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Analyzing Time-Frequency Relationship between Share Prices and Exchange Rates in India: Evidence from Continuous Wavelets

Abstract

The paper examines the relationship between exchange rates and share prices using the wavelets approach, and more specifically the continuous wavelet power spectrum, cross wavelet transform and cross wavelet coherency. Our results, based on Indian data, lend support to the traditional (Dornbush and Fischer 1980) as well as the new portfolio hypothesis (Frankel 1991), albeit over different time periods and across different time-scales. The wavelet approach used in the paper has helped to uncover some interesting economic relationships within the time–frequency which has remained hidden thus far.

Keywords: cyclical and anti-cyclical effects; cross wavelet transform; wavelet coherency, India

JEL Classification: G15, C40, E32, F21, F31

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1. Introduction

The search for a relationship between stock prices and exchange rates has led to a sizeable literature. The topic is important because these series are considered leading economic variables. There are two competing hypotheses on whether or not exchange rates Granger cause stock prices, and conversely. The traditional approach asserts that causal relationship runs from exchange rates to stock prices. The adherents of this approach argue that changes in the exchange rate affect competitiveness of a firm, which in turn influences firm’s earnings and net worth and thus on the stock prices, in general (see, e.g., Dornbush and Fischer 1980). The proponents of the new portfolio approach posit that stock prices Granger cause exchange rates. They point out that a decrease in stock prices is accompanied by reduction in the wealth of domestic investors, which leads to a lower demand for money, and thus lower interest rates. The lower interest rates trigger capital outflows, and leads to currency depreciation, ceteris paribus. Therefore, under the portfolio approach, stock price is expected to lead exchange rate. In other words, the correlation would be negative. If a market response is simultaneous, i.e. influences both approaches, a feedback relationship is likely to emerge. In that case the correlation between the two variables cannot be predicted, a priori.

The research purporting to examine the relationship between exchange rates and stock prices has been carried out in the context of different countries. For example, Smith (1992), Solnik (1987), Aggarwala (1981), Frank and Young (1972), Phylaktis and Ravazzolo (2000) find a significant positive relationship between the series. By contrast, Soenen and Hennigar (1998), Ajayi and Mougoue (1996), Ma and Kao (1990) report a significant negative relation between the two series. Granger et al. (2000) found that exchange rates lead stock prices in South Korea; but the reverse is true in Hong Kong, Malaysia, the Philippines, Singapore, Thailand and Taiwan. However, he did not find any relationship in Japan and Indonesia. Abdalla and Murinde (1997) found that stock prices Granger-cause exchange rates in the Philippines, but the opposite is true for Korea, Pakistan and India. Ajayi et al. (1998) found uni-directional causality from stock prices to exchange rates in Canada, Germany, France, Italy, Japan and the UK; but the results are mixed for emerging markets. In particular, they find bi-directional causality in Taiwan, uni-directional causality from stock prices to exchange rate in Indonesia and the

Philippines; from the exchange rate to stock prices in Korea and no significant causality in Hong Kong, Singapore, Thailand and Malaysia.

The studies on India produced mixed results, most rejecting an association between stock price and exchange rate (see e.g., Rahman and Uddin 2009; Muhammad and Rasheed 2002; Bhattacharya and Mukherjee 2003; Mishra 2004; and Venkateshwarlu and Tiwari 2005). The finding of a unidirectional causality from exchange rates to stock prices by Abdalla and Murinde (1997) lends support for the traditional approach. Overall the causal relationship between the two series is inconclusive in India – a major center of global economic and financial activity. Lack of conclusive results warrant further academic scrutiny perhaps, using refined methodological approach. Knowledge of the direction of causality might shed additional insight for the Indian policymakers and help to craft appropriate policy in a globalized world.

The earlier studies used time domain framework in their search for a relationship when the true relations might exist at different frequencies, something that can be justified on several grounds. For example, traders in the financial market deal at different time horizons i.e. ‘dealing frequencies’ which can be caused by market heterogeneity. In such case, each market component has its own reaction time to the information as they relate to its time horizon and the characteristic dealing frequency (Dacorogna et al. 2001). The link between stock returns and exchange returns can vary across frequencies, and may even change over time. The beauty of the wavelet approach lies in its ability to decompose a time series into different time scales. This flexibility plays favourably in modelling financial market heterogeneity. The general practice among economists is to decompose a time series using discrete wavelet transform or its variant, maximal overlap discrete wavelet transform, and apply the traditional econometric methods for a relationships at different frequencies. The continuous wavelet transform, by contrast, is easier to apply and can be used to carry out similar analyses without having to rely on conventional econometric techniques.

The objective of the study is to implement the continuous wavelet transform to revisit the relationship between stock returns and exchange rate returns. Specifically, we utilize the continuous wavelet power spectrum and three cross-wavelet tools: the cross-wavelet power spectrum, the wavelet transform and the cross wavelet coherency to detect transient effects, something the traditional methods may not deliver. The tool we apply can help to unearth some economic time-frequency relations that have not been captured thus far. In other words, the continuous wavelet transform might detect causality at different scales. And our results lend support to both the traditional (Dornbush and Fischer 1980) and the portfolio approach (Frankel 1993). We find causal and reverse causal relation between share prices and real exchange rates which varies across scale and time period in India. The evidence supports both cyclical and anti-cyclical relationship between the series. We find share price to lag, and receive cyclical effects from exchange rate shocks at higher time scales over the study period.

