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Price Lead-Lags in Indian Stock and Futures Market - A Wavelet Based Study

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This paper examines the relationship between the stock and futures markets in terms of cointegration (Jhonson Cointegration) and lead-lag relationship (Wavelet Approach). We applied the Maximum Overlap Discrete Wavelet Transform (MODWT) method to stock and futures prices of 12 near month contracts during the period April 2011 and March 2012. The study included 13 Scripts across sectors which are included both in BSE Sensex and Nifty 50. Empirical results show that stock and futures are cointegrated in the long run and there is either feedback relationship or futures lead across time scales and also we have seen in some scripts there is no lead lag neither contemporaneously nor in different time scales.

Key Words: Lead lag, Cointegration, Error Correction, Wavelets.

Introduction

When new information is released in an efficient and perfect capital market bias, prices of securities and their derivatives fully and instantaneously reflect all available relevant information. But, in real markets, there exist market frictions including various transaction costs and information asymmetry in real markets and the lead–lag relationship between markets is observed.

For cognate disciplines such as economics and biology, one of the most useful properties of the wavelet approach is the ability to decompose any signal into its time scale components. It is well known that physical and biological processes are phenomenological different across different time scales. In economics as well, one must allow for quite different behavior across time scales. A simple example will illustrate the concept. In the market for securities there are traders who take a very long view, year's infact, and consequently concentrate on what are termed “market fundamentals”, these traders ignore ephemeral phenomena. In contrast, other traders are trading on a much shorter time scale and as such are interested in temporary deviations of the market from its long term growth path; their decisions have a time horizon of a few months to a year. And yet other traders are in the market for which a day is a long time. An effort along these lines is illustrated in the paper by Davidson et al (1997), who investigated U.S commodity prices. Even though the differences across scales were not pursued fully, the authors did consider the different properties of the wavelet coefficients across scales and calculated a measure of relative importance of the coefficients between scales. In two related papers, Ramsey & Lampart (1998a) and Ramsey & Lampart (1998b) used the wavelet analysis to examine the relationship between variables across scales.

Several other applications of wavelet analysis to economics and finance have been documented in recent literature like stock market inefficiency (Pan and Wang 1998), scaling properties of foreign exchange volatility (Gencay, Selcuk, and Whitcher 2001), and systematic risk (the beta of an asset) in a capital asset pricing model (Gencay et al. 2003). Francis and Kim (2006) examined the lead lags in US markets using wavelets, and found the feedback relationship contemporaneously as well as in various time scales. Lee (2004) employed wavelet analysis to study the transmission of stock market movements; Yamada (2005) used a wavelet-based beta estimation to investigate Japanese industrial stock prices.

Studies other than wavelets which examine relation between stock and futures lead/lag find evidence on futures prices leading spot prices (Garbade and Silber 1983; Kawaller et al. 1987; Herbst et al. 1987; Chan 1992; Antoniou and Garrett 1993; Tse 1995; Cheung and Fung 1997; Nieto et al. 1998; Jong and Donders 1998; Min and Najand 1999; Gwilym and Buckle 2001, Kenourgios 2004; Floros and Vougas 2007; Cheung and Fung 1997) some of them find evidence on spot prices leading futures prices (Chan 1992; Antoniou and Garrett 1993; Jong and Nijman 1997; Cheung and Fung 1997; Kenourgios 2004; Wang et al. 2009). Additionally there are studies finding no evidence on lead-lag relationship between spot and futures prices (Brooks et al. 2001; Hasan 2005; In and Kim 2006). Thenmozhi (2002) studied lead lag relationship between Nifty spot index and Nifty index futures market in India using daily data. They find that the futures market in India lead the spot market by at least one to two days. They also find that futures market has more power in disseminating information and therefore has been found to play the leading role in price discovery. Mukherjee and Mishra (2006), by looking at six

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months intraday data from April 2004 to September 2004, find that neither Nifty index futures nor Nifty spot index lead and there is a strong contemporaneous and bi-directional relationship among the index and index futures market in India. Gupta and Singh (2006) examined the efficiency of Indian equity futures market by considering price discovery feature as the predominant feature of the efficient futures market and argued that in the event of high fluctuations, futures market provides significant information regarding the prospective move in the cash market. Mukherjee and Mishra (2006) exhibited the strong contemporaneous and bi-directional relationships between Nifty spot and futures market.

