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Oil price and exchange rates: A wavelet based analysis for India

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ABSTRACT

In this paper, we explore linear and nonlinear Granger causalities between oil price and the real effective exchange rate of the Indian currency, known as 'rupee'. First, we apply the standard time domain approach, but fail to find any causal relationship. So, we decompose the two series at various scales of resolution using the wavelet methodology in an effort to revisit the relationships among the decompose series on a scale by scale basis. We also use a battery of non-linear causality tests in the time and the frequency domain. We uncover linear and nonlinear causal relationships between the oil price and the real effective exchange rate of Indian rupee at higher time scales (lower frequency). Although we do not find causal relationship at the lower time scales, there is evidence of causality at higher time scales only.

1. Introduction

The nexus of exchange rates and oil prices has drawn much academic interest. The literature suggests the presence of a relationship between the two. The causality indicates that oil prices Granger-cause the exchange rate (see e.g. Bénassy-Quéré et al., 2007; Chaudhuri and Daniel, 1998; Chen and Chen, 2007; Coudert et al., 2008; Lizardo and Mollick, 2010). Some authors argue that movements in the exchange rates may Granger-cause the change of the crude oil prices and explain oil price movements (see e.g. Sadorsky, 2000; Zhang and Wei, 2010). Building their argument on the law of one price (LOP), Golub (1983), Krugman (1983a, 1983b) and Bloomberg and Harris (1995) provide a thorough description of the movements of exchange rate and oil prices. This law asserts that weakening of US dollar relative to other currencies, ceteris paribus, will induce the international buyers to pay more US dollars for oil.[1] Empirical work of Bloomberg and Harris (1995), Pindyck and Rotemberg (1990) and Sadorsky (2000) also supports the assertion that changes in exchange rates have impact on oil prices. Golub (1983) and Krugman (1983a,b) on the other end, suggest that movements in oil prices should affect exchange rates. In other words, increasing oil prices generate a current account surplus for oil exporters (like OPEC) and current account deficits for oil importers causing reallocation of wealth that may impact exchange rates.

The objective of this paper is to re-examine the causal relationship between the oil prices and exchange rates in an emerging economy like India. Initially we use the linear Granger causality within the traditional time domain approach to explore the oil price-exchange rate nexus but fail to find any causality between them. We again use a battery of non-linear Granger causality tests within time domain framework, and still no luck. The lack of a relationship motivated us to implement the linear and non-linear Granger causality tests within frequency domain. We find causality at lower frequency bands. Our results within frequency domain show causality from the exchange rate to oil prices at scales D4 and S4. These results are supported by linear and non-linear Granger causality tests. At scale S4, we also find causality that runs from oil prices to exchange rates. At scale D4 there is no evidence of linear causality from oil prices to exchange rates; but is captured by some of the non-linear causality tests. Our results are intuitively appealing and explain ambiguity in the relationships in the time scales.

Our study differs from the previous ones in several respects. Earlier studies use Granger (1969) based linear causality to test a relationship between exchange rate and oil price. Such test is ineffective certain nonlinear relations. We use a battery of non-linear granger tests. Secondly, following heterogeneous market hypothesis for financial markets, we innovate over the previous work and test causality within frequency bands using wavelet decomposition. Thus we are able to capture relation on the frequency aspect on one side, and nonlinearity on the other. The paper can thus be considered a contribution to the literature.

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[1] Oil being internationally traded and fairly homogeneous commodity Law of one Price is assumed to hold.

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The remainder of the paper is organized as follows. Section 2 describes the Granger tests using linear and nonlinear approaches. We describe the rationale for time scales decomposition of exchange rate and oil prices in section 3; and the wavelet methodology as used in the paper in section 4. Section 5 describes the data. In section 6, the results of the empirical estimation are reported. Finally, section 7 draws the conclusions based on the findings of the paper.

2. Causality tests

Granger (1969) developed a relatively simple approach to test causality between series. It starts from the premise that future cannot cause the present or the past. A variable y_t is said to Granger cause x_t if x_t can be predicted by using past values of the y_t. Since the seminal work by Granger (1969), causality test has seen many extensions, particularly in the area of nonlinear relationships. Baek and Brock (1992) suggested a generalization based on the BDS test. By relaxing the *iid* assumption, Hiemstra and Jones (1994) proposed another version of this test. Authors like Bell et al. (1996) developed non-parametric regression ("generalized" additive models) based procedure to test causality between two univariate time series. All these tests are however non-parametric and computationally intense. Based on parametric test Skalin and Teräsvirta (1999) proposed smooth transition regression model. Though this test is easy to compute, it relies on specific assumptions about the functional form of the relationship. Péguin-Feissolle and Teräsvirta (1999) propose two tests: (a) based on a Taylor expansion of the nonlinear model around a given point in a sample space; and (b) based on Artificial Neural Networks (ANN). These tests have good power properties and appear to be well-sized.

2.1. Granger based linear causality

The Granger-causality test for the case of two variables y_t and x_t involves the estimation of the following VAR model:

$$y_t = a_1 + \sum_{i=1}^{n} b_i x_{t-i} + \sum_{j=1}^{m} \gamma_j y_{t-j} + \varepsilon_{1t}$$

$$x_t = a_2 + \sum_{i=1}^{n} \theta_i x_{t-i} + \sum_{j=1}^{m} \delta_j y_{t-j} + \varepsilon_{2t} \tag{1}$$

where it is assumed that both ε_{1t} and ε_{2t} are uncorrelated white-noise error terms. Granger-causality testing in time series framework is conducted by using either a VAR or an ECM framework depending on the behavior of variables in terms of stationarity. In any case, to conduct the test for Granger causality, one exploits restrictions on variables. An F-test (restricted versus unrestricted) or Wald-type test is often of interest.