The findings are thus novel and might offer fresh insights into the causal link between exchange rate and stock returns in India. The methodological approach we apply has succeeded in capturing the simultaneous influence of the two models and thus helped to detect bidirectional causality at different time scales. To the best of our knowledge, this paper contributes to the literature in three distinct areas. First, this is the only study which has applied the methodology to economic time series. Second, the adoption of refined methodology, in departure from using the traditional tools, has been instrumental to the outcome. Third, this is the first study on India. Given the heightened global interest in Indian economy, academic inquiry into the relationship between the series is not only timely, but perhaps long overdue.

The rest of the paper is organized as follows. Section 2 describes the methodology and data. In section 3, the results are reported. Section 4 draws conclusions based on the findings.

2. Data and Methodology

2.1 Data

For estimation purposes, we use monthly data on share prices and exchange rates from April 1993 to February 2009. Exchange rate is measured by real effective exchange rate as provided by the Reserve Bank of India and sourced from the official website. The share prices data has been taken from the International Financial Statistics (IFS 2010) of the International Monetary Fund (IMF) CD-ROM. We transformed both variables to log first difference to work with return series (not for reason of stationarity).

2.2 Methodological issues

The paper implements the wavelet tools namely, continuous wavelet power spectrum for variance analysis; cross wavelet power to detect interaction; and wavelet coherency to capture the correlation between the two series, as understood in the frequency domain literature.

2.2.1 The Wavelet transform methodology

In this section we briefly describe the wavelet transform methodology. The literature suggests that within the time-domain approach one may capture relevant interesting relations that might otherwise exist at different frequencies. Among the different frequency traders, central banks and institutional investors are part of low frequency traders whereas, speculators and market makers belong to high frequency group. These market participants differ in various aspects e.g., their beliefs, expectations, risk profiles, informational sets, inter alia.

Despite its shortcomings, the tradition has been to apply the Fourier transform to examine relations between series of interest at different frequencies. In such transform, the information on time is completely lost, making it difficult to differentiate ephemeral relations from structural changes. The latter is very important in analyzing macro-economic time series, but results based on Fourier transform can be unreliable. Also, the technique is appropriate only if the time series is stationary, which is not common for macro-economic variables. Often these series tend to be noisy and complex.

To avoid the pitfalls and include time dimensions in the Fourier transform, Gabor (1946) introduced a method known as the short time Fourier transformation. In the Gabor method, a time series is broken into smaller sub-samples and then the Fourier transform is applied to each of them. However, the short time Fourier transformation approach has been criticized on grounds of efficiency as it considers equal frequency resolution across all dissimilar frequencies (see Raihan et al. 2005 for detail).

The wavelet transform method was introduced as a way to solve the above problems. The approach can perform "natural local analysis of a time-series in the sense that the length of wavelets varies endogenously: it stretches into a long wavelet function to measure the low-frequency movements; and it compresses into a short wavelet function to measure the high-frequency movements” (Aguiar-Conraria et al. 2011, p. 646). Wavelet has interesting features of conduction analysis of a time series in spectral framework, but as function of time. In other words, it shows the evolution of change in a time series over time and different periodic components i.e., frequency bands. It may be noted that the application of wavelet technique to economics and finance is mostly limited to the use of one or other variants of discrete wavelet transformation. One needs to consider several aspects when applying discrete wavelet analysis e.g. the level of decomposition. The results from discrete wavelet transformation at each scale in a time series can also be obtained with ease using the continuous transformation. As Fig. 2 shows, one can visualize the evolution of variance of the returns to share price and exchange rate series at several time scales over a span of 40 years simply from one single diagram!

In some sense, the wavelets approach is the preferred weapon of choice in exploring macro-finance relationships, particularly when the aim is to detect transient effects across frequencies and time. In the area of economics, the technique has been applied to decompose individual or several time series (one at a time) to study correlation or Granger causality within the traditional time-domain methods. Hudgins et al. (1993) and Torrence and Compo (1998) developed cross-wavelet power, cross-wavelet coherency, and phase difference methods to examine time frequency dependencies without recourse to traditional methods. Although applied to study science and climate, the wavelet based tools did not make much headway to economic time series until 2008[1]. However, in recent times, it has been applied to examine several economic concepts (see, business cycles, (Crowley and Mayes 2008; Baubeau and Cazelles 2009; Aguiar-Conraria and Soares 2011b; Caraiani 2012); co-movement in stock and energy markets (Rua and Nunes 2009; Fernandez 2012; Madaleno and Pinho 2012); oil and macroeconomy (Aguiar-Conraria and Soares 2011a; Jammazi 2012; Tiwari et al. 2013), and multi-scale macroeconomic relationships (Gallegati et al. 2011; Rua 2012)).

The cross-wavelet tools are helpful to directly examine the interactions between time series at different frequencies, and the evolution over time. The single wavelet power spectrum shows the evolution of variance of a time series at different frequencies. Here the periods of

[1] Aguiar-Conraria et al. (2008) is the first study to examine macroeconomic relations using continuous wavelets.

large variance are associated with periods of large power at different scales. In other words, the cross-wavelet power of two time series illustrates the case of confined covariance between two time series. The wavelet coherency is correlation coefficient in the time-frequency space. The term "phase" implies the position of a series in the pseudo-cycle as a function of frequency. The phase difference gives us information "on the delay, or synchronization, between oscillations of the two time series" (Aguiar-Conraria et al. 2008, p. 2867).

