Oil price and exchange rate in India: Fresh evidence from continuous wavelet approach and asymmetric, multi-horizon Granger-causality tests

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HIGHLIGHTS

● We assess the relationship between the oil price and India-US real exchange rate.
● We use a wavelet approach and asymmetric, multi-horizon Granger-causality tests.
● Co-movements are noticed in the post-reform period, especially for 2–4-years bands.
● The Granger-causal relationship between variables is non-linear and asymmetric.
● The short run oil price movements are important for the exchange rate stabilization.

ARTICLE INFO

Article history:
Received 5 January 2016
Received in revised form 21 June 2016
Accepted 29 June 2016
Available online 8 July 2016

JEL classification:
C40
E32

Keywords:
Cyclical and anti-cyclical effects
Wavelet coherence
Oil price-exchange rate
Granger causality
India

1. Introduction

The effectiveness of energy policies are of vital importance for the macroeconomic environment due to supply-side shocks which might generate. After the 1973 oil crisis many researchers have empirically examined the relationship between oil prices and various macroeconomic issues, underlining the link between oil shocks and recessions [1]. The empirical literature has blossomed again after the remarkable fluctuations recorded by international oil prices in 2008–2009, but especially after the 2014 free-fall in oil prices, highlighting the impact of energy policies in general and of oil prices in particular, on business cycles and inflation [2–4], on stock prices [5–7], on non-energy commodity markets [8], or on other monetary issues like the exchange rate [9,10]. However, because the oil represents one of the most traded commodities, assessing the impact of oil price shocks on the exchange rate deserve a special attention.

There is a well-established theoretical link between the international oil price and the US Dollar exchange rate. On the one hand, Golub [11] and Krugman [12] document how the oil price explains exchange rate movements. In brief, according to these authors an
oil-exporting (oil-importing) country may experience a currency appreciation (depreciation) when oil prices rise and depreciation (appreciation) when oil prices fall. On the other hand, Bloomberg and Harris [13] provide an explanation on the potential impact of exchange rates on oil price movements. In short, relying on the law of one price for tradable goods, they show that, since oil is a homogeneous and internationally traded commodity priced in US Dollars, a depreciation of this currency reduces the oil price to foreigners relative to the price of their commodities denominated in US Dollars. Thereby, as their purchasing power and oil demand increases, the crude oil price in US Dollars is pushed up. Further, as the US Dollar is the major billing and settlement currency in international oil markets, the domestic currency exchange rate with the US Dollar is the key channel through which an oil price shock is transmitted to the real economy, with different effects for oil-exporting and oil-importing countries [14]. Consequently, the response on monetary policies to oil price fluctuations can amplify the shocks in the oil price [2].

The empirical investigation of the oil price – exchange rate nexus shows mixed evidence. The dominant view in the literature, represented by Amano and van Norden [15], Chaudhuri and Daniel [16], Bénassy-Quéré et al. [17], Chen and Chen [18], Coudert et al. [19], Lizardo and Mollick [20] and more recently by Basher et al. [21], reports a unidirectional Granger causality from the oil price to the exchange rate. Another view argues that movements in the US Dollar exchange rate Granger-cause crude oil prices, showing thus the opposite phenomenon (see for example [22]). Most of these studies use cointegration techniques and one-shot measures of Granger-causality.

However, recent studies show that the relationship between the oil price and the exchange rate is time-frequency dependent and bidirectional at the same time [10,23,24]. In line with these studies, our paper aims to analyze the lead-lag relationship between the return series of the oil price and the Indian Rupee exchange rate against the US Dollar, applying continuous wavelets. This method allows to see if the direction and the strength of the Granger causality and the lead-lag relationship between variables vary in time and over different frequencies. In addition, by applying Continuous Wavelet Transform (CWT) we are able to identify cyclical and anti-cyclical relations, as well as periods of volatility/jumps and structural breaks.

Different from the works mentioned above, the present paper brings forward several contributions to the existing literature. First, the CWT methodology used in previous studies is largely based on Torrence and Compo [25], who use a parametric bootstrap approach to assess the significance of areas. However, the pointwise testing approach, especially for the phase difference, is questionable (for a discussion, see [26]). Therefore, in order to avoid this bias, we employ the bootstrapping method advanced by Cazelles et al. [27], who compare the consistency of different resampling techniques, and take into account the key components of a time series (i.e. mean, variance and distributions of values, in both time and frequency domains). Second, different from previous studies, the present paper explores the oil price – exchange rate relationship, applying a wavelet Granger-causality test, recently proposed by Olayeni [28]. This method circumvents the need for a minimum-phase transfer functions and is able to identify causality in both time and frequency.

We also contribute to the literature by employing a battery of newly proposed time-series based tests to disclose the Granger-causal relationship between the variables in question, and we compare them with frequency-domain and regime-switching based Granger-causal tests, in order to check the robustness of the wavelet Granger-causality test. All these tests allow to estimate the non-linear Granger-causal relationships between the oil price and the India-US exchange rate. In this line, we first use time-series tests, as multi-horizon Granger-causality tests [29], non-linear Granger-causality tests [30,31], and asymmetric Granger-causality tests [32]. Second, we employ the frequency-domain Granger-causality test proposed by Lemmens et al. [33], and the Markov regime-switching VAR (MRS-VAR) to account for regime-switching in the Granger-causal relationship. Finally, we combine the Hatemi-j [32] and Dufour et al. [29] methodologies, in order to see if the asymmetric Granger-causal relationship is instantaneous or gradual.

