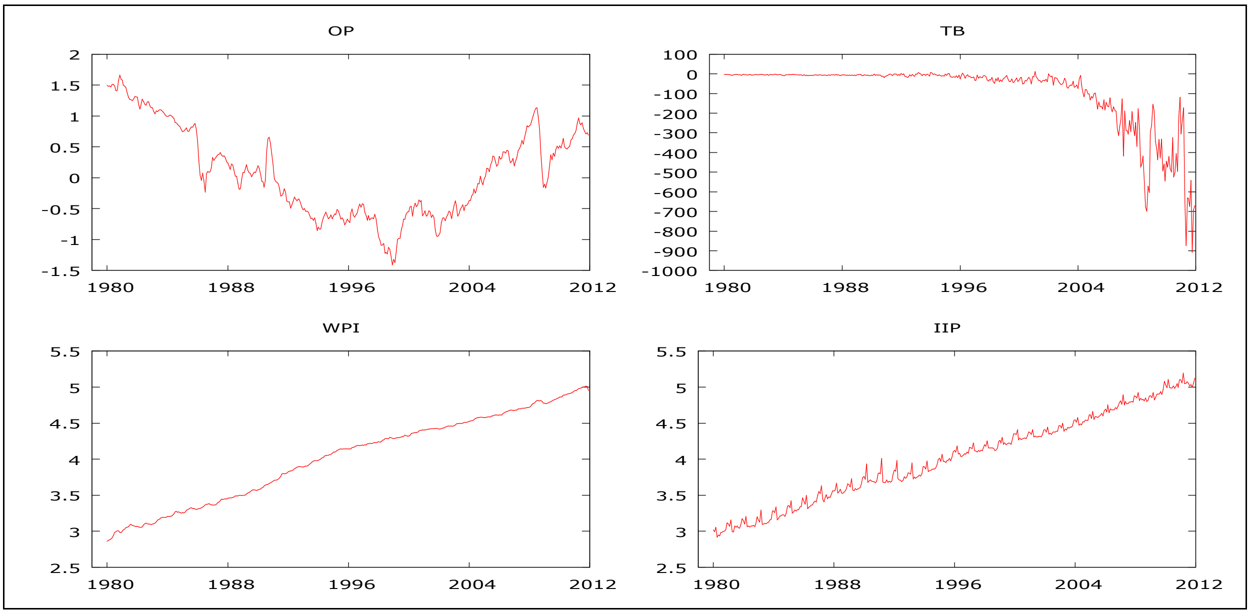
$$R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega).....\cos(p\omega) \\ \sin(\omega)\sin(2\omega).......\sin(p\omega) \end{bmatrix} \tag{12}$$