2.2. Non-causality testing based on a Taylor series approximation

Péguin-Feissolle and Teräsvirta (1999) propose Taylor approximation of the nonlinear function:

$$y_t = f^*\left(y_{t-1}, \ldots, y_{t-q}, x_{t-1}, \ldots, x_{t-n}, \theta^*\right) + \varepsilon_t \tag{2}$$

where θ^* is a parameter vector and $\varepsilon_t \sim iid(0,\sigma^2)$; the series $\{x_t\}$ and $\{y_t\}$ are weakly stationary and ergodic. It is assumed that functional form of f^* is unknown, but has a convergent Taylor expansion at any arbitrary point on the sample space for every $\theta^* \in \Theta$ (the parameter space) and adequately represents the causal relationship between $\{x_t\}$ and $\{y_t\}$. Eq. (2) is used to test the causality based on the assertion that $\{x_t\}$ does not cause $\{y_t\}$. More specifically, under the non causality hypothesis, we have:

$$y_t = f^*\left(y_{t-1}, \ldots, y_{t-q}, \theta\right) + \varepsilon_t. \tag{3}$$

To test Eq. (3) against Eq. (2), following Péguin-Feissolle and Teräsvirta (1999), f^* in Eq. (2) can be linearized by expanding the function into a kth-order Taylor series around an arbitrary fixed point in the sample space. By reparametrization, approximation of f^* and merging of terms we get:

$$\begin{aligned} y_t = {} & \beta_0 + \sum_{j=1}^{q} \beta_j y_{t-j} + \sum_{j=1}^{n} \gamma_j x_{t-j} + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q} \beta_{j_1 j_2} y_{t-j_1} y_{t-j_2} + \sum_{j_1=1}^{q}\sum_{j_2=2}^{n} \delta_{j_1 j_2} y_{t-j_1} x_{t-j_1} x_{t-j_2} \\ & + \sum_{j=1}^{n}\sum_{j_2=j_1}^{n} \gamma_{j_1 j_2} x_{t-j_1} x_{t-j_2} + \ldots + \sum_{j_1=1}^{q}\sum_{j_2=1}^{q} \cdots \sum_{j_k=1}^{q} \beta_{j_1 \ldots j_k} y_{t-1} \ldots y_{t-j_k} \\ & + \sum_{j=1}^{n}\sum_{j_2=j_1}^{n} \cdots \sum_{j_k=j_{k-1}}^{n} \gamma_{j_1 j_2} x_{t-j_1} \ldots x_{t-j_1} \ldots x_{t-j_k} + \varepsilon_t^* \end{aligned} \tag{4}$$

where $\varepsilon_t^* = \varepsilon_t + R_t^{(k)}(x,y)$, $R_t^{(k)}$ the remainder, and $n \le k$ and $q \le k$ for notational convenience. Eq. (4) contains all possible combinations of lagged values of y_t and x_t up to order k. Estimation of Eq. (4) however, raises couple of issues. One problem is that the regressors in Eq. (4) tend to be highly collinear if k, q and n are large. The other problem is that as the number of regressors increase rapidly with k, the number of degrees of freedom becomes low.[2] A pragmatic solution to both issues consists in replacing some observation matrices by their largest principal components. This involves division of regressors in Eq. (4) into two groups: those as function of lags of y_t and those as function of the rest. Then regressors in Eq. (4) are replaced by the first p^* principal components of each matrix of observations. The null hypothesis that principal components of the latter group have zero coefficients gives the following test statistic[3]:

$$General = \frac{(SSR_0 - SSR_1)/p^*}{SSR_1/(T-1-2p^*)} \tag{5}$$

where $\theta' = (\theta_g' \theta_f')'$ is the parameter vector; in this case, x_t does not cause y_t if $f(x_{t-1}, \ldots x_{t-n}, \theta_f) = \text{constant}$.

2.3. Non-causality test based on artificial neural networks

The ANN causality test is based on a single hidden layer network with a logistic neural function. This model assumes semi-additive functional form before applying test to the following equation

$$y_t = g\left(y_{t-1}, \ldots, y_{t-q}, \theta_g\right) + f\left(x_{t-1}, \ldots, x_{t-n}, \theta_f\right) + \varepsilon_t.$$

The approximation of equation $f(x_{t-1}, \ldots x_{t-n}, \theta_f)$ is then given by

$$\theta_0 + \tilde{w}'_t \alpha + \sum_{j=1}^{p} B_j \frac{1}{1 + e^{-\gamma_j' w_t}} \tag{6}$$

where, $\theta_0 \in R$, $w_t = \left(1, \tilde{w}_t'\right)'$ is a $(n+1)\times 1$ vector, $\tilde{\omega}_t = \left(x_{t-1}, \ldots, x_{t-n}\right)'$, $\alpha = (\alpha_1, \ldots \alpha_n)'$ are $n \times 1$ vectors, and $\gamma_j = (\gamma_{j0}, \ldots, \gamma_{jn})'$ for $j = 1, \ldots, p$, are $(n+1)\times 1$ vectors. The null hypothesis of Granger non-causality for two weakly stationary and ergodic series, i.e., $\{x_t\}$ does not cause $\{y_t\}$, is given by: H_0: $\alpha = 0$ and $\beta = 0$, where $\beta = (\beta_1, \ldots \beta_p)'$ is a $p \times 1$ vector. Under the null, the identification problem of γ_j is solved by generating γ_j $j = 1, \ldots, p$, randomly from a uniform distribution, Lee et al. (1993). Implementation of the Lagrange (LM) version of the test requires the computation of the $T \times (n+p+m)$ matrix

[2] The problem of degrees of freedom is less acute if we can assume that the general model is "semi-additive".