Another contribution of the present paper resides in the analysis of the particular case of India, which had in place a managed float exchange rate regime starting with 1975 (the pre-reform period), and introduced the Liberalized Exchange Rate Management System (LERMS) in March 1992 (the post-reform period). According to the Energy Information Agency (EIA) statistics, India recently became the fourth largest consumer of oil and petroleum products, and also the fourth largest importer. Between a wide range of oil suppliers, Nigeria stands as the main supplier at the moment, followed by the Saudi Arabia. India’s crude oil imports cover a basket of three varieties – Brent, Dubai and West Texas Intermediate (WTI). Given this composition, even if one of the three varieties experiences sharp increases in prices, the overall price of the basket does not get affected to the same extent. Consequently, when studying the oil price – exchange rate nexus, it is useful to refer to all the benchmarks, as we do in this paper, using the International Monetary Fund (IMF) statistics. We also focus on India because its dependence on oil imports has been growing rapidly in the recent years, creating a huge trade deficit. At the same time, the trade deficit can also widen due to the Rupee’s appreciation vis-à-vis other major currencies (i.e., the US Dollar). In this context conducting adequate energy policies is highly important for the Indian government.

Finally, the results we obtain represent by their own a distinct contribution of this paper to the existing literature, as they allow the comparison of the oil prices – exchange rate nexus over two exchange rate regimes. Different from other studies with a focus on India, we discover a significant Granger-causality relationship between oil prices and the Rupee-US Dollar exchange rate, which is non-linear and bidirectional. In addition, this relationship manifests differently in the short and long run, and exists only in the post-reform period.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature on the oil prices – exchange rate nexus. Information about the wavelet methodology and Granger-causality test in the CWT is given in Section 3. Section 4 describes the data. Section 5 presents and discusses the results while Section 6 concludes and draws policy implications for policymakers and traders.

2. The oil price – exchange rate relationship: literature review

There is a voluminous body of literature analyzing the causal relationship between the oil price and the exchange rate. A first strand finds evidence of unidirectional causal relationships, usually running from the oil price to the exchange rate [17,18,34]. Different from these studies, Zhang et al. [22] find that causality is running from the US Dollar exchange rate to the oil price and documents that the US Dollar depreciation is a key factor in driving up the international crude oil price. A second strand of research finds evidence of bidirectional Granger-causality between the oil price and exchange rates [35,36].

However, most of the previous studies analyze the oil price – exchange rate nexus in the case of developed countries, leaving small open economies and emerging countries outside the main research arena, with few exceptions (i.e., [37–40]). In line
with the research conducted on developed economies, most of these studies employ cointegration analyses and Granger-causality tests and find that the oil price influences the exchange rate for Russia [41], for China [37], for Fiji Islands [38] or for the African countries [39,40].

Nevertheless, in this case also we notice mixed results. On the one hand, Bashir et al. [21] examine the dynamic relationship between oil prices, exchange rates and emerging market stock prices, and find that a positive shock to oil prices tends to depress emerging market exchange rates in the short run. On the other hand, Turhan et al. [42] find that a rise in the oil price leads to a significant appreciation of emerging economies’ currencies against the US Dollar. These findings support the idea that the causality between the oil price and exchange rates might not be linear. So, recent studies use non-linear causality tests to investigate the causal relationships between oil prices and exchange rates (i.e., [23,43]).

In the case of India, the oil price – exchange rate nexus is empirically prospected by Ghosh [9], who uses daily data for the period 2007–2008 and an exponential-GARCH (EGARCH) model, and shows that an increase in oil price returns leads to the depreciation of the Indian currency vis-à-vis the US Dollar. The Indian case is also analyzed in the larger context of emerging markets. In this line, Beckmann and Czudaj [44] study the link between oil prices and the US Dollar exchange rates using monthly data for various oil-exporting and oil-importing countries and employ a Markov-switching vector error correction model. For India, they find a direct relationship between the nominal exchange rate and the oil price, where an increase in the oil price coincides with a depreciation of the Indian currency.

According to our records, the only study addressing the oil price – exchange rate relation in the case of India, using a wavelet framework, belongs to Tiwari et al. [10]. Applying a Discrete Wavelet Transform (DWT) and non-linear causality tests, the authors document both linear and non-linear causal relationships between the oil price and the India’s real effective exchange rate at higher time scales (lower frequency), but also at the lower time-scales (higher frequency). Bal and Rath [43] investigate in their turn the oil price – exchange rate nexus in the context of India and China applying the non-linear causality test advanced by Hiemstra and Jones [45]. They report significant bidirectional nonlinear Granger causality between oil prices and exchange rates in both countries.

However, different from the aforementioned studies, in the present paper we use the wavelet coheison following Rua [46] and we use the bootstrapping method advanced by Cazelles et al. [27]. Further, different from the above-mentioned papers, we employ the recent Granger-causality test in the CWT, following Olayeni [28]. Moreover, we compare the Granger-causality results for robustness purpose, using different newly proposed time-series, frequency-domain and regime-switching based Granger-causal tests.

3. Methodology

The wavelet approach was proposed to circumvent the limitations of the Fourier transform (see [47–49]) and it is based on two filters which operate with low- and high-frequency trend components, namely the father and the mother wavelet. While the wavelet approach was first applied in geophysics and signal processing [50–53], starting with Rua and Nunes [54] it became largely used in economics and finance [46,53–62]. Noteworthy studies investigate the impact of energy prices on the macroeconomy, with a focus on oil prices [10,23,63].

A distinctive category of wavelet transforms is the CWT, which allows the interpretation of the variables’ variances on a single diagram and it is recommended to assess the common movements of the series and the phase differences.