Methodology

We have first investigated the cointegration (Jhonson cointegration) between stock and their futures, followed by error correction mechanism (ECM) to see how quickly the temporary disequilibrium pricing errors are corrected and then have analysed the Granger causality in wavelet domain. The brief description of Jhonson cointegration, ECM and wavelet analysis is given here.

Jhonson Cointegration

Johansen's methodology takes its starting point in the Vector Autoregression (VAR) of order p given by

$$y_t = \mu + A_1 y_{t-} + \ldots\ldots + A_p y_{t-p} + \varepsilon_t \quad (1)$$

Where yt is an nx1 vector of variables that are integrated of order one- commonly denoted I (1) – and εt is an nx1 vector of innovations. This VAR can be re-written as

$$\Delta y_t = \mu + \prod y_{t-1} + \sum_{t=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon_t \quad (2)$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I and \Gamma_i = - \sum_{j=i+1}^{p} A_j$$

If the coefficient matrix $\prod$ has reduced rank r<n, then there exist nxr matrices α and β each with rank r such that $\Pi = \alpha\beta' and \beta' y_t$ is stationary. r is the number of cointegrating relationships, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector. It can be shown that for a given r, the maximum likelihood estimator of β defines the combination of yt-1 that yields the r largest canonical correlations of Δyt and Δyt-1 after correcting for lagged differences and deterministic variables when present. Johansen proposes two different likelihood ratio tests of the significance of these canonical correlations and thereby the reduced rank of the Π matrix: the trace test and maximum eigen value test, shown in equations below;

$$j_{trace} = -T \sum_{i=r+t}^{n} \ln(1 - \hat{\lambda}_i)$$

$$j_{\max} = -T \ln(1 - \hat{\lambda}_{r+1})$$

Here T is the sample size and λ^i is the i:th largest canonical correlation. The trace test, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The maximum eigen value test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r+1 cointegrating vectors.

Error Correction Mechanism

Following Granger (1986) a time series model of a cointegrated series may be rewritten in error correction form. Such a transformation renders the series stationary, and allows for standard hypothesis testing. A prototypical ECM useful for testing the short-run relationship between spot and futures prices may be specified as

$$\Delta S_t = -\rho u_{t-1} + \beta \Delta F_{t-1} + \sum_{i=2}^{m} \beta \Delta F_{t-1} + \sum_{j=1}^{k} \psi \Delta S_{t-j} + v_t$$

Where Δ is a first difference operator such that ΔSt = St – St-1; ut-1 is the error correction term, the coefficient of which indicates the speed of adjustment of any disequilibrium towards the long-run equilibrium state.

Wavelets and Wavelet Analysis

A natural concept in financial time series is the notion of multiscale features. That is, an observed time series may contain several structures, each occurring on a different time scale. Wavelet techniques possess an inherent ability to decompose this kind of time series into several sub-series which may be associated with a particular time scale. Processes at these different time scales, which otherwise could not be distinguished, can be separated using wavelet methods and then subsequently analyzed with ordinary time series methods. Wavelet methods present a lens to the researcher, which can be used to zoom in on the details and draw an overall picture of a time series in the same time. Gençay et al. (2002a) argue that wavelet methods provide insight into the dynamics of economic/financial time series beyond that of standard time series methodologies. Also wavelets work naturally in the area of non-stationary time series, unlike Fourier methods which are crippled by the necessity of stationarity. In recent years the interest for wavelet methods has increased in economics and finance. This recent interest has focused on multiple research areas in economics and finance like exploratory analysis, density estimation, analysis of local in homogeneities, time scale decomposition of relationships and forecasting (Crowley 2005). By decomposing a time series on different scales, one may expect to obtain a better understanding of the data generating process as well as dynamic market mechanisms behind the time series. Investigation methods applied to a financial time series over the last decades can now be implemented to multiple time series presenting different scales (frequencies) of the original time series. Therefore efficient discretization of the time-frequency space allows isolation of many interesting structures and features of economic and financial time series which are not visible in the ordinary time-space analysis or in the ordinary Fourier analysis.