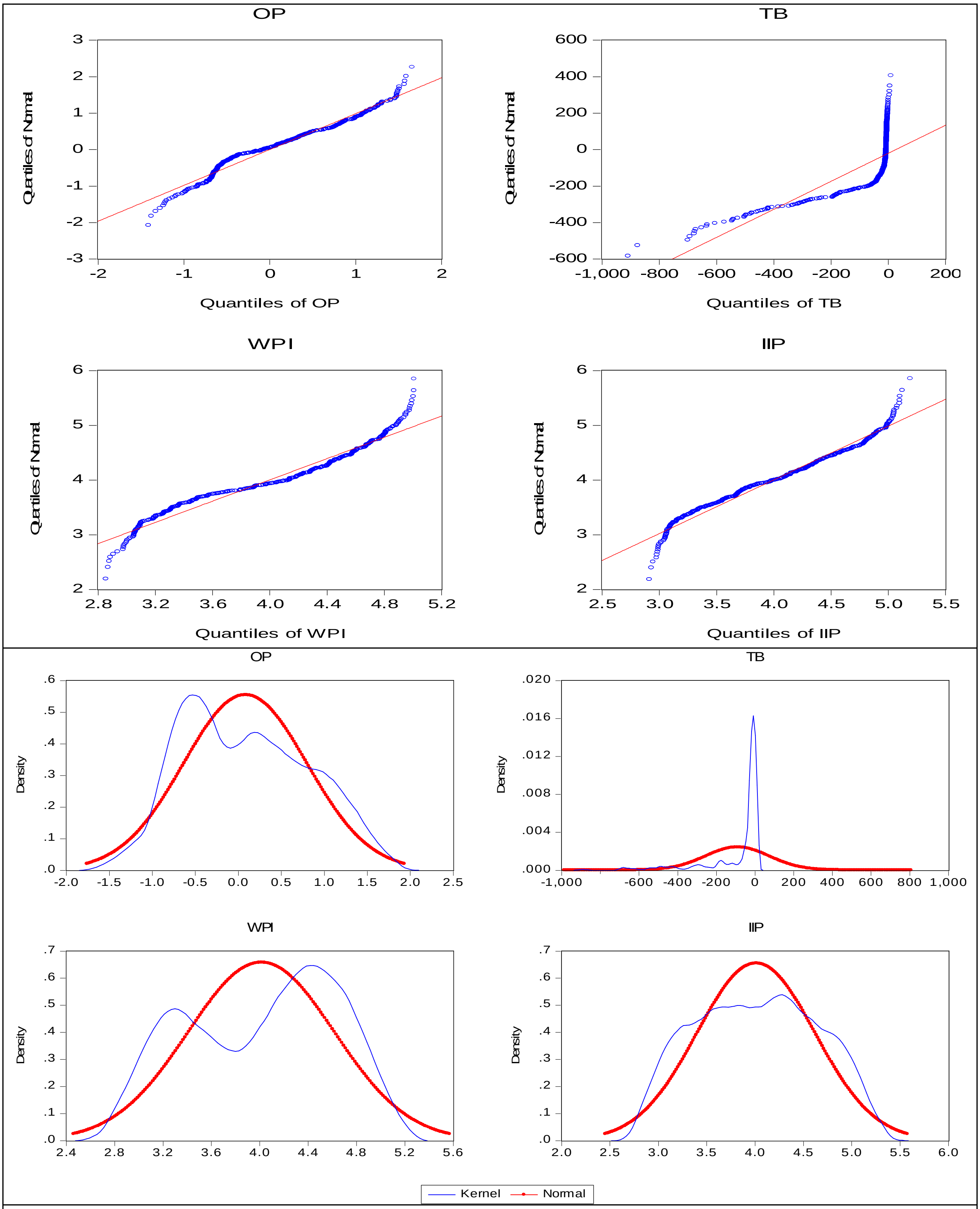
The ordinary F statistic for (11) is approximately distributed as $F(2, T-2p)$ for $\omega \in (0, \pi)$. It is interesting to consider the frequency domain causality test within a co-integrating framework. To this end, Breitung and Candelon (2006) suggested replacing x_t in regression (7) with Δx_t, with the right-hand side of the equation remaining the same (see Breitung and Candelon (2006) for a more detailed discussion of this and for the case in which one variable is $I(1)$ and the 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 a stationary framework no long-run relationship exists between time series; a series may nevertheless explain future low-frequency variations 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 one period ahead.

4. Data analysis and empirical findings

To examine the characteristics of the variables used, their time series plots along with their distribution plots are presented in Figure 1.

Figure 1: Plots 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.

The time series plots show that the OP declined until 1999 and afterwards it again increased rapidly, albeit with fluctuations; the trade balance has worsened since 2004 and is continuing on a more negative trend; and the WPI and IIP show a linear trend relationship but the growth of IIP has been experiencing volatility. Quantile plots of the studied variables show that they are all distributed non-normally. This finding is confirmed by their kernel distribution plots relative to the theoretical kernel distribution plots. Further, to see the sample property, we present the descriptive statistics of the variables in Table 1 below.