3.1. Continuous wavelet transform

Wavelet transforms are used to decompose the signal or time series over dilated and translated functions called mother wavelets. These wavelets (function of two parameters, one for the time position and the other for the time scale) could be defined as:

$$\psi_a(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t - \tau}{a}\right)$$ (1)

where $a$ and $\tau$ denote the dilation (scale factor) and translation (time shift), respectively. A time series $x(t)$ with respect to a chosen mother wavelet can be decomposed as:

$$W_a(x, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \varphi\left(\frac{t - \tau}{a}\right) dt = \int_{-\infty}^{+\infty} x(t) \varphi\left(\frac{t - \tau}{a}\right) dt$$ (2)

where $\psi^*$ denotes the complex conjugate form and the wavelet coefficients, $W_a(x, \tau)$, represents the contribution of the scales $a$ at different time positions $\tau$. The factor $\frac{1}{\sqrt{a}}$ normalizes the wavelets so that they have unit variance and hence are comparable for all scales $a$.

In line with previous studies, we have chosen the Morlet wavelet in our analysis:

$$\varphi(t) = e^{-\pi t^2} \exp\left(-i2\pi f_d t\right) \exp\left(-t^2 / 2\right)$$ (3)

A complex number $W_a(x, \tau)$ can be written in terms of its phase $\phi_a(x, \tau)$ and modulus $||W_a(x, \tau)||$. The phase of the Morlet transform varies cyclically between $-\pi$ and $\pi$ over the duration of the component wave forms and is defined as:

$$\phi_a(x, \tau) = \tan^{-1} \frac{\Re[W_a(x, \tau)]}{\Im[W_a(x, \tau)]}$$ (4)

The “local wavelet power spectrum” is given by:

$$S_a(x, \tau) = ||W_a(x, \tau)||^2$$ (5)

The “global wavelet power spectrum”, defined as the averaged variance contained in all wavelet coefficients of the same scale $a$, can be written as:

$$S_{a}(\tau) = \frac{\sigma^2}{T} \int_{0}^{T} ||W_a(x, \tau)||^2 dt$$ (6)

with $\sigma^2$ being the variance of the time series $x$ and $T$ its duration. The mean variance at each time location is obtained by averaging the frequency components and is given as:

$$S_{a}(\tau) = \frac{\sigma^2}{T} \int_{0}^{\infty} a^{1/2} ||W_a(x, \tau)||^2 da$$ (7)

In economics, it is often desirable to quantify statistical relationships between two non-stationary time series. To quantify the relationships between two non-stationary signals, the “wavelet cross spectrum” and the “wavelet coherence” are often of interest. The wavelet cross-spectrum is given by $W_{xy}(a, \tau) = W_x(a, \tau) W_y^*(a, \tau)$ where $^*$ denotes the complex conjugate. The wavelet coherence is defined as the cross-spectrum normalized by the spectrum of each signal:

$$R_{xy}(a, \tau) = \frac{||W_{xy}(a, \tau)||}{||W_x(a, \tau)||^{1/2}||W_y(a, \tau)||^{1/2}}$$ (8)

where $'\cdot'$ denotes a smoothing operator in both time and scale. Using this definition, $R_{xy}(a, \tau)$ is bounded by $0 \leq R_{xy}(a, \tau) \leq 1$.  

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1 The elaboration of this section is based on Cazelles et al. [27].
However, the CWT is useful for bivariate cases only. As several macroeconomic variables are asymmetrically or non-linearly related to each other, the CWT fails to take them into account as endogenous variables and obtain the true relationship. Therefore, in order to assess the statistical significance of the patterns exhibited by the wavelet approach we adopt bootstrapping methods. Thus, following Cazelles et al. [27], we use a resampling procedure of the observed data, and a Markov process scheme that preserves only the short temporal correlations.

### 3.2. Causality in continuous wavelet transform

As an alternative to the discrete wavelet transform (DWT) usually employed for Granger causality tests, we employ the CWT for the Granger causality proposed by Olayeni [28], which in turn is built on the CWT-based correlation measure by Rua [64]. It is given by:

$$G_{Y \rightarrow X}(s, \tau) = \frac{\zeta^{-1} |R(W_{YX}(s, \tau))I_{Y \rightarrow X}(s, \tau)|}{\zeta^{-1} \sqrt{|W_{XX}(s, \tau)|^2 \cdot \zeta^{-1} \sqrt{|W_{YY}(s, \tau)|^2}}$$

(8)

where \(W_{YX}(s, \tau)\) and \(W_{XX}(s, \tau)\) and \(W_{YY}(s, \tau)\) are the wavelet transforms and \(I_{Y \rightarrow X}(s, \tau)\) is the indicator function defined as [28]:

$$I_{Y \rightarrow X}(s, \tau) = \begin{cases} 1, & \text{if } \phi_{YX}(s, \tau) \in (0, \pi/2) \cup (-\pi, -\pi/2) \\ 0, & \text{otherwise} \end{cases}$$

(9)

In order to check for the robustness of the results provided by the Granger causality in the CWT analysis, we apply several time-series, frequency-domain, and regime-switching based Granger-causal tests, which emphasize the asymmetry and non-linearity which might appear between variables. The Hatemi-J’s [32] test is asymmetric in the sense that it performs Granger causality between positive and negative components of the data, where the positive component represents the positive shock, and the negative component represents the negative shock. The Dufour et al. [29] propose a multi-horizon Granger-causality test which helps us to find out if the Granger-causal relationship is instantaneous (significant Granger-causality at horizon 1) or gradual, i.e., indirect (significant Granger-causality at horizons higher than 1). We also analyze non-linear Granger-causalties using the Péguin-Feissolle et al. [30] test (in mean), and the Nishiyama et al. [31] test (in mean and variance). However, all the above stated time-domain approaches ignore the importance of the frequency component. Therefore, we use the frequency-domain Granger-causality test proposed by Lemmens et al. [33]. Furthermore, in order to estimate the influence of business cycles, we use the Markov regime-switching VAR (MRSVAR), to account for the regime switching in the Granger-causal relationship.

