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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:

$$\begin{aligned} y_t &= a_1 + \sum_{i=1}^{n} b_i x_{t-i} + \sum_{j=1}^{m} \gamma_j y_{t-j} + \varepsilon_{1t} \\ x_t &= a_2 + \sum_{i=1}^{n} \theta_i x_{t-i} + \sum_{j=1}^{m} \delta_j y_{t-j} + \varepsilon_{2t} \end{aligned} \tag{1}$$

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.