Table 1: Descriptive statistics of series

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

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

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

Further, to test for the unit root among the variables, we use the Zivot and Andrews (1992) test. To test for stationarity, traditionally the augmented Dickey–Fuller (1979) test and Phillips and Perron (1988) test were widely used. Nevertheless, these tests fail to allow for an existing break, which leads to a bias reducing the ability to reject a false unit root null hypothesis (Perron, 1989). 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 has been criticized, most notably by Christiano (1992), as “data mining”. Since then, several studies have developed unit root tests using different methodologies and accounting for endogenous determination of the break dates, such as Perron and Vogelsang (1992), Zivot and Andrews (1992), Perron (1997) and Lumsdaine and Papell (1998). In this paper, we apply the Zivot and Andrews (1992) unit root test. This test is advantageous in the sense that it determines endogenously structural break dates over the full sample using a different dummy variable for each possible break date. The break date is selected where the t-statistic from the ADF test of the unit root is at its minimum. The results of the unit root test based on the Zivot and Andrews (1992) test are presented in Table 2 below.

Table-2: Unit root tests for constant and trend model

Test	IIP	OP	WPI	TB
Zivot-Andrews test [k]	-9.557184 [4]	-5.170162 [1]	-4.868577 [4]	-8.446917 [4]
(10% critical value)	(-4.82)	(-4.82)	(-4.82)	(-4.82)
DST statistic (corrected) [k]	-4.220510 [3]	-12.767118 [4]	-9.746265 [2]	-5.955622 [3]
(p-value of DST)	(0.00002437)	(0.000000)	(0.000000)	(0.00000)

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. In DST statistic [k] is the Final AR(p) order selected by BIC. DST statistic is proposed by Dickey and Zhang (2010).

It is evident from Table 2 that the null hypothesis of a unit root is rejected for all the variables in the level at 10%. The results obtained from DST statistic also support the finding of Zivot and Andrews (1992) test.[4] This implies that all the variables are integrated of order zero, i.e., I(0). Thus, to analyse the Granger causality in the frequency domain, we utilize all the variables in the level and choose an AR(p) specification based on the AIC, LR and FPE information criteria. However, to compare the findings of our frequency domain with the traditional VAR-based Granger causality, we also analyse the conditional VAR Granger causality model and report the results in Table 3 below.

Table-3: VAR Granger Causality/Block Exogeneity Wald Tests

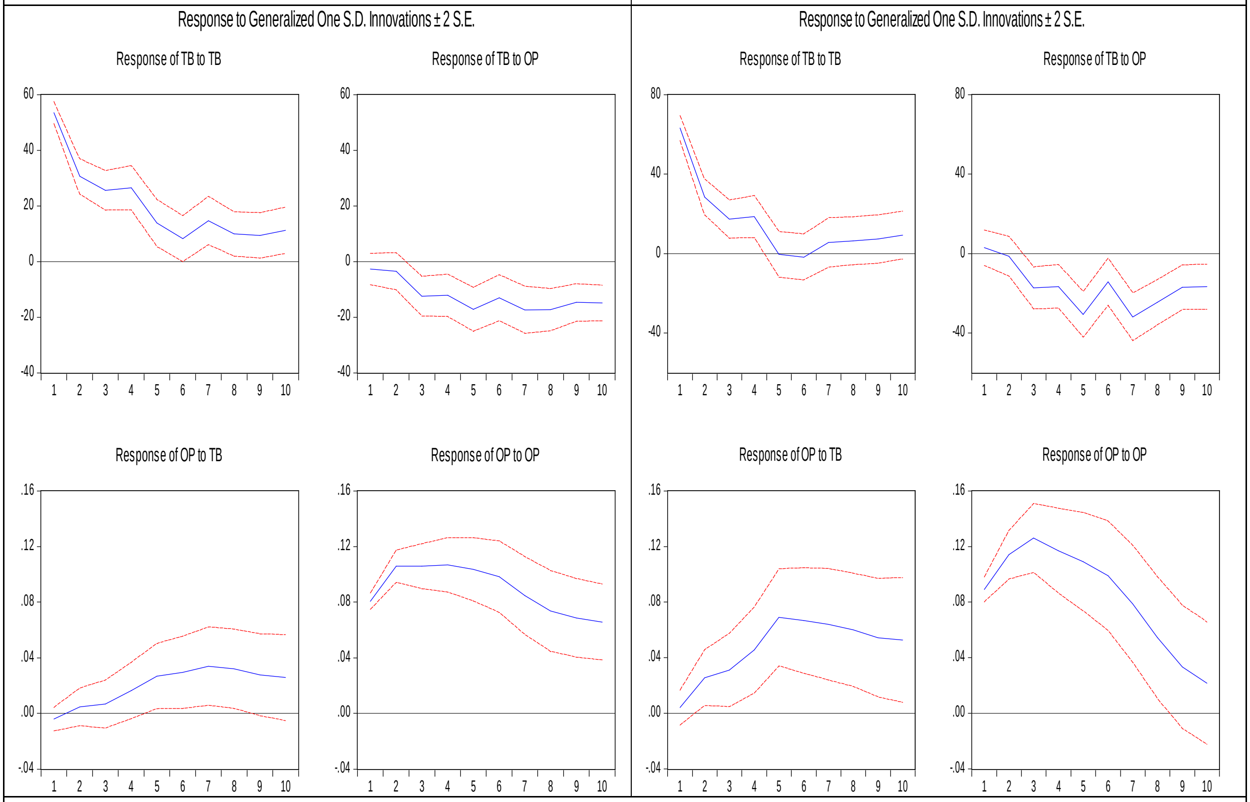
	Dependent variable: Trade Balance				Dependent variable: Oil Price			
	Excluded	Chi-sq	Df	Prob.	Excluded	Chi-sq	Df	Prob.
Period=1980 -2011	Oil price	43.50702	7	0.0000	Trade Balance	14.5856 4	7	0.0417
Period=1994 -2011	Oil price	64.08833	7	0.0000	Trade Balance	28.9405 6	7	0.0001