### 4. Data description

We use monthly data covering the period 1980M1–2016M2. The exchange rate is measured by the India-US real exchange rate, provided by the Federal Reserve Bank of St. Louis (FRED St. Louis). The oil price is measured by the average of Brent, Dubai, and WTI benchmarks and the data are extracted from the IMF (External data), being thus available starting with 1980. Even if the WTI monthly statistics can be found on a historical basis, Dubai represents the main benchmark in the case of India, and this benchmark gained importance only in the 1980s. Further, given India’s reduced oil consumption before 1980 (less than 1% out of the world consumption, compared to almost 5% at present), the investigation of the oil price–exchange rate nexus for the selected period is reasonable. In addition, before 1975, India had in place a fixed exchange rate regime, as the Rupee was pegged to the Pound Sterling until 1966, and to the US Dollar afterward. The fact that the Rupee experienced a managed floating regime only after 1975 also sustains the choice of the analyzed time-span. Before proceeding to the estimations, both series are transformed to the first difference of their natural logarithms and then were standardized.

### 5. Empirical findings and discussions

#### 5.1. Wavelets results

The wavelet approach enables the description of the evolution of oscillating characteristics of a given time-series. Therefore, we present summarized results of the wavelet analysis in Fig. 1a-e. Fig. 1a presents the time-series plot of the standardized variables i.e., the oil price (DLNOP) and the exchange rate (DLNEXNUS). Both series have high peaks around 1987, 1992, and 2008. The results of the wavelet analysis are summarized in Fig. 1b-e. Fig. 1b and d presents the plots of local wavelet power spectra (LWPS) of the oil price returns and exchange rate. The LWPS is helpful in detecting common islands or regions where (i.e., at which time-frequency) variance of both series is very high, and where the wavelet coherence and phase differences give meaningful results.

Fig. 1c and e presents the global wavelet power spectrum (GWPS), or the average WPS for the two series. By the visual assessment of color contour plots in Fig. 1b and d, we notice that the WPS is not constant over time, as well as across frequencies. While the power spectrum shows that high power (variance) is concentrated in medium and higher frequencies (i.e., lower and medium time-scales) for the oil price, in the case of the exchange rate it is concentrated in lower and medium frequencies (i.e., high and medium time-scales). Nevertheless, it is not clear from the GWPS at which time actually the highest power is concentrated. Thus, we focus on the LWPS to analyze the local variance of the series. For the oil price, the WPS shows a continuous oscillating mode at both 1–2–years and 2–4–years bands, but with varying time periods (Fig. 1b). However, these modes of oscillation vary in strength. The dominant modes for the oil price are 1986–1988, 1990–1991 and 2006–2010 at the 1–2–years band, and 1998–2001 at the 2–4–years band. Similarly, for the India-US exchange rate, the WPS shows a continuous oscillating mode at the 1–2 years, at the 2–4 years and at the 2–8 years band, with a varying time period (Fig. 1d). Consequently, although the wavelet analysis reveals similar oscillating components for the time-series, these components are not always present at the same moment in time.

Figs. 1b and 2d show that there are several common islands for the two series. In particular, the common features in the wavelet power of the two time-series are evident during 1990–1992 and 2007–2010. During these periods, both series have the power above the 5% significance level, as marked by the thick black dotted contour. In other words, the wavelet coherence that quantifies the co-movements between the time-series should be significant only for 1991–1992 and 2008–2009, around the 1–2 years band and 2–4 years band modes.

The similarity between the portrayed patterns of both series in these periods can be assessed through the CWT, if it is merely a coincidence. But, as the wavelet cross-spectrum describes the common power of two processes without normalization to the single WPS, it may produce misleading results because the CWT is multiplied. For instance, if one of the spectra is local, and the other exhibits strong peaks, these may have nothing to do with any relation of the two series. Therefore, in our analysis, we rely on the wavelet coherence (a measure of co-movements developed by [46]) and on the wavelet coherence, along with the phase relationship.
The wavelet coherence is used to disclose the correlation between the oil price and the India-US exchange rate (Fig. 2). This measure ranges from +1 to −1, similar to the correlation.

We notice from Fig. 2 that there is a high degree of positive correlation between the oil price and the India-US exchange rate during 1991–1993 and 1998–2002, in the 0.5–1.0-years of scale. However, we also find evidence of high negative correlation in the 1–2-years of scale up to 1990, and in the 2–4-years of scale since 1994. These findings reconfirm the need to evaluate the degree of correlation over scale and time. Hence, in the final step of the wavelet analysis, we estimate the wavelet coherence, along with the phase-difference for three scale bands (2–4-years, 4–6-years and 8–10-years). We also analyze the normality of phase difference plots for these scale bands and their oscillating nature. All these results are presented in Fig. 3.

The wavelet coherence is used to identify both, frequency bands and time intervals within which pairs the two series are co-varying (Fig. 3a). We focus the 2–4-years band because the WPS indicates a significant amount of common power for this band only. So, in the case of the 2–4-years band, there is a significant degree of coherence around 1986–1987, 1990–2000, and 2005–2010. Fig. 3f shows that the phase difference around 1986–1987 lies in $[0, -\pi/2]$ indicating that both series move in-phase, and the oil price is leading.

The period 1990–2000, which is the period of first-generation economic reforms, experiences huge inconsistency in the phase and lead-lag relationship between variables questioned across time-scales. For example, the phase difference during the period 1990–1992 lies in $[0, \pi/2]$, indicating that both series move in-phase, and the exchange rate leads the oil price. Further, the phase difference during the 1993–1997 interval, lies in $[\pi/2, \pi]$, indicating that both series have an anti-phase relation.