[3] The SSR_0 and SSR_1 are obtained as follows. Regress y_t on 1 and the first p^* principal components of the matrix of lags of y_t only, form the residuals $\hat{\varepsilon}_t$, $t = 1, \ldots, T$, and the corresponding sum of squared residuals SSR_0. Then regress $\hat{\varepsilon}_t$ on 1 and all the terms of the two principal components matrices, form the residuals and the corresponding sum of squared residuals SSR_1. The test statistic has approximately an F-distribution with p^* and $T-1-2p^*$ degrees of freedom.

$R=[Z\,F]$ where Z is a $T\times m$ matrix containing all the variables due to the k-th order Taylor expansion of g, the t-th row of F has the form

$$[F]_t = \left(\tilde{w}'_t, \frac{1}{1+e^{-\gamma'^{*}_1\omega_t}}, \ldots, \frac{1}{1+e^{-\gamma'^{*}_p\omega_t}}\right) \tag{7}$$

where, $\gamma_{j^*} j = 1, \ldots, p,$ contains the randomly drawn values of corresponding unidentified parameter vectors. There is a tendency of collinearity between the second sub-matrix of F with first part of F. A test using the first principal components of the second sub-matrix of F is then conducted. This generates the test statistic called Neural where we generate the hidden unit weights, i.e. the different elements of the vectors γ_{j^*} for $j = 1, \ldots, p,$ randomly from the uniform distribution.

3. Rationale for a multi-scale decomposition of the exchange rate and oil prices

Heterogeneous market hypothesis categorizes the traders according to their characteristic time horizons or dealing frequencies. Among the different frequency traders, institutional investors and central banks constitute low frequency traders whereas, speculators and market makers are classified as high frequency traders. These market participants differ in terms of expectations, beliefs, risk profiles, informational sets and many others aspects. The market heterogeneity leads to the presence of different dealing frequencies and thus, different reactions to the same news in the same market. Each market component has its own reaction time to information, related to its time horizon and dealing frequency characteristic (Dacorogna et al., 2001).

The literature on oil price suggests that the oil price should not be studied as a gross variable since a lot of information is lost by doing so. Prominent examples are Mork's (1989) decomposition of the oil price into two components, increases and decreases; Lee et al.'s (1995) "surprise effect" measure, Kilian's (2006) decomposition of the oil prices into three shocks such as; supply shocks, aggregate demand shocks (which affects other commodities) and oil specific demand shocks (affects only oil demand). In reality, a rise in oil price could be caused by a variety of reasons ranging from a few hours for an OPEC meeting, a few days of strikes in Venezuela, a few months of attacks in Nigeria, a few years of the Iran–Iraq war or the 2nd Gulf war. The last item could affect decisions on investment policy in the oil sector or in substitution of energy sources well into 20 years or more (Naccache, 2011). These factors, irrespective of their working on the supply or on the demand side, operate at very different time scales. The diversity in these time horizons induces the diverse underlying cycles in the variations of oil price. In order to have better understanding of the underlying dynamics of the oil price variable, and to better assess its impact on the economy, it may be necessary to separate these various contributions according to their own time scales. Given its ability to decompose the time series into different time scales and modeling financial market heterogeneity, the wavelet approach is the effective tool.

4. A brief note on wavelet approach

To overcome the limitations of the Fourier[4] transform, the wavelet analysis was introduced. For example, the Fourier transform requires that the time series under study is periodic and assumes that frequencies do not evolve in time etc.[5] In the wavelet transform, its window is adjusted routinely to high or low frequency. This is because it uses short window at high frequency and conversely by utilizing time compression or dilatation, rather than a variation of frequency in the modulated signal which is achieved by separating the time axis into a sequence of successively smaller segments. The discrete wavelet transform (DWT) transforms a time series by dividing it into segments of time domain called 'scales' or frequency 'bands'. These scales represent the progressivity of the frequency fluctuation i.e., the shortest scale represents progressively high and the largest scale represents progressively low frequency fluctuations.

The basic wavelets in any wavelet family are classified into two types namely — father wavelets φ and mother wavelet ψ, and can be represented as follows:

Father wavelets $\quad \int\varphi(t)dt = 1, \quad$ and

Mother wavelets $\quad \int\psi(t)dt = 0.$

The father wavelets are used for the low frequency smooth components parts of a signal and the mother wavelets are used for the high-frequency details components. The father wavelets are used for the trend components and mother wavelets for deviation from the trend. A sequence of mother wavelets is used to represent a function, but only one father wavelet represents a function. While a number of wavelets families have been introduced in the literature, a majority is concentrated on the orthogonal wavelets such as, Haar, Daublets, Symmlets and Coiflets. A time series $f(t)$ can be decomposed by the wavelet transformation, and expressed as follows:

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots\ldots + \sum_k d_{1,k}\psi_{1,k}(t) \tag{8}$$

where, J is the number of multi resolution levels, and k ranges from 1 to the number of coefficients in each level. The wavelet coefficients, $s_{J,k}$, $d_{J,k}$, …., $d_{1,k}$ are the wavelet transform coefficients and $\varphi_{J,k}(t)$ and $\psi_{j,k}(t)$ represent the approximating wavelets functions. The wavelets transformations can be expressed as

$$s_{J,k} = \int\varphi_{J,k}(t)f(t)dt \tag{9}$$

$$d_{j,k} = \int\psi_{j,k}(t)f(t)dt, \quad \text{for} \quad j = 1, 2, \ldots\ldots J \tag{10}$$

where J is the maximum integer such that 2^J takes value less than the number of observations.