[4] DST statistic is a recently proposed seasonal unit root tests. We used this test to see the robustness of our results obtained from Zivot and Andrews (1992) test because Zivot and Andrews (1992) test might have suffered from the problem of seasonality.

Table 3 shows that there is strong evidence of a bidirectional causal relation between the variables after conditioning the VAR model for both time periods. Note that our VAR model is stable and does not suffer from the problem of serial correlations (all the results are presented in Table 1A and Figure 1A in the appendix). Further, Figure 2 below reports the impulse response functions.

Figure 2: Conditional Impulse-Response functions analysis

Period=1980-2011	Period =1994-2011



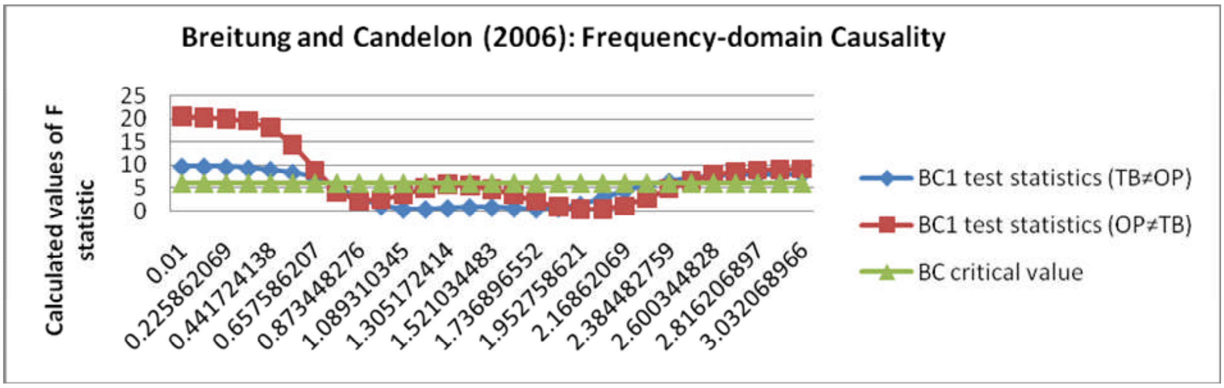
Note: OP and TB, stands for, respectively, oil price and trade balance.