All in all, the wavelets results are pointing toward the fact that economic agents might have specific reactions to oil price changes, depending on their long or short run perspectives on the relationship between the oil price and the exchange rate. Moreover, the influence of the exchange rate upon the oil price is time-frequency dependent. Therefore, we need further clarification and we resort to a battery of Granger-causality tests.

5.2. Results of Granger-causality tests between the oil price and the exchange rate

We start this analysis with the wavelet Granger-causality advanced by Olayeni [28]. We notice from Fig. 4a that the wavelet causality from the exchange rate to the oil price is significant around the year 2000, for the 0.5–1-years band (i.e., 6–12-months band). A second moment which characterizes the Granger-causality from the exchange rate to the oil price can be noticed between 1992 and 1995, for the 2–4-years band. This result is in agreement with the findings generated by Fig. 3f, where both series move in-phase and the exchange rate is leading.

Fig. 4b shows that the oil price Granger-causes the exchange rate in two different periods. The first period arises around 1995, for the 4–6-months band (that is 0.5-years band), while the second period can be noticed after the outburst of the recent financial crisis, for the 2–4-years band, when the oil price significantly Granger-causes the India-US exchange rate. This result corresponds to the findings presented in Fig. 3a for the 2–4-years band, and remains unchanged if we modify the time-span to the 1973M1–2012M4 period (see Appendix A).

We also check for the robustness of these findings using several recently developed time-series Granger-causality tests. For all these tests, we first present the results for the full sample, and later break it into pre- and post-reform periods. Further, we use two types of data in the estimation process i.e., the first difference of
the series and the standardized first difference. As in the wavelet
analysis, the standardized first difference data are used. Thus, in
purely time-series analysis, our conclusions would be based on
the latter type of data set.2

We begin with the asymmetric Granger-causality test proposed
by Hatemi-J [32]. When standardized data are used (Table 1), we
find that in the case of the full sample there is no significant
Granger-causality, either in the negative components, or in
the positive components. So, the asymmetric Granger-causality test
shows no impact of the oil price shocks on the Indian Rupee’s
exchange rate.

These results do not support the general findings of the wavelet
analysis. However, we must notice that here we could not capture
whether the Granger-causal relationship is instantaneous or
gradual. Therefore, in the next step we use the multi-horizon
causality test proposed by Dufour et al. [29]. The multi-horizon
causality test is also applied to the positive and negative
components obtained from the procedure described by Hatemi-J
[32]. Table 2 presents the results for the standardized series.

We find a significant evidence of bidirectional
Granger-causality at different horizons. Most of the causal
relationships appear for the full sample, where the exchange rate
Granger-causes the oil price at horizons 4–8, while the oil price
Granger-causes the exchange rate at horizons 3. In the case of
the full data sample, for the negative components of both variables

* The results for all time-series Granger-causality tests for raw data can be
provided upon request.
we find unidirectional Granger-causality running from the India-US exchange rate to the oil price at horizons 4–7.

In the pre-reform period, we find only one instance of significant Granger-causality, running from the exchange rate to the oil price, at horizon 5. For the post-reform period, the results show that the exchange rate Granger-causes the oil price at horizons 4–8, whereas the oil price does not Granger-causes the exchange rate. As in the case of the full sample, for the negative components we find a unidirectional causality from the exchange rate to the oil price. These results support our previous findings, stating that the Granger-causal relationship between the India-US exchange rate and the oil price is not only indirect but also asymmetric. We further apply a more powerful non-linear Granger-causality test proposed by Nishiyama et al. [31]. Table 3 shows significant evidence of unidirectional Granger-causality running from the oil price to the exchange rate, only in the post-reform period.3

We continue the analysis with the Markov regime-switching VAR (MRS-VAR) model to account for the regime switching in the Granger-causal relationship in time-series. This is due to the fact that, sufficiently long time-series data often exhibit dramatic shifts in their behavior, due to changes in the government policies, technological shocks, and financial crises. Hamilton [65] proposes a probabilistic model, called the Markov regime-switching model, where such institutional changes are approximated by a random variable instead of a deterministic dummy variable.4 Thus we estimated a two-state MRS-VAR model following Perlin [68] and Ding [69]. The Perlin [68] packages assume that the transition probabilities are constant, whereas Ding [69] packages assume that the transition probabilities are time-varying. We define the two states for an oil price shock as increasing and decreasing regime of the oil price. Table 4 exhibits the MRS-VAR estimation results for both states. As shown in Table 4, in the regime represented by the state 1, an oil price shock, with a two months lag, has a significant and negative impact on the India-US exchange rate. At the same time, a positive shock in the exchange rate has a positive impact on the oil price, indicating that the Rupee’s appreciation increases the oil demand, with a positive influence on international oil prices.

The transition probability matrix in Table 5 shows that regime 1 is highly persistent. The probability that the state 1 will be followed by 5 months of state 2 is 0.87. Furthermore, Table 5 shows that regime 1 will persist for 8 months while regime 2 will stay for 5 months in average. The conditional probability of

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3 We also use the non-linear Granger-causality test proposed by Pégouin-Feissolle et al. [30], but the results obtained for the standardized data seem to be contrary to the results obtained through the application of Nishiyama et al. [31], which represent a more powerful test (see the authors for argumentation).

4 For other developments of the Markov regime-switching models, please refer to Hansen and Seo [66] and Lam [67].

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Table 1
Results of asymmetric Granger-causality analysis for standardized series [32].