A wavelet is a 'small wave' which has its energy concentrated in a short interval of time. The wavelet analysis allows researchers to decompose signals into a parsimoniously countable set of basic functions at different time locations and resolution levels. Due to the Compact support property of wavelets, the wavelet analysis is capable of capturing short lived, transient components of data in shorter time intervals, as well as capturing trends and patterns in longer time intervals. The studies which included wavelet analysis are; outlier detection (Greenblatt 1994), processing of nonstationary data (Goe 1994), examination of the time-frequency (Wigner) distributions (Ramsey and Zhang 1995, 1996), the study of the statistical self-similarity of financial data (Ramsey, Zaslavsky, and Usikov (1995),examination of the relationship among key macroeconomic variables (Ramsey, and Lampart (1998a, 1998b), estimation of long-memory processes (Jensen 1998), and discussion of potential difficulties involved in shifting from deterministic models to stochastic processes in the analysis of economic and financial data (Priestly 1996). Recently, Davidson et al. (1998) have made a revolutionary contribution to this line of research by placing the wavelet analysis in a semi-non parametric regression framework. By doing so not only does it allow one to easily handle inherent restrictions in the wavelet analysis, but it also allows one to utilise the well established statistical properties of semi-nonparametric regression to assess output from such an analysis. Pan and Wang (1998) combine the wavelet analysis with regression and state space formulation to study the potential stochastic relationship between the S&P500 index price and S&P dividend Yields.

Basic wavelets are characterized into father and mother wavelets, f(t) and w(t), respectively. These wavelets are functions of time only. A father wavelet represents the smooth baseline trend, and mother wavelets are used to describe all deviations from trends. Any time series, for example f(t), can be decomposed by wavelet trans-formations, which can be given by

$$f(t) \approx \sum_k S_{j,k}\Phi_{j,k}(t) + \sum_k d_{j,k}\Psi_{j,k}(t) + \sum_k d_{j-1,k}\Psi_{j-1,k}(t) + \ldots\ldots + \sum_k d_{1,k}\Psi_{1,k} \quad (3)$$

Where J is the number of scales and k ranges from one to the number of coefficients in the specified component. The coefficients are Sj,k, dj,k,…,d1,k are the wavelet transform coefficients. The functions Φj,k(t) and Ψj,k(t), where j= 1,……., j-1, j, are the approximating wavelet functions. Wavelet transforms can now be implemented given the family of wavelets described. The wavelet transforms are the wavelet series coefficients defined as Sj,k= ∫ Φj,k(t)f(t)dt and dj,k = ∫ Ψj,k(t)f(t)dt, where j is the maximum integer such that 2j is less than the number of data points. Their magnitude gives a measure of the contribution of the corresponding wavelet function to the approximation sum, and wavelet series coefficients approximately specify the location of the corresponding wavelet function. More specifically, the detail coefficients dj,k, …..,d1,k, which can capture the higher-frequency oscillations, represent increasingly fine scale deviations from the smooth trend. The coefficient Sj,k represents the smooth coefficients that capture the trend. Given these coefficients, the wavelet series approximation of the original signal f(t) is given by the sum of the smooth signal SJ,k and the detail signals Dj,k, Dj-1,k,……., D1,k:

$$f(t) = S_{j,k} + D_{j,k} + D_{j-1,k} + \ldots\ldots + D_{1,k} \quad (4)$$

Where $S_{j,k} = \sum_k S_{j,k}\Phi_{j,k}(t), D_{j,k} = \sum_k d_{j,k}\Psi_{j,k}(t), a$