Figure 2 shows that the results are almost the same for the two periods, i.e., for 1980–2011 and 1994–2011. It is very clear that the response of OP, due to one standard deviation shock to TB, is positive throughout the study period (indicating that fluctuations in the Indian trade balance could increase the oil prices). However, the response of TB due to one standard deviation shock to OP is negative throughout the period (indicating that an increase in the prices of oil may deteriorate the trade balance of India).

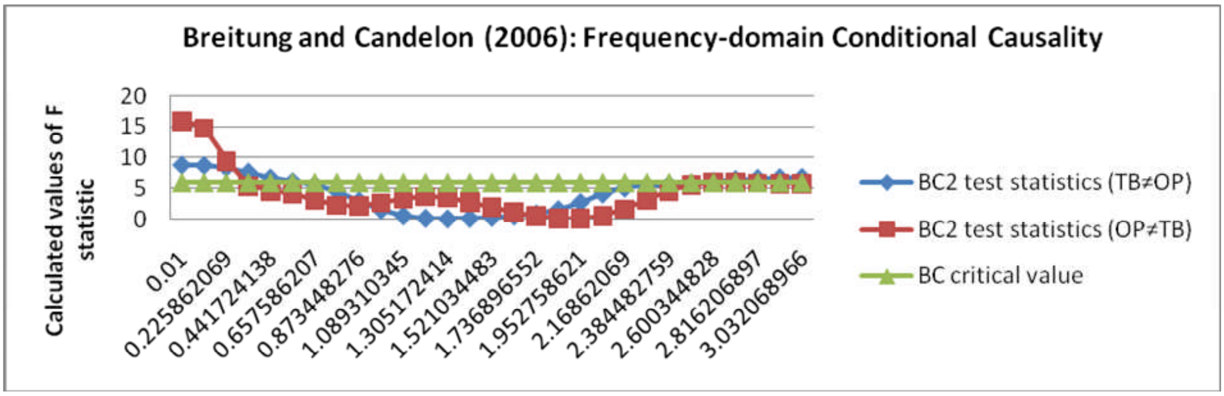
Finally, we present the results of the frequency domain analysis. Here, we have also adopted two approaches. In the first case, a bivariate model is estimated without conditioning the model, and, in the second case, a bivariate model is estimated with conditioning of the model. We present the results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

Figure 3: Frequency domain Granger-causality (Period= 1980-2011)

A



B



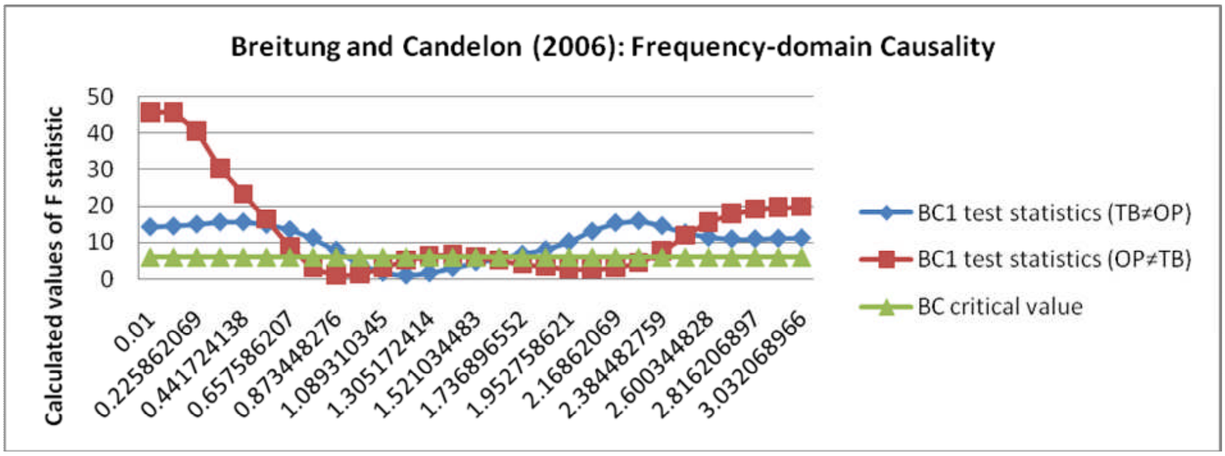
Note: OP and TB, stands for, respectively, oil price and trade balance.
Frequency (ω)= *2π/cycle length (T)*