The detail coefficients, $d_{J,k}$, …., $d_{1,k}$, represents increasing finer scale deviation from the smooth trend and $s_{J,k}$ which represent the smooth coefficient and capture the trend. The wavelet series approximation of the original series $f(t)$ can be expressed as follows:

$$f(t) = S_{J,k}(t) + D_{J,k}(t) + D_{J-1,k}(t) + \ldots\ldots + D_1(t). \tag{11}$$

where $S_{J,k}$ is the smooth signal and $D_{J,k}$, $D_{J-1,k}$, $D_{J-2,k}$…. $D_{1,k}$ detailed signals. These smooth and detailed signals are expressed as follows:

$$S_{J,k} = \sum_k s_{J,k}\phi_{J,k}(t), D_{J,k} = \sum_k d_{J,k}\psi_{J,k}(t), \quad \text{and} \quad D_{1,k} = \sum_k d_{1,k}\psi_{1,k}(t), \quad j = 1, 2, \ldots., J-1. \tag{12}$$

[4] Fan and Gençay (2010, p.1307) documented that "The Fourier approach is appealing when working with stationary time series. However, restricting ourselves to stationary time series is not appealing, since most economic/financial time series exhibit quite complicated patterns over time (e.g., trends, abrupt changes, and volatility clustering). In fact, if the frequency components are not stationary such that they may appear, disappear, and then reappear over time, traditional spectral tools may miss such frequency components. Wavelet filters provide a natural platform to deal with the time-varying characteristics found in most real-world time series, and thus the assumption of stationarity may be avoided. The wavelet transform intelligently adapts itself to capture features across a wide range of frequencies and thus is able to capture events that are local in time. This makes the wavelet transform an ideal tool for studying nonstationary time series."

[5] Interested reader can refer to Ramsey and Lampart (1998a,b) and Kim and In (2003) among others for more detailed explanations on it. In our elaboration of wavelet we have heavily followed Kim and In (2003).

The $S_{J,k}$, $D_{J,k}$, $D_{J-1,k}$, $D_{J-2,k}$.... $D_{1,k}$ are listed in increasing order of the finer scale components.

4.1. The discrete wavelet transform

If $h_1 = (h_{1,0}, \ldots h_{1,L-1}, 0, \ldots, 0)^T$ represents the wavelet filter coefficients of a Daubechies compactly supported wavelet Daubechies (1992) for unit scale, zero padded to length N.

Then, by defining $h_{1,j} = 0$ *for* $l > L$, three properties must be satisfied by a wavelet filter, viz;,

$$\sum_{i=0}^{L-1} h_{1,l} = 0; \quad \sum_{l=0}^{L-1} h_{1,l}^2 = 1 \quad \sum_{l=0}^{L-1} h_{1,l} h_{1,l+2n} = 0 \quad \text{for all non zero integers } n. \tag{13}$$

This condition implies that wavelet filter must meet the conditions, (a) sum to zero (zero mean), (b) have unit energy, and (c) be orthogonal to its even shifts.

Suppose $g_1 = (g_{1,0}, \ldots g_{1,L-1}, 0, \ldots, 0)^T$ be the zero padded scaling filter coefficients, defined through $g_{1,l} = (-1)^{l+1} h_{1,L-1-1}$ and let $x_0, \ldots, x_{N-1}$ be a time series. For scales having, $N \geq L_j$, where $L_j = (2^j - 1)(L-1) + 1$, time series can be filtered using h_j to obtain the wavelet coefficients.

$$W_{j,t} = 2^{j/2} \tilde{W}_{j,2^j(t+1)+1}, \quad \left[(L-2)\left(1 - \frac{1}{2^j}\right)\right] \leq t \leq \left[\frac{N}{2^j} - 1\right], \tag{14}$$

where,

$$\tilde{W}_{j,t} = \frac{1}{2^{j/2}} \sum_{2^{j/2}}^{L_j-1} h_{j,l} x_{t-1}, \qquad t = L_j - 1, \ldots\ldots N-1.$$

The $\tilde{W}_{j,t}$ coefficients which are associated with changes on a scale of length $\tau_j = 2^{j-1}$ are obtained by sub sampling every $2^j th$ of the $\tilde{W}_{j,t}$ coefficients.

Orthogonal discrete wavelet transform (DWT) however, comes with two main drawbacks: the dyadic length requirement (i.e. a sample size divisible by 2^j), and the fact that the wavelet and scaling coefficients are not shift invariant due to their sensitivity to circular shifts because of the decimation operation.

4.2. Maximal overlap DWT (MODWT)

An alternative to DWT is represented by a non-orthogonal variant of DWT: the maximal overlap DWT (MODWT). Contrary to DWT, the MODWT does not decimate the coefficients. So, the number of scaling and wavelet coefficients at every level of transform is the same as the number of sample observations. The price of MODWT is loss of orthogonality and computational efficiency, the transform does not have any sample size restriction and is shift invariant. Wavelet coefficients, $\tilde{w}_{j,t}$ and scaling coefficients $\tilde{V}_{j,t}$ at levels $j; j = 1, \ldots, J$, can be obtained as:

$$\tilde{W}_{j,t} = \sum_{l=0}^{L-1} \tilde{g}_l \tilde{v}_{j-1,t-1 \bmod N} \text{ and } \tilde{v}_{j,t} = \sum_{l=0}^{L-1} \tilde{h}_i \tilde{v}_{j-1,t-1 \bmod N}. \tag{15}$$

The wavelet and scaling filters, $\tilde{g}_l$, $\tilde{h}_l$ are rescaled as $\tilde{g}_j = g_j / 2^{j/2}$, $\tilde{h}_j = h_j / 2^{j/2}$. The non-decimated wavelet coefficients represent differences between generalized averages of data on scale $\tau = 2^{j-1}$. MODWT comes with all the functions of DWT, but also offers extra benefits. For example, it can handle any sample size, it is translation invariant, as shift in the signal does not change the pattern of wavelet transform coefficients; and provides increased resolution at coarser scales. In addition, MODWT provides a larger sample size in the wavelet correlation analysis and produces a more asymptotically efficient wavelet covariance estimator than the DWT.