$ndD_{1,k} = \sum_k d_{1,k}\Psi_{1,k}(t)$ The original signal components Sj,k, Dj,k, Dj-1,k and D1,k are listed in the order of increasingly fine scale components. Signal variations on high scales are acquired using wavelets with large supports. The discrete wavelet transform (DWT) calculates the coefficients of the wavelet series approximation for a discrete signal f1,……..,fn of finite extent. The DWT maps the vector $f = (f_1, f_2, \ldots\ldots, f_n)^{/}$ to a vector of n wavelet coefficients $w = (w_1, w_2, \ldots\ldots\ldots\ldots, w_n)^{/}$ The vector w contains the coefficients Sj,k, dj,k, ……, d1,k, j= 1,2,….,j of the wavelet series approximation, equation (4). Our analysis adopts the maximum overlap DWT (MODWT) instead of DWT. It provides basically all functions of the DWT, such as multi resolution analysis (MRA) decomposition and analysis of variance.

Data and Empirical Results

In this paper, we used cash prices of 13 Scripts and their futures. Our data is composed of daily closing prices for each cash and futures for a period April 2011 to March 2012, thereby having 12 contracts for each script. We computed the daily returns for both cash and future series. For the futures price, to generate a continuous futures contract series, we switch to a new contract as contract maturity approaches. The daily changes of both stock and futures indices are calculated by log (Pt) - log (Pt-1).

A preliminary consideration for cointegration is to determine if, the data are stationary. For two nonstationary series to be cointegrated they must be integrated of the same order. For this we employed two different unit root tests; the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test. The optimal number of augmenting lags for the model was determined by using Akaike's information criterion 2 (AIC2). For each series all tests indicated the presence of one unit root (Tables 1 and 2); each price series may therefore be regarded as difference stationary. Given that each cash and futures prices are integrated of the same order, I(1) , cointegration techniques may be used to determine if a stable long-run relationship exists between the price pairs.

Using Johansen's (1988) procedure, tests for cointegration were performed. Johansen's procedure is a multivariate approach based on maximum likelihood estimates of the cointegrating regression. The VAR (Vector Autoregressive) specification was estimated by using from one to seven lags, with the AIC criterion used to choose optimal lag length. Maximal eigen value and trace test statistics , presented in Table 3, indicate the null hypothesis of no cointegration is rejected at the 5% significance level for each Script whether cash or futures. On the other hand, in every instance the null hypothesis of one cointegrating relationship cannot be rejected. Overall, Johansen's test results support the hypothesis that cash and futures prices for each script are cointegrated. Table 4 shows the speed of adjustment of any disequilibrium towards the long-run equilibrium state. Estimated speeds of adjustment parameters are significant for all scripts.

To examine the lead-lag relationship in wavelet analysis, first we test for Granger causality in original series and then up to level 3 i.e. behavior of price series in 2-4 days, 4-8days and 8-16 days. The results of the Granger causality tests are reported in table 5. As can be seen from table 5, the stock and futures markets show a feedback relationship contemporaneously as well as in various time scales in case of BHEL, no lead/lags at all in case of Bharti Airtel, Maruti, RIL, SBI, and Tata Motors in both original and different time scales. In case of Cipla, HDFC Bank, Tata Power and Tata Steel, we see no lead lag in original series but in different time scales feedback relationship is seen. For Infosys futures lead in original and time scales while in NTPC no lead/lag in original series is seen but futures having more tendencies to lead in different time scales. We can say that the informational flow is bi-directional in case of BHEL, CIPLA, HDFC Bank, Tata Power and Tata Steel. For Infosys and NTPC informational flow is from futures to spot. Bharti Airtel, Maruti, RIL, SBI, and Tata Motors react instantaneously to the new information so there is no lead lag found.