<table>
<thead>
<tr>
<th>Pre-reform</th>
<th>Post-reform</th>
<th>H0: OP ≠ ER</th>
<th>Test value</th>
<th>BCV at 1%</th>
<th>BCV at 5%</th>
<th>BCV at 10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>OP↑ → ER↑</td>
<td>0.064</td>
<td>14.54</td>
<td>6.774</td>
<td>5.020</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OP↓ → ER↑</td>
<td>1.420</td>
<td>9.878</td>
<td>6.493</td>
<td>4.901</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OP↑ → ER↓</td>
<td>1.061</td>
<td>9.239</td>
<td>5.964</td>
<td>4.576</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OP↓ → ER↓</td>
<td>0.054</td>
<td>8.776</td>
<td>4.719</td>
<td>4.719</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Post-reform</th>
<th>H0: ER ≠ OP</th>
<th>Test value</th>
<th>BCV at 1%</th>
<th>BCV at 5%</th>
<th>BCV at 10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>OP↑ → ER↑</td>
<td>0.362</td>
<td>12.79</td>
<td>3.704</td>
<td>2.159</td>
<td></td>
</tr>
<tr>
<td>OP↓ → ER↑</td>
<td>0.554</td>
<td>10.54</td>
<td>4.247</td>
<td>2.553</td>
<td></td>
</tr>
<tr>
<td>OP↑ → ER↓</td>
<td>0.069</td>
<td>11.40</td>
<td>3.677</td>
<td>2.183</td>
<td></td>
</tr>
<tr>
<td>OP↓ → ER↓</td>
<td>0.115</td>
<td>9.745</td>
<td>3.967</td>
<td>2.441</td>
<td></td>
</tr>
</tbody>
</table>

Notes: (a) The max lag order considered is 12; (b) the symbol OP → ER means that the oil price does not cause the exchange rate; (c) BCV means critical value; (d) * shows causality significant at 10% level of significance.
MSVAR results for a constant probability model.

Multi horizon Granger-causality tests for standardized data [29].

Table 2

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>H = 1</th>
<th>H = 2</th>
<th>H = 3</th>
<th>H = 4</th>
<th>H = 5</th>
<th>H = 6</th>
<th>H = 7</th>
<th>H = 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>OP =&gt; ER</td>
<td>0.4505</td>
<td>0.3198</td>
<td>0.1675</td>
<td>0.1853</td>
<td>0.2491</td>
<td>0.3682</td>
<td>0.3386</td>
<td>0.4384</td>
</tr>
<tr>
<td>ER =&gt; OP</td>
<td>0.1591</td>
<td>0.2995</td>
<td>0.3604</td>
<td>0.0878</td>
<td>0.0489</td>
<td>0.0439</td>
<td>0.0491</td>
<td>0.0637</td>
</tr>
<tr>
<td>OP^+ =&gt; OP</td>
<td>0.3505</td>
<td>0.1281</td>
<td>0.0805</td>
<td>0.1659</td>
<td>0.2710</td>
<td>0.3845</td>
<td>0.4517</td>
<td>0.5054</td>
</tr>
<tr>
<td>ER^+ =&gt; OP</td>
<td>0.1541</td>
<td>0.1473</td>
<td>0.3673</td>
<td>0.3131</td>
<td>0.1936</td>
<td>0.1534</td>
<td>0.1281</td>
<td>0.0794</td>
</tr>
<tr>
<td>OP =&gt; ER</td>
<td>0.1802</td>
<td>0.1569</td>
<td>0.1874</td>
<td>0.2345</td>
<td>0.272</td>
<td>0.4002</td>
<td>0.3793</td>
<td>0.5209</td>
</tr>
<tr>
<td>ER =&gt; OP</td>
<td>0.0594</td>
<td>0.1764</td>
<td>0.1374</td>
<td>0.0849</td>
<td>0.0357</td>
<td>0.022</td>
<td>0.0282</td>
<td>0.1057</td>
</tr>
<tr>
<td>OP^+ =&gt; ER</td>
<td>0.3783</td>
<td>0.6039</td>
<td>0.5219</td>
<td>0.5029</td>
<td>0.4179</td>
<td>0.3137</td>
<td>0.4718</td>
<td>0.4264</td>
</tr>
<tr>
<td>ER =&gt; OP</td>
<td>0.0914</td>
<td>0.2576</td>
<td>0.3436</td>
<td>0.5968</td>
<td>0.1739</td>
<td>0.1618</td>
<td>0.0997</td>
<td>0.3352</td>
</tr>
<tr>
<td>OP =&gt; ER^+</td>
<td>0.6062</td>
<td>0.5681</td>
<td>0.4166</td>
<td>0.3731</td>
<td>0.4108</td>
<td>0.3807</td>
<td>0.4706</td>
<td>0.5094</td>
</tr>
<tr>
<td>ER^+ =&gt; OP</td>
<td>0.0904</td>
<td>0.6319</td>
<td>0.5523</td>
<td>0.3059</td>
<td>0.2827</td>
<td>0.3325</td>
<td>0.3676</td>
<td>0.3919</td>
</tr>
</tbody>
</table>

Notes:
(a) The max lag order considered is 12. The optimal lag order is selected based on AIC for each combination; (b) the symbol OP => ER means that the oil price does not cause the exchange rate; (c) only p-values are presented; (d) OP^+ are the positive components of the oil price series, while OP^- are the negative components (the same applies for the ER); (e) significant causal relationships are marked in bold.

Table 3

Results of non-linear Granger-causality tests for standardized data [31].