2.2.2 The Continuous Wavelet Transform (CWT)[2]

A wavelet is a function with zero mean that is localized in both frequency and time. We can characterize a wavelet by how localized it is in time (Δt) and frequency ($\Delta\omega$ or the bandwidth). The classical version of the Heisenberg uncertainty principle tells us that there is always a trade-off between localization in time and frequency. Without properly defining Δt and $\Delta\omega$, we will note that there is a limit to how small the uncertainty product $\Delta t \cdot \Delta\omega$ can be. One particular wavelet, the Morlet, is defined as:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2}. \tag{1}$$

where ω_0 refers to frequency and η to time, both dimensionless. In extracting wavelet features, the Morlet wavelet (with $\omega_0 = 6$) is a good choice due to its balance between time and frequency localization. So, we restrict our further treatment to Morlet wavelet. The idea behind the CWT is to apply the wavelet as a band pass filter to a time series. The wavelet is stretched in time by varying its scale (s), so that $\eta = s \cdot t$ and normalizing it to have unit energy. For the Morlet wavelet (with $\omega_0 = 6$), the Fourier period (λ_{wt}) is almost equal to the scale ($\lambda_{wt} = 1.03\,s$). The CWT of a time series ($x_n, n = 1,..., N$) with uniform time steps δt, is defined as the convolution of x_n with the scaled and normalized wavelet. We can write,

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi_0\left[(n'-n)\frac{\delta t}{s}\right]. \tag{2}$$

[2] The description of CWT, XWT and WTC is drawn from the work of Grinsted et al. (2004). We are grateful to Grinsted and co-authors for making the codes available at: http://www.pol.ac.uk/home/research/waveletcoherence/ which we used in the present study.

where, we define the wavelet power as: $\left|W_n^X(s)\right|^2$. The complex argument of $W_n^X(s)$ can be interpreted as the local phase. The wavelet is not completely localized in time, so CWT has edge artifacts. It is therefore, useful to introduce a Cone of Influence (COI) in which edge effects cannot be ignored. The COI is an area where the wavelet power, caused by a discontinuity, at the edge drops to e^{-2} of the value at the edge.

Although Torrence and Compo (1998) have shown how the significance of wavelet power can be determined against the null hypothesis that the data generating process is given by an *AR (*0*)* or *AR (*1*)* stationary process with a certain background power spectrum (P_k) however, for a more general processes one needs to rely on Monte-Carlo simulations. Torrence and Compo (1998) computed the white noise and red noise wavelet power spectra from which they derived, under the null, the corresponding distribution for the local wavelet power spectrum at each time *n* and scale *s* as follows:

$$D\left(\frac{\left|W_n^X(s)\right|^2}{\sigma_X^2} < p\right) = \frac{1}{2} P_k \chi_v^2(p), \tag{3}$$

where v is equal to 1 for real, and 2 for complex wavelets.

2.2.3 The Cross Wavelet Transform (XWT)

The XWT of two time series x_n and y_n is defined as $W^{XY} = W^X W^{Y*}$ where, W^X and W^Y are the wavelet transforms of x and y, respectively, and * denotes complex conjugation. We further define the cross wavelet power as $\left|W^{XY}\right|$. The complex argument arg(W^{xy}) is interpreted as the local relative phase between x_n and y_n in time frequency space. The theoretical distribution of the cross wavelet power of two time series with background power spectra P_k^X and P_k^Y is given in Torrence and Compo (1998) as,

$$D\left(\frac{\left|W_n^X(s)W_n^{Y*}(s)\right|}{\sigma_X \sigma_Y} < p\right) = \frac{Z_v(p)}{v} \sqrt{P_k^X P_k^Y}, \tag{4}$$

where $Z_v(p)$ is the confidence level associated with the probability p for a probability density function, defined by the square root of the product of two χ^2 distributions.

2.2.4 Wavelet Coherence (WTC)

As in the Fourier spectral approaches, WTC can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series. As a measure of local correlation between two time series in time and frequency, a value of the coherency close to one shows a high similarity between the time series. A value closer to zero suggests absence of a relationship. Wavelet power spectrum depicts the variance of a time-series. A large variance implies a large power. The cross wavelet power of two time-series is the covariance between two time-series at each scale or frequency. Aguiar-Conraria et al. (2008) define wavelet coherency as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series" (p. 2872).

Following Torrence and Webster (1999) we define the wavelet coherence of two series as

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right)\cdot S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)}, \tag{5}$$

where, S is a smoothing operator. As noted, this definition resembles the traditional correlation coefficient. Without the smoothing coherency, it is identically 1 at all scales and times. We may further write the smoothing operator S as a convolution in time and scale:

$$S(W) = S_{scale}(S_{time}(W_n(s))) \tag{6}$$

where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} denotes smoothing in time. The time convolution is done with a Gaussian, while the scale convolution is performed with a rectangular window (see, for more details, Torrence and Compo 1998). For the Morlet wavelet, a suitable smoothing operator is given by,

$$S_{time}(W)\,|_s = \left(W_n(s) * c_1^{-t^2/2s^2}\right)|_s \tag{7}$$

$$S_{scale}(W)\,|_n = \left(W_n(s) * c_2\Pi(0{,}6s)\right)|_n \tag{8}$$

where, c_1 and c_2 are normalization constants, and Π is the rectangle function. The factor of (0, 6) is the empirically determined scale de-correlation length for the Morlet wavelet (Torrence and

Compo 1998). In practice both convolutions are done discretely and therefore, the normalization coefficients are determined numerically.