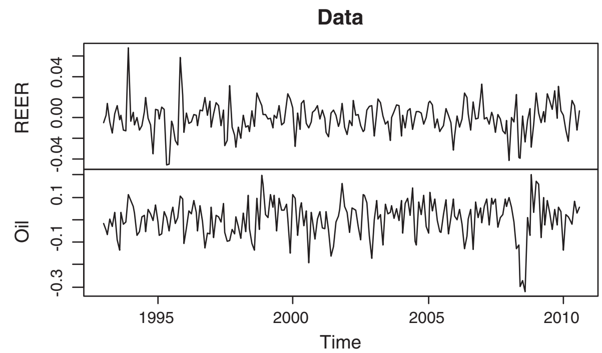

Fig. 1. Plot of the real effective rupee exchange returns and oil returns.

5. Data

We use monthly data from 1993.4 to 2010.12. Exchange rate is measured by real effective exchange rate, obtained from the official website of the Reserve Bank of India. The crude oil price is in real terms, deflated by U.S. consumer price index (following Faria et al., 2009). Crude oil prices are the spot prices: West Texas Intermediate (WTI)-Cushing Oklahoma (source: U.S. Department of Energy: Energy Information Administration).

Prior to estimation, we transformed each series to natural logarithms. Time series plot of each series (in log first difference form) is presented in Fig. 1; and the descriptive statistics in levels and also returns in Table 1. The sample means of level data set are positive for the real exchange rate, but negative for real oil prices. For return data set it is positive for the real oil prices and negative for the real exchange rate. The measure of skewness indicates that in level form real effective exchange rate is negatively skewed; and the return series oil price is negatively skewed. Data series in level as well as in returns demonstrate excess kurtosis, except for real oil price, which indicates that distributions of returns for oil prices and real effective exchange rate are leptokurtic relative to normal distribution. The Jarque–Bera normality test rejects normality of all series at the level as well as in the return. To test for stationarity, we applied the LM unit root test proposed by Lee and Strazicich (2003, 2004). This test takes into account at most two endogenously determined structural breaks. Results of the test, presented in Table 2 suggest that irrespective of models the oil price series is non-stationary at their level while, the exchange rate series is non-stationary only in one model that

Table 1
Descriptive statistics of level and returns series.

	LnREER	LnROP	D (LnREER)	D (LnROP)
Mean	4.592673	−1.015340	−5.08E−05	0.005009
Median	4.599756	−1.143609	0.000357	0.013971
Maximum	4.664288	0.178445	0.067996	0.202245
Minimum	4.471410	−2.000408	−0.045718	−0.320890
Std. dev.	0.040487	0.496317	0.015353	0.081639
Skewness	−0.672224	0.390565	0.198991	−0.727636
Kurtosis	3.297305	2.156050	5.559989	4.554429
Jarque–Bera	16.82637	11.68134	59.28876	40.05091
Probability	0.000222	0.002907	0.000000	0.000000

Table 2
Univariate unit root test with structural breaks.

Variables	Lee–Strazicich's LM unit root test								
	T_{B1}	T_{B2}	k	Test statistics	1	B_{t1}	B_{t2}	D_{t1}	D_{t2}
Results for univariate LM unit root test with 1 and 2 structural break in intercept only (Model A and AA)									
LnREER (model A)	2009:02	–	7	−0.1365*** (−4.5126)	−0.0027 (−2.3557)	−0.044*** (−2.9299)	–	–	–
LnREER (model AA)	2000:03	2009:02	7	−0.1442*** (−4.6353)	−0.0032*** (−2.7103)	0.0150 (1.0619)	−0.045*** (−3.0173)	–	–
LnROP (model A)	2004:09	–	1	−0.0588 (−2.7650)	−0.0087 (−1.1543)	0.1431* (1.8138)	–	–	–
LnROP (model AA)	1997:01	2002:12	2	−0.0659 (−2.9323)	−0.0072 (−1.0009)	−0.1240 (−1.5806)	0.1444* (1.8398)	–	–
Results for univariate LM unit root test with one and two structural break in intercept/constant and trend both									
LnREER (model C)	2008:04	–	1	−0.1094 (−3.8862)	−0.0017 (−1.5039)	−0.037*** (−2.5886)	–	−0.0021 (−0.7397)	–
LnREER (model CC)	1998:08	2008:07	8	−0.2602** (−6.3132)	0.0073*** (2.9777)	−0.0161 (−1.1480)	0.044*** (3.0587)	0.0065*** (2.8351)	−0.026*** (−5.2073)
LnROP (model C)	2004:12	–	10	−0.1359 (−3.9611)	−0.0344*** (−2.8616)	0.0883 (1.0963)	–	0.051*** (3.0406)	–
LnROP (model CC)	1997:09	2005:07	12	−0.1947 (−4.8997)	−0.0073 (−0.6022)	0.1068 (1.3483)	0.0516 (0.6464)	−0.037** (−2.174)	0.0359** (2.3956)

T_{B1} and T_{B2} are the dates of structural breaks; k, lag length; B_{t1} and B_{t2} dummy variables for structural breaks in the intercept. D_{t1} and D_{t2} are the dummy variables for the structural breaks in the slope. Figures in parentheses are t-values. Critical values of both test (i.e. when breaks occur intercept and intercept and trend jointly are reported in Lee and Strazicich (2003, 2004)) are two-break and one-break cases respectively. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

correspond to one structural break in the intercept as well as in trend (Model C).