Conclusion

In this paper, we used wavelet analysis to examine the relationship between the stock and futures markets over different time scales. To examine the lead-lag relationship between the two markets, we employ the Granger causality test for various time scales. The main advantage of using wavelet analysis is the ability to decompose the data into the various time scales. This advantage allows researchers to investigate the relationship between two variables in various time scales, whereas the traditional methodology allows examination of only two time scales: short and long-run scales. From Jhonson Cointegration we saw that both stock as well as futures series in all scripts are cointegrated in long run. While examining the lead/lags we got mixed results, from no lead/lags, feedback relationship, to futures leading.

Footnotes

1. We have taken the closing prices from NSE. We checked results for Adjusted Close Prices (taken from CMIE Prowess), there was almost no difference in results.

2. The AIC2 criterion choose s the number of lags that minimizes the AIC criterion and then adds two additional lags.

3. In this wavelet analysis, note that with consideration for the balance between the sample size and the length of the wavelet filter, we settle on the MODWT based on the Daubechies least asymmetric wavelet filter of length 8 (LA(8); we decompose our data up to level 3.

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Table 1: Unit Root Analysis of Stock Prices

Script	ADF		PP	
	Level	First Difference	Level	First Difference
Bharti Airtel	-1.984 (0.294)	-14.971 (0.000)	-1.943 (0.312)	-14.981 (0.000)
BHEL	-0.933 (0.776)	-14.848 (0.000)	-0.912 (0.783)	-14.861 (0.000)
CIPLA	-1.812 (0.000)	-16.580 (0.000)	-1.723 (0.418)	-16.580 (0.000)
HDFC BANK	-1.524 (0.519)	-15.200 (0.000)	-1.518 (0.522)	-15.199 (0.000)
HUL	-1.126 (0.705)	-15.792 (0.000)	-1.060 (0.731)	-15.830 (0.000)
INFOSYS	-2.498 (0.116)	-14.229 (0.000)	-5.507 (0.115)	-14.219 (0.000)
MARUTI	-1.270 (0.643)	-14.786 (0.000)	-1.270 (0.643)	-14.785 (0.000)
NTPC	-2.754 (0.066)	-15.821 (0.000)	-2.664 (0.081)	-15.979 (0.000)
RIL	-2.154 (0.223)	-14.402 (0.000)	-2.140 (0.229)	-14.400 (0.000)
SBI	-2.115 (0.238)	-11.402 (0.000)	-1.890 (0.336)	-11.135 (0.000)
TATA MOTORS	-1.388 (0.587)	-14.155 (0.000)	-1.386 (0.588)	-14.137 (0.000)
TATA POWER	-0.930 (0.777)	-15.158 (0.000)	-0.923 (0.779)	-15.158 (0.000)
TATA STEEL	-1.628 (0.446)	-14.010 (0.000)	-1.628 (0.466)	-14.013 (0.000)