Outside economics, some work has been done on theoretical distributions involving the wavelet power, but for the cross-wavelets and the wavelet coherency (see e.g. Ge 2007, 2008; Marun et al. 2007), the null hypotheses in the tests are too restrictive to fit an economic model. In order to assess the statistical significance of estimated wavelet power and wavelet coherency, we therefore, rely on Monte Carlo simulation. We generate a large ensemble of surrogate dataset pairs with the same AR(1) coefficients as the input datasets and then calculate Wavelet Coherence and estimate significance level for each scale using only values that lie outside of the Cone of Influence (COI).

We will focus on the wavelet coherency, instead of the wavelet cross spectrum. Aguiar-Conraria and Soares (2011, p.649) provide us with two arguments in favor of using the wavelet coherency: "(1) the wavelet coherency has the advantage of being normalized by the power spectrum of the two time-series, and (2) that the wavelets cross spectrum can show strong peaks even for the realization of independent processes suggesting the possibility of spurious significance tests".

2.2.5 Cross Wavelet Phase Angle

Given our interest in the phase difference between components of the two series, we need to estimate the mean and confidence interval of the phase difference. To quantify the phase relationship, we use the circular mean of the phase over regions with better than 5% statistical significance that lie outside of the COI. This is a general but useful method for calculating the mean phase. The circular mean of a set of angles ($a_i, i = 1,...,n$) is defined as

$$a_m = \arg(X,Y) \text{ with } X = \sum_{i=1}^{n} \cos(a_i) \text{ and } Y = \sum_{i=1}^{n} \sin(a_i) \quad (9)$$

A major challenge in computing the phase angles is that they are not independent which makes the computation of confidence interval of the mean angle unreliable. The number of angles used in calculation can be set arbitrarily high simply by increasing the scale resolution. However, it is of interest to know the scatter of angles around the mean. For this we define the circular standard deviation as,

$$s = \sqrt{-2\ln(R/n)}, \tag{10}$$

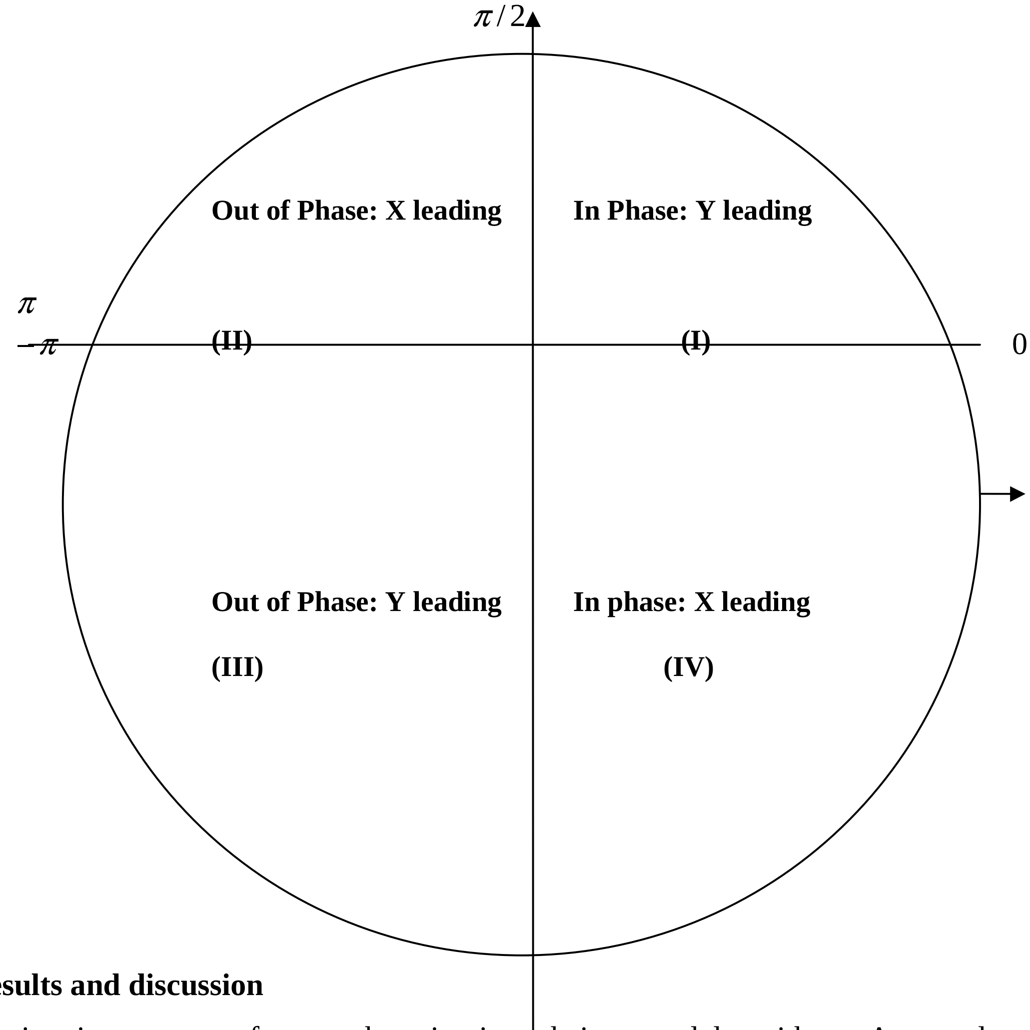
where, $R = \sqrt{(X^2 + Y^2)}$. The circular standard deviation is analogous to the linear standard deviation. It varies from zero to infinity; and yields similar results, if the angels are distributed closely around the mean angle. In some cases it may be necessary to calculate the mean phase angle for each scale. Then the phase angle can be quantified as the number of years.