6. Empirical results and discussion

We carry out linear Granger causality test between oil price returns and rupee exchange returns within time domain framework. Our results presented in Table 3 indicate that there is no linear causality between the two series. Some authors argue that the traditional Granger causality test, designed to detect linear causality, is ineffective in uncovering certain nonlinear causal relations and recommend the use of nonlinear causality tests (e.g. Baek and Brock, 1992; Bell et al., 1996; Chen et al., 2004; Diks and Panchenko, 2005; Hiemstra and Jones, 1994; Hiemstra and Kramer, 1997; Li, 2006; Péguin-Feissolle and Teräsvirta, 1999; Péguin-Feissolle et al., 2008; Skalin and Teräsvirta, 1999). Accordingly, we revisit the relationship between oil price and exchange rate using the nonlinear tests proposed by Péguin-Feissolle and Teräsvirta (1999) and Péguin-Feissolle et al. (2008). These tests based on a Taylor series approximation and artificial neural networks however, are data-demanding and require large number of cross products which affects the degrees of freedom as lag length increases. We choose to take two lags on the endogenous variables ($q=2$), three lags on the exogenous ($n=3$) and a three order for the Taylor expansion ($k=3$). The results are reliable because simulations generally produce favorable results even for low lags (Benhmad, 2012). Following Lee et al. (1993), we chose 20 hidden ($p=20$) units, to generate different elements of the vectors γ_j, for $j=1,\ldots, p$, randomly from the uniform $[-\mu, \mu]$ distribution with $\mu=2$. Finally, the largest principal component that explains at least 80% of the variation in the corresponding matrix variation is chosen. Our results based on non-linear granger causality tests within time domain, also fail to provide any evidence of causality (Table 3).

Motivated by the heterogeneous market hypothesis of financial markets and diversity in the short, medium and long run factors that affect cyclical variations of the oil price and exchange rate [detail in Section 3], we examine the causality in different time horizons. Granger (1969, 1980) first suggested that a spectral-density approach would give a more comprehensive and richer picture than a one-shot

Table 3
Results of linear and nonlinear causality tests (p-values).

Time domain		Frequency bands (months)				
		D1	D2	D3	D4	S4
ER→OIL						
Linear	0.31	0.13	0.04	0.29	0.02	0.00
General	0.62	0.14	0.19	0.30	0.00	0.00
Semi-additive	0.62	0.14	0.19	0.30	0.00	0.00
P-general Taylor based	0.31	0.13	0.04	0.29	0.02	0.00
ANN-based	0.20	0.16	0.11	0.41	0.00	0.00
OIL→ER						
Linear	0.11	0.00	0.02	0.03	0.66	0.00
General	0.39	0.10	0.17	0.66	0.00	0.04
Semi-additive	0.39	0.10	0.17	0.66	0.00	0.04
P-general Taylor based	0.11	0.00	0.02	0.03	0.66	0.00
ANN-based	0.51	0.08	0.31	0.89	0.11	0.00

Note: ER→OIL and OIL→ER are for the null hypothesis of no causality from: exchange rate to oil prices and oil prices to exchange rates respectively. *Linear* is the linear Granger causality test, *General* and *semi-additive* and *P-general Taylor based* are the nonlinear causality tests based on a Taylor series approximation, and *ANN-based* is the nonlinear causality test based on artificial neural networks. To compute each test statistic, the number of lagged values of y_t is $q=2$, the number of lagged values of x_t is $n=3$ and the order of Taylor expansion is $k=3$. In the neural network test, the number of hidden units is $p=20$ and we generate the different elements of the vectors γ_j, for $j=1,\ldots,p$, randomly from the uniform $[-\mu, \mu]$ distribution with $\mu=2$. Moreover, the number of principal components is determined automatically in each case (include the largest principal components that together explain at least 80% of the variation in the corresponding matrix).

causality that is supposed to apply across all periodicities. Thus exploring bivariate causality over the spectrum is preferred to the one-shot test. So, we decompose the two time series into different time scales using Daublets basis which is orthogonal, near symmetric and has compact support and good smoothness properties. We choose the *Maximal Overlap Discrete Wavelet Transform* (MODWT) over the more conventional orthogonal DWT, in exchange for orthogonality. The MODWT possesses attributes that are far more desirable in economic applications. For example, the MODWT can handle input data of any length, not just powers of two; it is translation invariant — that is, a shift in the time series results in an equivalent shift in the transform. It also has increased resolution at lower scales since it oversamples data, i.e. more information is captured at each scale. However, the choice of a particular wavelet filter is not so crucial (Percival and Walden, 2000). Figs. 1 and 2 (in the appendix) show the Multi-resolution Analysis (MRA) of order $J=4$ for return series of oil and real effective exchange rates respectively. We carried out the wavelet decomposition of oil price and real effective exchange rate return time series into a set of 4 orthogonal components D1, D2, D3 and D4 that represent different frequency components of the original series in details, and a trend/smoothed component (S4) in the returns series (Figs. 1–2, in the appendix). This decomposition allows time-frequency domain representation of the original series. The time scale interpretation of different MRA levels is given in Table 1 (in the appendix). For example, the time scale Dl represents the highest frequency that occurs at the 2–4 scale, D2 stands for the next finest level in the series and represents the 4–8 month scale, etc. The decomposition level was set to 4 levels since for higher level decompositions, feasible wavelet coefficients get critically smaller. The results of the causality tests between two series, on a frequency band by frequency band basis, are reported in Tables 3 and 4. The results of causality tests on the two return series in the time domain clearly show that the null hypothesis of no causality from real oil price returns to real effective rupee exchange return, and real effective rupee exchange return to real oil price returns, is not rejected. In other words, oil prices have no significant effect on exchange returns and vice-versa. From a non-linear granger non-causality perspective in time domain no causal relation is found. However, within a frequency domain framework, it is worth mentioning that the causal relationship between the real oil price returns and real effective exchange rate of rupee returns varies depending on the time scale or frequency band. In the short run corresponding to scales D1, D2 and D3, evidence of causal relationship in either direction, based on both linear and non-linear tests, is least evident.