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 ranges 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 TB in the frequency ranges of 0.01

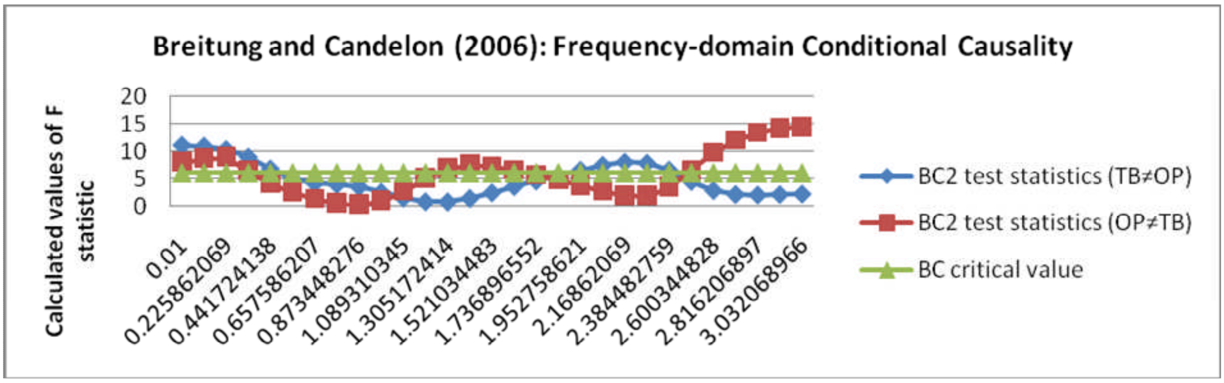
to 0.77 and 2.49 to 3, indicating business cycles of 8 to 629 months and 2 to 2.5 months, respectively. In panel B, TB Granger-causes OP in the frequency ranges of 0.01 to 0.55 and 2.6 to 3, indicating business cycles of 11 to 629 and 2 to 2.4 months, respectively. In panel B, OP Granger-causes TB in the frequency ranges 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 analyse the model for the period of post capital account liberalization and report the results in Figure 4 below.

Figure 4: Frequency domain Granger-causality (Period=1994-2011)

A



B



Note: OP and TB, stands for, respectively, oil price and trade balance.
Frequency (ω)= *2π/cycle length (T)*

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 ranges 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 ranges 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 ranges of 0.01 to 0.44 and 1.84 to 2.38, indicating business cycles of 14.3 to 629 and 2.6 to 3.4 months, respectively. In panel B, OP Granger-causes TB in the frequency ranges 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 analysed the lead–lag relationship between the oil price and the trade balance for India by using monthly data covering the period from January 1980 to December 2011, as well as for the post current account convertibility period, i.e., August 1994 to December 2011. To analyse the issue in depth, we decomposed the causal relationship into frequency components using Breitung and Candelon's (2006) approach. To the best of our knowledge, this is the first study to use this very rich approach to investigate the relationship between the oil price and the trade balance. The VAR-based conditional Granger causality tests provide evidence of bidirectional causality. However, the impulse response analysis shows that the oil price has a negative impact on the trade balance, whereas the impact of the trade balance on the oil price is positive. The results of the VAR-based conditional Granger causality analysis are robust as there is no difference in the findings for the two sample periods. Further, frequency domain analysis throws more light on the strength of the direction of causality and its cyclical nature. Evidence of the bivariate model as well as the bivariate conditional model for the period 1980–2011 shows that there are significant bidirectional long-run as well as short-run business cycle causalities between TB and OP. Evidence of the bivariate model as well as the bivariate conditional model for the period 1994–2011 shows that there are bidirectional long-run as well as short-run business causalities 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 the oil price and the trade balance at short and long frequencies. However, the frequencies of the bidirectional causal relationship are not the same for the two variables. Moreover, greater strength is found when causality runs from the oil price to the trade balance. In addition, a high degree of cyclicality is found when the causality runs from the oil price to the trade balance. Interestingly, the results of the post current account convertibility provide evidence of significant frequency domain causality running from the oil price to the trade balance in the short, medium and long run, not otherwise. Hence, our study shows that the oil price has become a leading indicator of the Indian trade balance for the short, medium and long horizons.