The statistical significance level of the wavelet coherence is obtained from Monte Carlo methods. As noted earlier, from the AR(1) coefficients we estimate the significance level for each scale using only values outside the COI. The phase for wavelets shows lag or lead relationships between the two time series, and is defined as

$$\phi_{x,y} = \tan^{-1}\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}, \phi_{x,y} \in [-\pi, \pi] \tag{11}$$

where, I and R are the imaginary and real parts, respectively, of the smooth power spectrum.

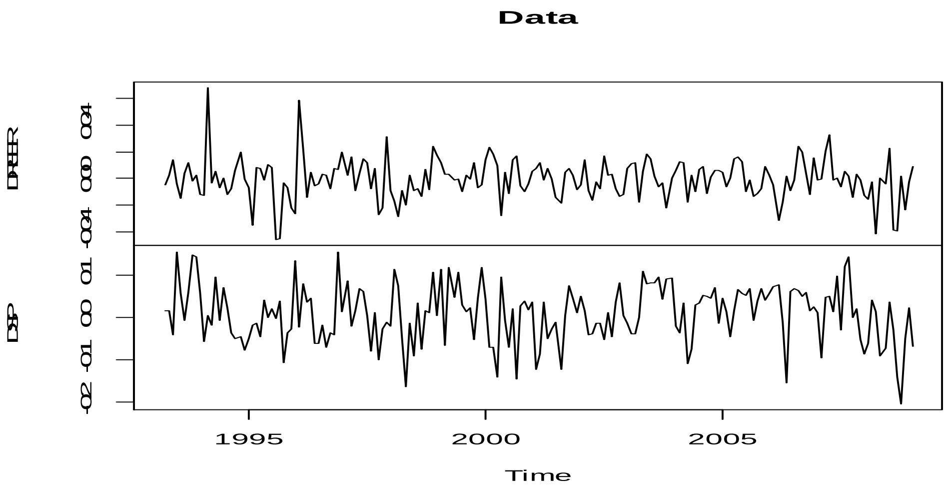
Phase differences are useful in characterizing phase relationships between two time series. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency. If $\phi_{x,y} \in [0, \pi/2]$, then the series move in-phase, and the time-series y leading x. On the other hand, if $\phi_{x,y} \in [-\pi/2, 0]$ then x is leading. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of π or, $-\pi$ meaning $\phi_{x,y} \in [-\pi/2, \pi] \cup [-\pi, \pi/2]$. If $\phi_{x,y} \in [\pi/2, \pi]$ then x is leading. The time series y is leading if $\phi_{x,y} \in [-\pi, -\pi/2]$. Note that we are measuring the angle counter-clockwise (Figure below); so that 160 degree angle falls in Quadrant (II) therefore, X is leading. Now, when we measure the same angle clock-wise, it will be -200 degrees and will still be in the same Quadrant at same location, therefore X will be leading again. Thus, 160 degree angle (counter-clock wise) is identical to -200 degree angle (clockwise).



3. Results and discussion

Prior to estimation, we transform each series into their natural logarithms. As noted earlier, investors are interested in *returns* instead of prices. So, the transforming the level series into return by taking first difference of logarithms makes sense. Each series thus represents monthly returns. Their time plot is presented in Figure. 1.

Figure1: Plot of each series



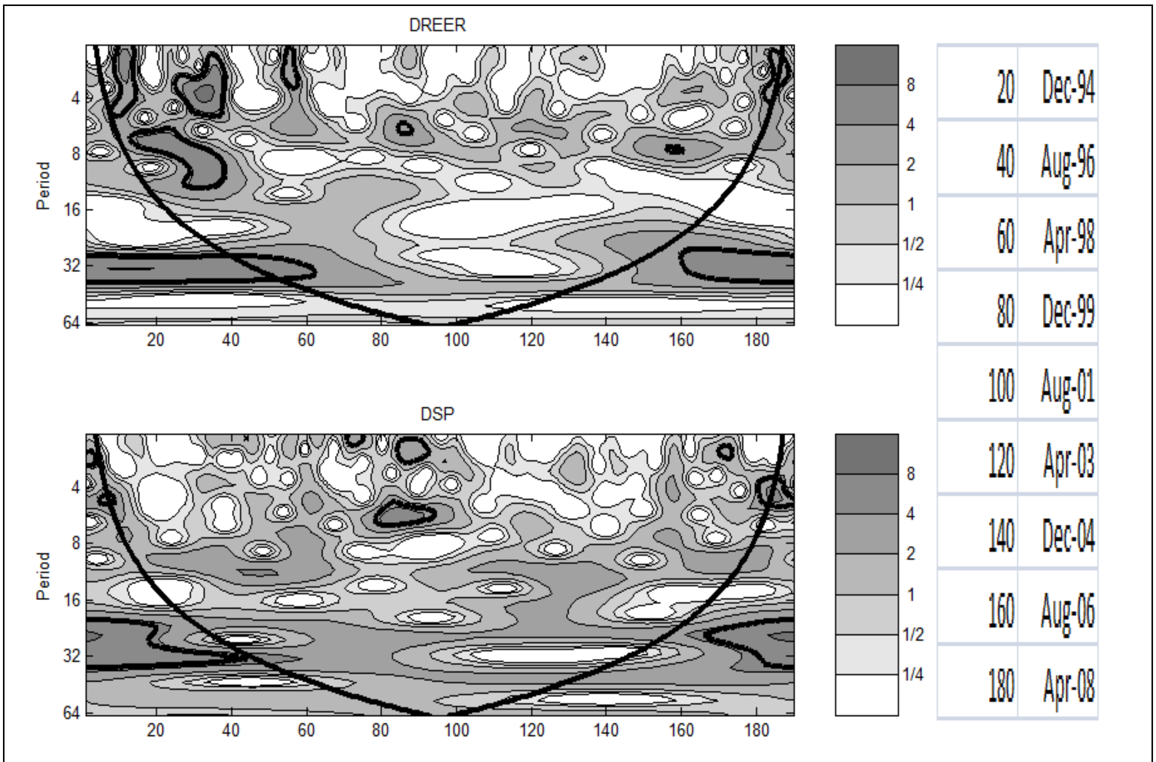
The descriptive statistics for the return series of stock prices (DSP) and real effective exchange rate (DREER), reported in Table 1, show that the sample mean is negative for the DREER, while positive for the DSP. The measure of skewness indicates that the REER series is skewed positively and DSP negatively. The data series of DSP and DREER exhibits excess kurtosis, which implies distributions are leptokurtic relative to the normal distribution.