It seems that nonlinearities are not an important feature of the data in terms of explaining the causality within time domain framework. At the first frequency band (D1) which corresponds to a class of traders (mostly high frequency speculative traders) for whom investment horizon is about 2–4 months (say, 3-months); there is no evidence of causality. At the second and third frequency bands (D2) and (D3) which represent an investment horizon of 4–8 months (say, 6-months), and 8–16 months (say, one year) there are no causal relationships between real oil price returns and rupee exchange returns. From the fourth (D4) to fifth frequency band (S4) representing the spectrum of time horizons running from 16 months to over 32 months (approximately a part of Indian business cycle). This corresponds to the fundamental traders especially, fund managers and institutional investors. Here we find a causal relationship between the real oil price returns and the rupee exchange rate returns. In particular at scale D4 based on linear causality, we find evidence of unidirectional causality from exchange rate to oil prices; but none in the reverse direction. This relationship is captured by a few non-linear causality tests. At scale S4 there is strong support for bi-directional causality. To test the robustness of the results we conducted the analysis by changing the lag length of the exogenous variable to 2 (n = 2). Our results (Table 4) are almost robust to the changes in lag length of the exogenous variable. Overall, our results point to evidence of causality when analyzing at higher time scales (lower frequency bands) compared to causality tests in time domain and lower time scales. Wavelet decomposition helps to unveil the relationships which otherwise would have remained hidden.

Table 4
Results of linear and nonlinear causality tests (p-values).

	Time domain	Frequency bands (months)				
		D1	D2	D3	D4	S4
ER → OIL						
Linear	0.18	0.19	0.01	0.63	0.02	0.00
General	0.43	0.03	0.12	0.53	0.00	0.00
Semi-additive	0.44	0.03	0.12	0.53	0.00	0.00
P-general Taylor based	0.18	0.19	0.01	0.63	0.02	0.00
ANN-based	0.00	0.08	0.06	0.33	0.00	0.00
OIL → ER						
Linear	0.06	0.49	0.05	0.04	0.85	0.00
General	0.24	0.66	0.22	0.54	0.00	0.00
Semi-additive	0.24	0.66	0.22	0.54	0.00	0.02
P-general Taylor based	0.06	0.49	0.05	0.04	0.85	0.00
ANN-based	0.30	0.57	0.28	0.29	0.04	0.00

Note: ER → OIL and OIL → ER are for the null hypothesis of no causality from: exchange rate to oil prices and oil prices to exchange rates respectively. *Linear* is the linear Granger causality test, *General* and *semi-additive* and *P-general Taylor based* are the nonlinear causality tests based on a Taylor series approximation, and *ANN-based* is the nonlinear causality test based on artificial neural networks. To compute each test statistic, the number of lagged values of y_t is $q=2$, the number of lagged values of x_t is $n=2$ and the order of Taylor expansion is $k=3$. In the neural network test, the number of hidden units is $p=20$ and we generate the different elements of the vectors γ_j, for $j=1,\ldots,p$, randomly from the uniform $[-\mu,\mu]$ distribution with $\mu=2$. Moreover, the number of principal components is determined automatically in each case (include the largest principal components that together explain at least 80% of the variation in the corresponding matrix).

7. Conclusions and policy implications

In this paper we investigate linear and non-linear causalities between the real effective rupee exchange returns and oil price returns within time domain framework. We find that there is no linear or non linear causal relationship between the two series. Motivated by the heterogeneous market hypothesis of financial markets and diversity of short, medium and long run factors that drive cyclical variations, we decompose the series into different time scales (frequency bands) using the wavelets methodology. Overall, we find causality between the rupee exchange rate and oil prices is frequency dependent. At lower time scales (high frequency), no causal relationship is found; but at higher scales (low frequency) we find causality. In particular, we find evidence of unidirectional causality from exchange rates to oil prices, unlike Benhmad (2012) at scale corresponding to 16 to 32 months; and bidirectional causality corresponding to time horizon of 32 to 64 months as in Benhmad (2012). Wavelets decompositions turn out to be useful in unveiling the relationships which otherwise would have remained hidden.

Our findings, based on linear and non-linear causalities on frequency-domain have important implications for policy makers and traders in the areas of effective risk management, choice of monetary policies to control inflationary pressures originating in oil or exchange rate fluctuations, the rupee–dollar-pegging policies for India, a major oil-importing country, pricing of oil-related assets and/or products, and also for appropriate fiscal policy measures in India. For example, at the first frequency band (3 months) which corresponds to speculative trading (high frequency or noise trading), there is no strong evidence of causality from any direction. However, for the fundamentalists e.g. fund-managers and institutional investors, for time horizons 32 months and more, strong bidirectional causal relationships between real oil and real effective exchange rate of Indian Rupee returns are found. Further, as a major player on the global stage, performance of the Indian economy depends on the consumption of oil. Oil is a major factor of production and when prices are non-sticky, oil price shocks can lead to reduced output, increased inflation, and real exchange rate depreciation. The output losses will depend on the sensitivity of the consumer durables (where oil is a factor of production) to the oil prices. However, for a major economy like India flexible exchange rates produce larger output losses and higher volatility in inflation in the tradable and non-tradable sector vis-à-vis the fixed exchange rates.