<table>
<thead>
<tr>
<th>H0: OP =&gt; ER</th>
<th>H0: ER =&gt; OP</th>
</tr>
</thead>
<tbody>
<tr>
<td>S^1_j</td>
<td>S^2_j</td>
</tr>
<tr>
<td>Pre-reform</td>
<td>4.188 16.78 3.365 5.458</td>
</tr>
</tbody>
</table>

Notes:
(a) S^1_j and S^2_j are the test statistics for first moment (i.e., mean) and second moment (i.e., variance), respectively. That is, the first and second test checks the null hypothesis of non-linear Granger-non-causality in mean and variance, respectively. The procedure runs as follows: we start testing the null for the first movement and if it is not rejected, then we test for the second moment and continue the procedure till the null is rejected. (b) H => H denotes results are not calculated. Critical value at 5% level of significance is 14.38. (c) ^+ means that the null hypothesis of Granger-causality is rejected from the oil prices to the exchange rate for example (denoted as OP => ER).

Table 4

MSVAR results for a constant probability model.

<table>
<thead>
<tr>
<th>Equation: OP</th>
<th>Equation: ER</th>
</tr>
</thead>
<tbody>
<tr>
<td>State 1</td>
<td>State 2</td>
</tr>
<tr>
<td>OP(1)</td>
<td>0.08 (0.27)</td>
</tr>
<tr>
<td>OP(2)</td>
<td>-0.10* (0.09)</td>
</tr>
<tr>
<td>ER(1)</td>
<td>-0.19 (0.15)</td>
</tr>
<tr>
<td>ER(2)</td>
<td>0.16 (0.19)</td>
</tr>
</tbody>
</table>

Notes:
(a) p-values in brackets; (b) *, **, and *** denotes respectively, significance at level 10%, 5%, and 1% of significance level; (c) OP – the oil price, ER – the exchange rate; (d) the lag order is chosen based on AIC information criteria.

Table 5

Transition probability matrix and expected duration of each state.

<table>
<thead>
<tr>
<th>States</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.87</td>
<td>0.19</td>
</tr>
<tr>
<td>2</td>
<td>0.13</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Duration of stay 7.76 time periods ~ 8 months 5.19 time periods ~ 5 months

regimes 1 and 2 is shown in Appendix B, which verifies that the probability of regime 1 is more prevalent than regime 2 in the entire sample period.

Last but not least, we use the frequency-domain Granger-causality test developed by Lemmens et al. [33]. For the standardized data (Fig. 5), we notice that there is a bidirectional Granger-causality between the oil price and the India-US exchange rate, around the frequency 0.5-years. However, for lower frequencies (i.e., over a year), significant evidence of unidirectional Granger-causality running from the exchange rate to the oil price is found.

5.3. Discussions

Our results show the importance of energy policies on monetary issues and complement previous findings on the oil price – exchange rate nexus, underlining the non-linear, asymmetric and indirect effects which characterize this relationship in the context of India. The first set of results is based on the CWT analysis and its developments, namely the wavelet power spectrum and the
wavelet cohesion. One must note that our major discussion about these results and phase difference is for the 2–4-years band, where a high degree of coherence is observed around 1986–1987, 1990–2000, and 2005–2010.

First, between 1986 and 1987 both series move in-phase, and the oil price is leading. This period corresponds to the situation when India is experiencing a lot of political uncertainty and implements a managed floating regime (the Rupee is pegged to a basket of currencies of India’s trading partners and the exchange rate is officially determined by the Reserve Bank of India within a nominal band of ±5%), starting with 1975, till 1992. The period starting with 1985 is marked by continuous downward adjustments in the external value of the Rupee which is mainly brought by the sharp increase in the oil price in 1986–1987, as a result of the oil demand shock. Thus, these results confirm the arguments put forward by Golub [11] and Krugman [12].

Second, 1990–2000 is the period of the first-generation economic reforms, characterized by huge inconsistency in the phase and lead-lag relationship between variables questioned across time-scales. For example, during the period 1990–1992 both series move in-phase, and the exchange rate leads the oil price. In the same period, the Reserve Bank of India devalues the Rupee two times, on July 1, and 3, 1991 (with 18% and 19% respectively). In March 1992, the partial convertibility of the Rupee is introduced, also known as a dual exchange rate system. For this period, the supply side argument put forward by Bloomberg and Harris [13] holds very well. That is, during this period the economy experiences mounting inflation, which reduces the consumption capacity and consequently decreases the demand of non-tradable goods, contributing to a fall in their prices. Thus, the real exchange rate depreciates, which in turn leads to increases in the oil price. On contrary, during the interval 1993–1997 the variables are out-of-phase. This is the period when the oil price falls in general and the Rupee consistently depreciates because of demand shocks, phenomenon explained by Turhan et al. [42]. The phase difference in 2000–2002 shows that both series move in-phase and the oil price is leading. This is again the result of an oil demand shock.

These results highlight the fact that the oil price – exchange rate relationship is largely influenced by the presence of oil demand shocks and monetary reforms. Therefore, on the one hand the findings based on the CWT analysis are similar with those reported by Tiwari et al. [10] who discover the leading relationship of the oil price upon the Rupee exchange rate for the 16–32-months band (approximately a part of Indian business cycle). On the other hand, different from Tiwari et al. [10] the present paper underlines that we may have periods where the exchange rate is leading (i.e. 1990–1992). The bootstrapping method that we use allows to see the complexity of the oil price – exchange rate nexus in the case of India.

The second set of results is generated by the use of wavelet Granger-causality test advanced by Olayeni [28] and of various multi-horizon, non-linear and asymmetric Granger-causality tests. The wavelet Granger-causality test documents a bidirectional causality in the very short run for some periods, while for the 2–4-years band, which corresponds to fundamental traders and institutional investors, a unidirectional causality is shown between 1992 and 1995, running from the exchange rate to the oil price. In general, the oil price Granger-causes the exchange rate in the short run, while the opposite applies in the long run. The remaining time domain tests show in general a bidirectional causality (dominated however by the exchange rate influence on the oil price), which manifests in particular in the post-reform period.