Brackets show the p values, Critical value at 5% = -2.874

Table 2: Unit Root Analysis of Futures Prices

Script	ADF		PP	
	Level	First Difference	Level	First Difference
BHARTI AIRTEL	-1.987 (0.292)	-14.817 (0.000)	-2.014 (0.280)	-14.828 (0.000)
BHEL	-0.940 (0.774)	-15.322 (0.000)	-0.905 (0.280)	-15.343 (0.000)
CIPLA	-1.806 (0.376)	-16.824 (0.000)	-1.667 (0.446)	-16.825 (0.000)
HDFC BANK	-1.579 (0.491)	-15.181 (0.000)	-1.573 (0.494)	-15.180 (0.000)
HUL	-1.150 (0.696)	15.807 (0.000)	-1.099 (0.716)	-15.826 (0.000)
INFOSYS	-2.556 (0.103)	-14.218 (0.000)	-2.581 (0.098)	-14.205 (0.000)
MARUTI	-1.308 (0.626)	-14.594 (0.000)	-1.308 (0.626)	-14.594 (0.000)
NTPC	-2.702 (0.075)	-15.459 (0.000)	-2.660 (0.082)	-15.535 (0.000)
RIL	-2.175 (0.216)	-14.321 (0.000)	-2.179 (0.214)	-14.311 (0.000)
SBI	-2.111 (0.240)	-11.578 (0.000)	-1.900 (0.331)	-11.355 (0.000)
TATA MOTORS	-1.383 (0.590)	-14.246 (0.000)	-1.381 (0.591)	-14.232 (0.000)
TATA POWER	-0.933 (0.776)	-15.156 (0.000)	-0.927 (0.778)	-15.156 (0.000)
TATA STEEL	-1.641 (0.459)	-14.481 (0.000)	-1.650 (0.455)	-14.481 (0.000)

Brackets show the p values, Critical value at 5% = -2.874

Table 3: Johansen test for cointegration

Script	λ_{trace}		λ_{max}	
	r=0	$r \leq 1$	r=0	r=1
Bharti Airtel (2)	37.09* (15.49)	3.70 (3.84)	33.38* (14.26)	3.70 (3.84)
BHEL (7)	15.55* (15.49)	1.18 (3.84)	14.36 * (14.26)	1.18 (3.84)
CIPLA (2)	26.45 * (15.49)	2.38 (3.84)	24.07* (14.26)	2.37 (3.84)
HDFC BANK (4)	56.89* (15.49)	2.69 (3.84)	54.20 * (14.26)	2.69 (3.84)
HUL (2)	46.51 * (15.49)	1.74 (3.84)	44.77* (14.26)	1.74 (3.84)
INFOSYS (1)	112.85 * (15.49)	8.01* (3.84)	104.83* (14.26)	8.01* (3.84)
MARUTI (1)	26.98 * (15.49)	1.97 (3.84)	25.00* (14.26)	1.97 (3.84)
NTPC (2)	36.82* (15.49)	7.52* (3.84)	29.30* (14.26)	7.52* (3.84)
RIL (2)	33.75 * (15.49)	5.50* (3.84)	28.25* (14.26)	5.50* (3.84)
SBI (2)	31.53 * (15.49)	4.63* (3.84)	26.89* (14.26)	4.63* (3.84)
TATA MOTORS (2)	16.17 * (15.49)	2.30 (3.84)	14.87* (14.26)	2.30 (3.84)
TATA POWER (1)	64.99 * (15.49)	1.08 (3.84)	63.90* (14.26)	1.08 (3.84)
TATA STEEL (2)	30.52* (15.49)	3.17 (3.84)	27.35* (14.26)	3.17 (3.84)

The trace test was used to test the null hypothesis that the number of cointegrating vectors is less than or equal to r, where r is 0 or 1.
*Indicates that the null hypothesis is rejected at 5% level
The critical values at the 5% level are taken at from λtrace and λmax tables, Osterwald-Lenum (1992), and are shown in parentheses below the test statistics.
The lag length chosen by the AIC criteria is shown in parenthesis after the relevant script.

Table 4: Speed of Adjustment of disequilibrium towards the long run equilibrium state

Parentheses show the Standard errors

Script	Bharti Airtel	BHEL	Cipla	HDFC Bank	HUL	Infosys	Maruti	NTPC	RIL	SBI	Tata Motors	Tata Power	Tata Steel
Speed of Adjustment(ρ)	-0.400 (0.054)	-0.770 (0.066)	-0.438 (0.055)	-0.338 (0.032)	-0.865 (0.67)	-0.987 (0.051)	-0.246 (0.044)	-0.506 (0.058)	-0.410 (0.053)	-0.336 (0.050)	-0.197 (0.040)	-0.682 (0.063)	-0.594 (0.061)