Table 1: Descriptive statistics of returns series

	DREER	DSP
Mean	-0.00	0.00
Median	0.00	0.01
Maximum	0.06	0.15
Minimum	-0.04	-0.20
Std. Dev.	0.01	0.06
Skewness	0.24	-0.28
Kurtosis	6.00	3.04
Jarque-Bera	73.56	2.66
Probability	0.00	0.26

The Jarque-Bera test rejects normality of DREER, but fails to reject that of DSP. Fig. 2 presents results of continuous wavelet power spectrum of real DREER (top) and DSP (lower panel).

Figure 2: The continuous wavelet power spectrum of DREER (top) and DSP (bottom)

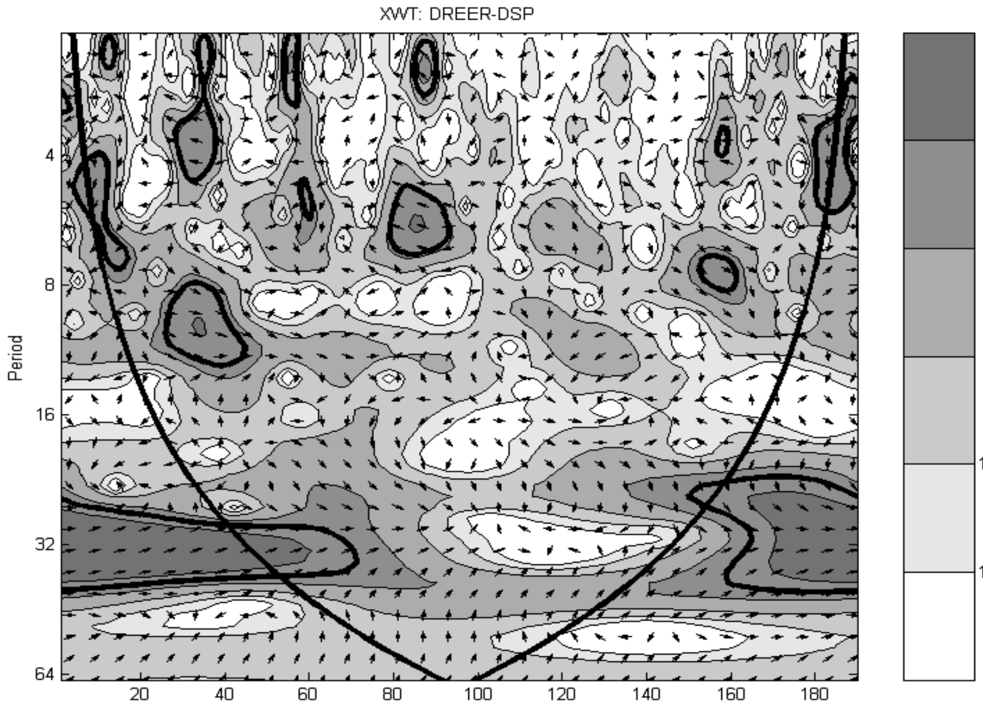


Note: The continuous wavelet power spectrum shown is for DREER (top) and DSP (bottom). The thick black contour indicates the 5% significance level against red noise and the cone of influence where edge effects might distort the picture are shown outside of the black line. The color code for power ranges from white (low) to dark grey (high). The Y-axis measures frequencies (time scales) and X-axis the time period.

It is evident from the Fig. 2 that there are some common islands in the wavelet power spectrum for the two series during 1999-01 and late in 2008 at 4~8 month time scales**.** The similarity between the portrayed patterns in these periods is not very clear which makes it hard to isolate the result from mere coincidence. This is where the cross wavelet transform can come to rescue. The results of analysis of the nature of data using cross wavelet are presented in Fig. 3.