These findings are somehow different from those reported by Tiwari et al. [10] who do not find any causal relationship at lower time scales and only unidirectional causality from the exchange rate to the oil price at higher scales. However, our findings are in line with those reported by Bal and Rath [43] regarding the time domain Granger-causality tests. As in Bal and Rath [43] we find a significant bidirectional non-linear Granger causality between the oil price and the Indian Rupee exchange rate.

All in all we show on the one hand that the India-US exchange rate Granger-causes the oil price in the long run, while the opposite applies in the short run. This main results can be explained by the fact that oil prices are more volatile and shocks in oil prices are rapidly transmitted to the India-US exchange rate (with a two months lag according to the MRS-VAR test). On contrary, the exchange rate Granger-causes the oil price only in the long run because, on the one hand, oil prices are established on the international market where different factors determine the oil supply and demand and, on the one hand, the increasing role of India which became the fourth largest oil consumer and importer cannot be neglected. Thus, a real appreciation of the Indian Rupee will be followed by a higher demand for oil products, which finally will generate an increase in international oil prices. These findings are supported by the newly proposed non-linear and regime-switching Granger-causality tests.

Therefore, the findings of previous studies should be considered with caution because, on the one hand, the lead-lag relationship is documented only for certain frequencies (i.e. 2–4-years band) and time intervals, and, on the other hand, the bidirectional relationship is not only non-linear, but also asymmetric.

6. Conclusions and policy implications

Energy policies and macroeconomic issues are closely related. The particular subject of oil price – exchange rate nexus is intensively investigated by the empirical literature, due to numerous
interdependences which can arise between shocks in the oil price and the monetary policy. Because India became one of the major oil importers, it represents an interesting case study for analyzing this relationship. For this purpose, the present paper uses novel techniques, as the CWT, wavelet Granger-causality tests, together with several recently proposed time-series, frequency-domain and regime-switching Granger-causality models.

The wavelet cohesion shows a high degree of positive correlation between the oil price and the India-US exchange rate in the post-reform period, in particular in the short run. Our time-frequency analysis reveals some more interesting findings. For example, we document a significant amount of common power in the WPS for both series for the 2–4-years band. In the post-reform period, we find the existence of both phase- and anti-phase relationships, at different frequencies. In the post-reform period, we also observe, for particular year-scales at different frequencies, that the direction of the lead-lag relationship varies. The wavelet Granger-causality test shows that in general the exchange rate Granger-causes the oil price in the long run, while the opposite applies in the short run. In order to prove the robustness of these findings, a battery of newly proposed Granger-causality tests are performed. From the findings of the time-series causality tests, we conclude that: (1) the significant Granger-causal relationship between the variables in question is non-linear and bidirectional and exists only in the post-reform period; (2) the significant lead-lag relationship is indirect and asymmetric; (3) there is a significant regime effect. The frequency-domain analysis shows a significant bidirectional Granger-causality running from the India-US exchange rate to the oil price for higher frequencies.

The above findings have some important policy implications for the policy makers and market traders. In the first case, the authorities shall be aware that in a floating exchange rate regime, which corresponds to the post-reform period, the currency appreciation makes imports cheaper. However, in the long run the Rupee appreciation will lead to an increase of international oil prices. Consequently, in the short run the appreciation of the Rupee, favored by higher economic growth, will contribute to the correction of the current account deficit generated by the increased oil consumption. In the long run the opposite applies.

At the same time, the monetary authorities shall consider the short run oil price movements when establishing their exchange rate strategies. An oil price shock will generate a shock in the exchange rate. This means that the general equilibrium models and the systemic stress-tests used by the Reserve Bank of India should incorporate the short run (gradual) asymmetries existing between the analyzed variables. Further, there are implications in terms of the choice of adequate monetary policies to control inflationary pressures originating from oil prices or exchange rate fluctuations.

In the second case, the market traders who invest in oil and exchange rate products can better adapt their investment strategies, depending on their risk profile. For example, the short run oriented speculative traders might diversify their portfolios toward oil and exchange rate market products, as there is no evidence of causality from any direction. However, for the institutional investors, it is noteworthy to know that oil price – exchange rate co-movements are time-frequency dependent and manifest especially for the 2–4-years band. So, considering this time-frequency interval, it is not recommended to invest in both categories of products as their higher correlation negatively affects the potential gains and the risk mitigation. In addition, our findings have real applications for the investors acting on energy derivative markets. For the forward contracts, in order to anticipate the oil price movements, it is highly recommended to correctly estimate the oil demand coming from emerging markets as India. In this context, forecasting the exchange rate of emerging markets currencies is compulsory for a correct assessment of international oil price trends.

**Appendix A. Wavelet Granger-causality between the oil price and the exchange rate (robustness check on the time-span 1973M1–2012M4)**

Notes: The white (red) contour indicates a 5% (10%) significance level. The significance levels are based on 3000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The green line is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. The scale has been converted to period using the relation: $F_t = \lambda - s$, where $\lambda = 4\pi/\left(o_w + \left(2 + o_w^2\right)^{1/2}\right)$ for the Morlet wavelet function. Using $o_w = 6$ for optimal balance [25], we have $F_t = 1.033 \cdot s$. Monthly
bands are represented. The oil price is represented by the WTI Cushing and the data are extracted from Macro Trends database. (For interpretation of the references to colour in this figure note, the reader is referred to the web version of this article.)

Appendix B. The conditional probability of regimes 1 and 2 for the MSVAR model

Smoothed states probability of the system being in regime 1 and regime 2.

References