Table 5: Granger Causality Test in Wavelet Domain

Script		Original	d1	d2	d3
Bharti Airtel	Futures → Stock	0.681 (0.507)	0.0600 (0.941)	2.020 (0.134)	1.253 (0.287)
	Stock → Futures	0.210 (0.810)	0.229 (0.795)	1.698 (0.185)	0.975 (0.378)
BHEL	Futures → Stock	33.940* (0.000)	32.182* (0.000)	33.201* (0.000)	7.282* (0.000)
	Stock → Futures	35.580* (0.000)	35.436* (0.000)	31.679* (0.000)	6.649* (0.001)
CIPLA	Futures → Stock	0.182 (0.833)	1625.10* (0.000)	260.555* (0.000)	337.506* (0.000)
	Stock → Futures	0.755 (0.471)	11.266* (0.000)	3.161* (0.044)	2.468* (0.087)
HDFC BANK	Futures → Stock	0.033 (0.967)	455.917* (0.000)	319.600* (0.000)	148.324* (0.000)
	Stock → Futures	0.006 (0.993)	9.254* (0.000)	40.907* (0.000)	6.382* (0.002)
HUL	Futures → Stock	3.277 (0.039)	2.952* (0.054)	0.616 (0.541)	2.818* (0.061)
	Stock → Futures	0.758 (0.469)	1.101 (0.334)	0.367 (0.693)	0.436 (0.646)
INFOSYS	Futures → Stock	67.189* (0.000)	27.608* (0.000)	1.933 (0.147)	37.094* ((0.000)
	Stock → Futures	0.247 (0.781)	6.401* (0.002)	1.152 (0.317)	1.842 (0.160)
MARUTI	Futures → Stock	0.742 (0.477)	0.145 (0.864)	0.287 (0.750)	0.731 (0.482)
	Stock → Futures	0.202 (0.817)	0.482 (0.617)	0.139 (0.869)	0.325 (0.722)
NTPC	Futures → Stock	2.249 (0.107)	0.856 (0.426)	3.531* (0.031)	0.126 (0.881)
	Stock → Futures	0.705 (0.495)	0.804 (0.448)	2.042 (0.132)	0.412 (0.662)
RIL	Futures → Stock	0.058 (0.943)	0.035 (0.965)	0.134 (0.874)	0.735 (0.480)
	Stock → Futures	0.705 (0.929)	0.067 (0.934)	0.393 (0.675)	0.591 (0.554)
SBI	Futures → Stock	0.135 (0.873)	0.769 (0.464)	0.889 (0.412)	0.061 (0.940)
	Stock → Futures	0.193 (0.824)	0.205 (0.814)	1.820 (0.164)	0.162 (0.850)
TATAMOTORS	Futures → Stock	0.105 (0.900)	0.051 (0.949)	1.675 (0.189)	1.197 (0.303)
	Stock → Futures	0.203 (0.816)	0.053 (0.948)	1.938 (0.146)	0.970 (0.380)
TATAPOWER	Futures → Stock	2.982* (0.052)	2.220 (0.111)	6.380* (0.002)	1.605 (0.203)
	Stock → Futures	2.812* (0.062)	2.348 (0.097)	6.139* (0.002)	1.445 (0.237)
TATASTEEL	Futures → Stock	0.803 (0.449)	2.202 (0.113)	11.300* (0.000)	4.949* (0.000)
	Stock → Futures	0.005 (0.994)	2.931* (0.055)	9.146* (0.000)	8.140* (0.000)

Note.—The original data have been transformed by the wavelet filter (LA(8) up to time scale 3. The significance levels are in parentheses. The first detail (wavelet coefficient) d1 captures oscillations with a period length two to four days, d2 captures a period of 4-8 days and the last detail d3 captures oscillations with a period length of 8-16 days. *Significant at the 10% level