It is interesting to see that the direction of arrows at different frequency bands over the study period is not same (Fig. 3). For example, in 1994 for lower scale of 4-7 months arrows are left down; in 1996 arrows are right down in the scale of 8-12 months; and for less than 4 months scale arrows are left up. During 1998-99 arrows are right up in 32-40 months scale; and in 2006 the arrows are right down. The pattern suggests that the variables exhibit both phase and anti-phase relationship – they are characterized by cyclical and anti-cyclical effects on each other.

Fig. 3: Cross wavelet transform of the DREER and DSP time series



20	Dec-94
40	Aug-96
60	Apr-98
80	Dec-99
100	Aug-01
120	Apr-03
140	Dec-04
160	Aug-06
180	Apr-08

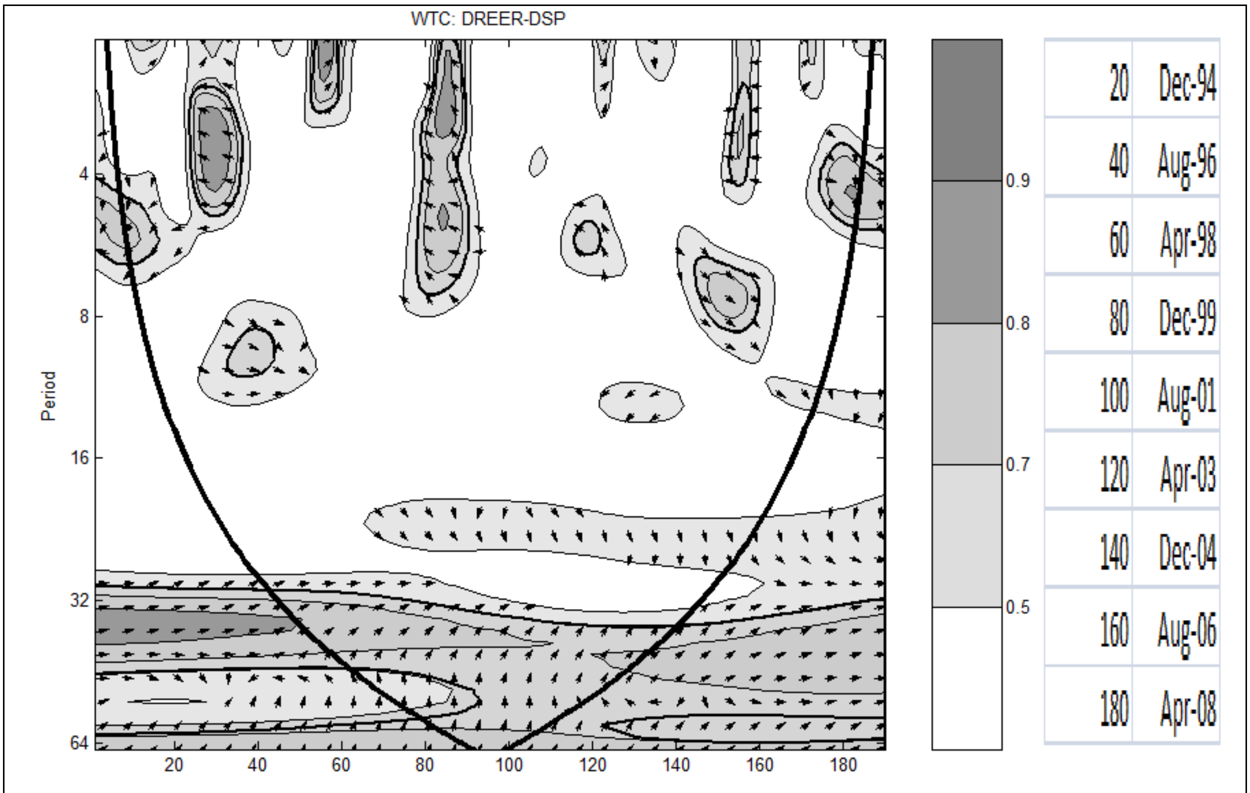
Note: The thick black contour designates the 5% significance level against red noise, obtained from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is shown outside of the black line. The color code for power ranges from white (low) to dark grey (high). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, with DREER is lagging. To the right and down, with DREER is leading. Arrows pointing to the left mean that the variables are out of phase. To the left and up, DREER is leading. To the left and down, DREER is lagging. In phase indicate that variables have cyclical effect on each other; and out of phase or anti-phase shows that the variables have anti-cyclical effect on each other.

A glance at Fig.3 suggests that during 1994 for the lower scale of 4~7 months, variables are out of phase and DSP is leading (i.e., anti-cyclical effects are observed and exchange rate is affecting share prices). During 1996, however, we observe both cyclical and anti-cyclical effects at the 8~12 months time scale; with DSP lagging. During the same period, for less than 5 months scale, we observe that variables are out of phase (arrows left up) indicating DREER is leading. For the period from 1998 through 1999, in 32-40 months scale, we find that variables are in phase (arrows right up) and DSP is leading. For 2006 the variables are in phase (evidence of cyclical effects) and DREER is leading (arrows right down) at the time scale of 6~8 months. We further observe some significant common islands in higher as well as lower frequencies but they are within the cone of influence. Due to distortion by the edge effects, we ignore these areas. Overall it appears that there is a link between return series of share prices and exchange rates, implied by the cross wavelet power.