Appendix A

Table 1
Frequency interpretation of MRA scale levels.

Scale	Monthly frequency
D1	2–4 months
D2	4–8 months
D3	8–16 months
D4	16–32 months
S4	More than 32 months

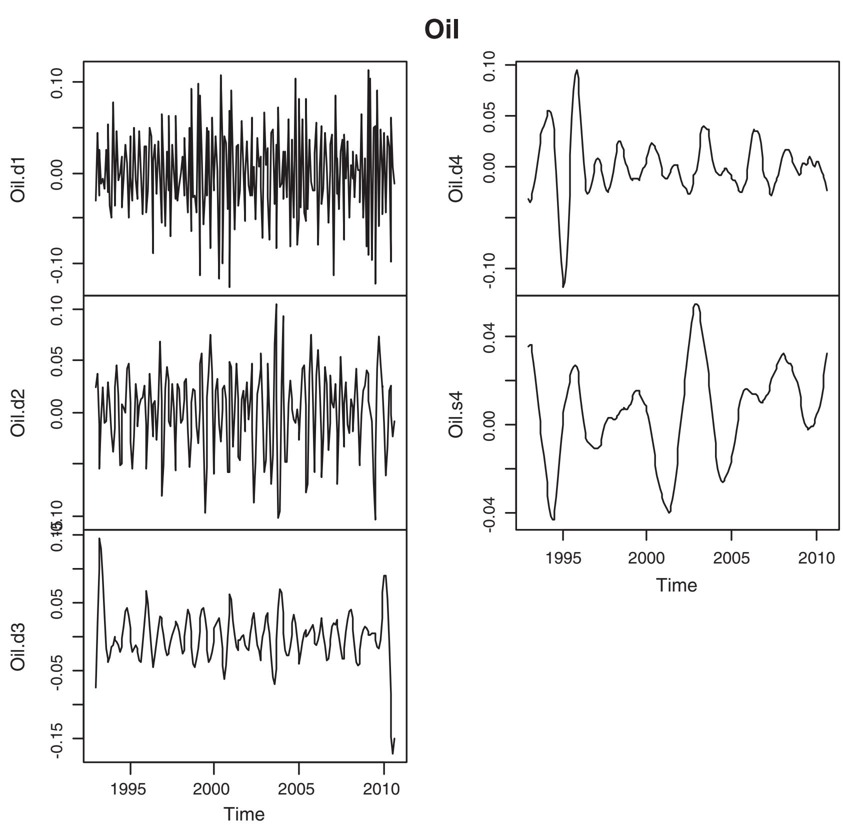

Fig. 1. Plot of wavelet decomposed results of oil returns into different frequency bands.

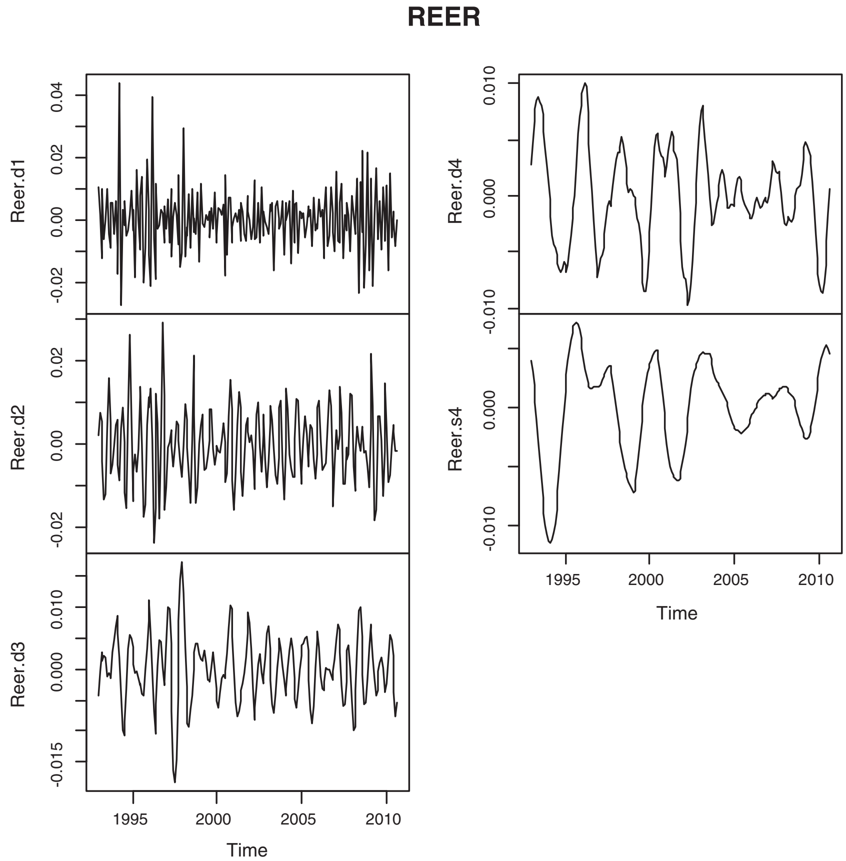

Fig. 2. Plot of wavelet decomposed results of real effective rupee exchange returns into different frequency bands.

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