Our findings have important policy implications for the Indian Government and policy formulations as India is experiencing a growing trade deficit. We recommend that the 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 the oil import basket further, which may to some extent be helpful in minimizing the negative consequences of the growing oil prices on the trade balance.

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Appendix

Figure 1A: VAR stability analysis

VAR model (1980-2011)	VAR model (1994-2011)

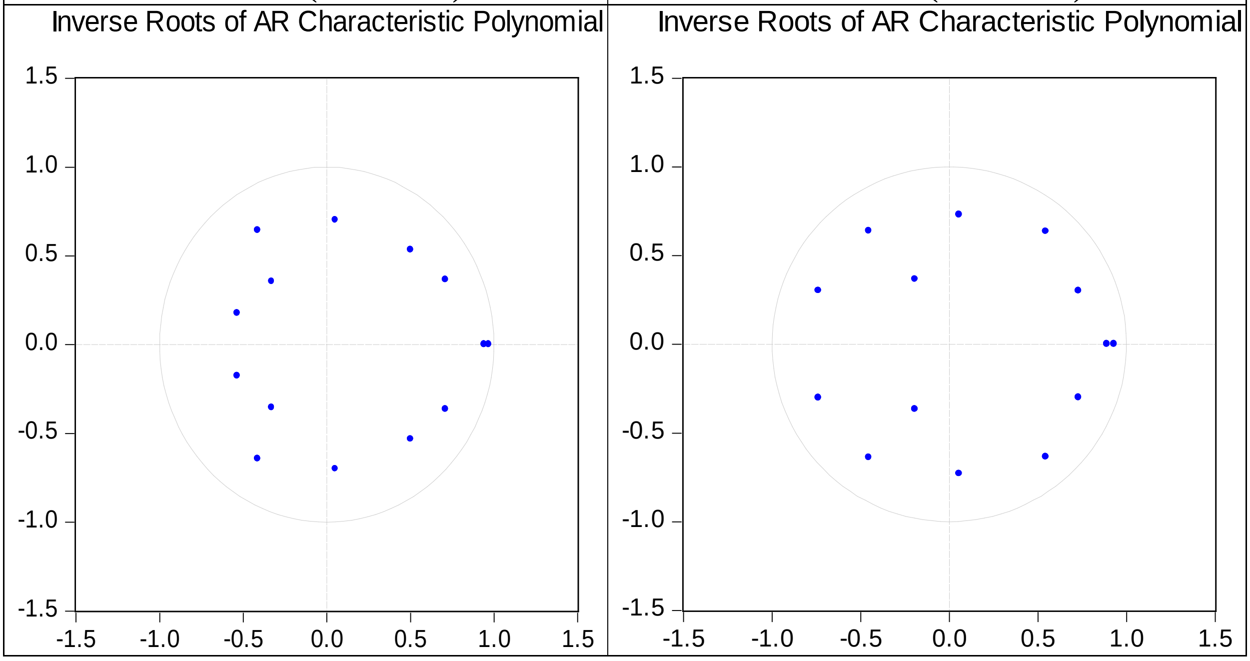

Table 1A: VAR residual serial correlation test

	VAR model (1980-2011)		VAR model (1994-2011)	
Lags	LM-Stat	Prob	LM-Stat	Prob
1	5.060709	0.2811	9.619769	0.0473
2	11.77822	0.0191	6.931480	0.1396
3	7.580759	0.1082	7.719847	0.1024
4	9.758885	0.0447	6.374125	0.1729
5	9.589800	0.0479	5.751754	0.2185
6	15.48821	0.0038	17.90314	0.0013
7	5.478990	0.2416	6.832229	0.1450
Probs from chi-square with 4 df.				