It may be noted that wavelet cross-spectrum (i.e., cross wavelet) describes the common power of two processes without normalization to a single wavelet power spectrum. This can produce misleading results, because here one has to deal with the product of continuous wavelet transform of two time series. For example, if one of the spectra is local and the other exhibits strong peaks, then the peaks in the cross spectrum can be produced that has nothing to do with any relation between the two series. This leads us to conclude that wavelet cross spectrum is not the best tool to test the significance of relationship between two series. So, in drawing our conclusions we relied on the wavelet coherency (see section 2.2). However, one can still use wavelet cross-spectrum to estimate the phase spectrum. The wavelet coherency is used to identify both frequency bands and time intervals within which pairs of indices vary together.

The results of cross-wavelet coherency are presented in Fig. 4. If we compare results of WTC and XWT i.e., compare Fig. 3 with Fig. 4, we find the results of phase difference of lead-lag relationship between the two series (Fig.4). Fig. 4 shows that during late 1994 and early 1995, in the time scale of 4~6 months, arrows are left down indicating that variables are out of phase (anti-cyclical effects on each other) and DSP is leading. However, during late 1995, at the time scale of 2~5 months, we observe that arrows are left up indicting that variable are out of phase and DSP is lagging. Similar results are found during 1999-2000 for the time scale of 2~7 months. The intriguing part in Fig. 4 is that over the study period, for the time scales of 32~48 months, arrows are right up indicating that variables are in phase and DSP is leading. Thus, during 1995 and 1999-2000, we observe evidence of bidirectional causality (though not at same time scale) which lends support to traditional (Dornbush-Fischer 1980) as well as new portfolio hypothesis (Frankel 1991) for India. For the year 1996 the arrows are right down indicating variables are in phase and DREER is leading. Similar results are also found during late 2004 and 2005 at the time scale of 7~10 months and during early 2008 for the time scale of 3~5 months.

Fig. 4: Cross-wavelet coherency or squared wavelet coherence



Note: The thick black contour designates the 5% significance level against red noise, estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown outside of the black line. The color code for coherency ranges from white (low, close to 0) to dark grey (high, close to 1). The phase difference between the two series is indicated by arrows. Arrows pointing to the right indicate that the variables are in phase. To the right and up, the DREER is lagging. To the right and down, DREER is leading. Arrows pointing to the left indicate that the variables are out of phase. To the left and up, DREER is leading. To the left and down, DREER is lagging. In phase indicate that the variables have cyclical effect on each other; and out of phase or anti-phase shows that variables have anti-cyclical effect on each other.

We identify some areas with significant region of WTC, but those are contaminated by edge effects. The most fascinating aspect is the evidence of bidirectional causality (not present in the XWT analysis) between the two series. However, it may be noted that they are on different time scale. The analysis using the WTC tool clearly shows evidence of lead-lag relationship between the series. Further, we also know whether one variable influences or, is influenced by the other through anti-cyclical or cyclical shocks. These results would have not surfaced had the standard time series or Fourier transformation been applied.

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4. Conclusions

The paper implements the continuous wavelet approach to examine a causal relationship between the return series of share prices and exchange rates. We decompose the time-frequency relationship to Indian monthly data. To the best of our knowledge this is the first ever study that uses this approach to examine stock price- exchange rate nexus. We find evidence of common features in the wavelet power of the two time series during 1999-2001 and in late 2008 at 4~8 month time scale. The results of XWT, which measure the covariance between the series, fail to offer any clear-cut results although, indicate that both the variables have been in- and out-phase (i.e., anti-cyclical and cyclical) at some durations. The WTC results suggest that, both the variables are out of phase and the stock returns are leading during the late 1994 and early 1995 at 4~6 month time scales. During 1995, however, the variables are out of phase and stock return is lagging at the time scale of 2~5 months. During the late 1999 and 2000 for the time scale of 2~7 months, exchange rate is leading, and out of phase; and between 32-48 months stock returns are leading but in phase. In 1995 and during 1999-2000, we find bidirectional causality along with cyclical and anti-cyclical relationship albeit, at different time scales. We observe that, both the variables are in phase and exchange rate returns is leading during 1996, late 2004, 2005 in the time scale of 7~10 months, and in 2008 for the time scale 3~5 months. Our results show that during the study period, for the time scales of 32-48 months, both series are in the phase and stock returns are leading.

Our results suggest causality as well as reverse (bidirectional) causality between stock price and exchange rate which vary across time-scales and over frequency in the Indian context. We also find evidence of cyclical and anti-cyclical relationship between the series. For higher time scales, we find that share price is lagging and receiving cyclical effects emanating from exchange rate shocks. The results are in sharp contrast with those found earlier on India. While offering mixed evidence, most studies (Rahman and Uddin 2009; Muhammad and Rasheed 2002; Bhattacharya and Mukherjee 2003; Mishra 2004; and Venkateshwarlu and Tiwari 2005) tend to reject an association between the two series; or find unidirectional causality (Abdalla and Murinde 1997) from exchange rates to stock prices. Overall we unveil the causal relationship in both the directions though at different time scales.

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Our results are the outcome of the particular methodological choice which otherwise could not have been achieved under the conventional approaches; and is thus a contribution to the literature. Knowledge of the direction of causality is the essence for insight which helps to craft appropriate policy.

While we recognize the limits of bivariate approach, in the future researchers might apply a multivariate approach to revisit the relation. It might be of interest to assess the nexus by including variables e.g., interest rates, oil price return, money supply and other macroeconomic variables as can be justified on theoretical grounds in the particular economic context.

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