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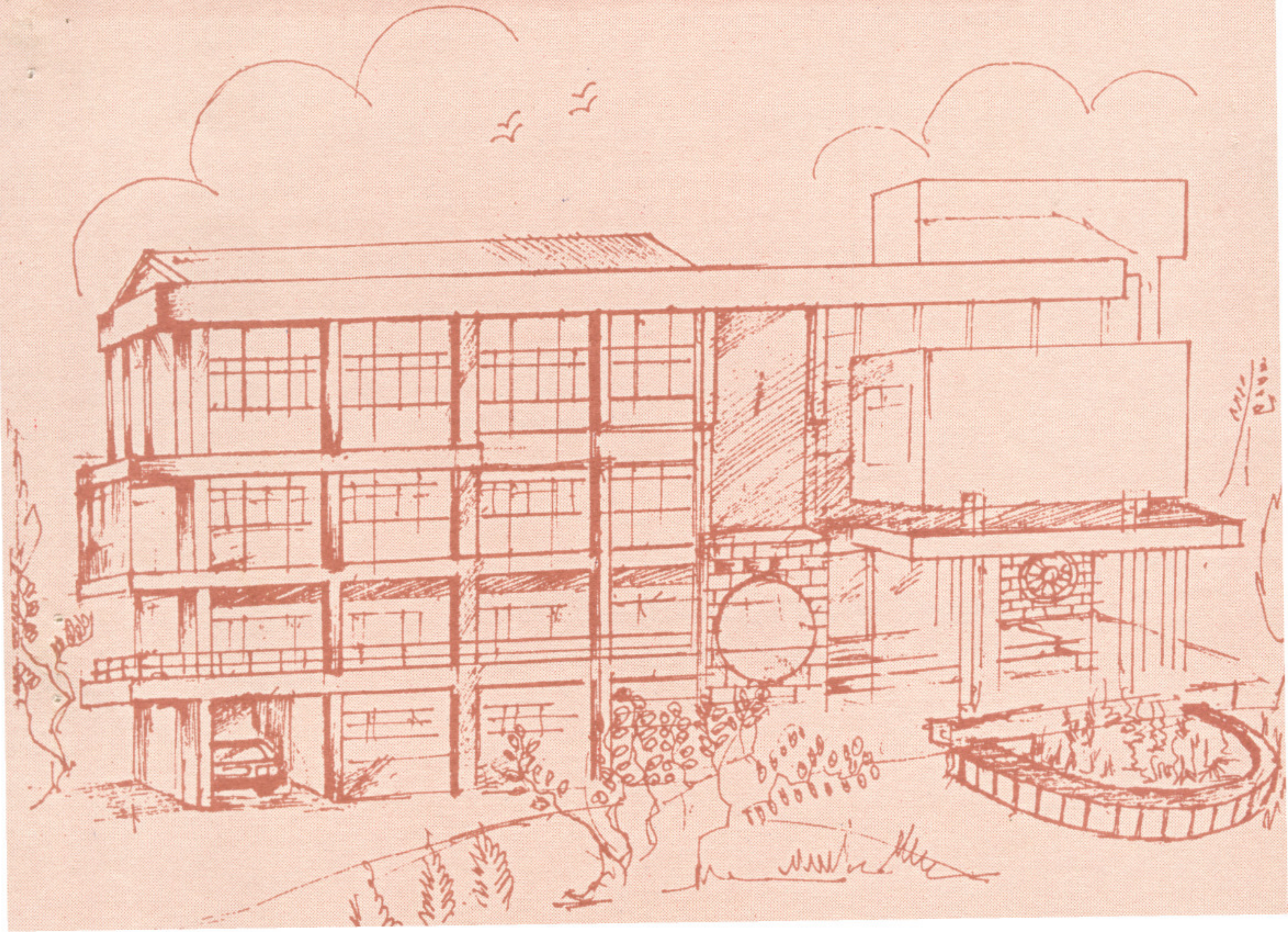
Wavelet Analysis Of Price And Volatility Spillovers In Stock Markets: The Case Of India And The US



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WAVELET ANALYSIS OF PRICE AND VOLATILITY SPILLOVERS IN STOCK MARKETS: THE CASE OF INDIA AND THE US

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ABSTRACT

This study uses wavelet analysis to examine the price and volatility spillovers between the U.S. and Indian stock markets. The empirical results suggest that there is price spillover effect from the U.S. market to its Indian counterpart during the period September 1998 – August 2003. However, the volatility spillovers, between these two stock markets, do not have any empirical support. (JEL Code: C3, G14).

Keywords: Spillover effect, Wavelets, Scaling, Decomposition, Transmission.

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1. INTRODUCTION

In recent years the stock markets across the nations have realized the increasing degree of interdependency, thanks to liberalized capital flows, integration of global economy, cross listing of stocks in different markets and rapid development of communication technology and computerized trading system. This has encouraged the academics as well as practitioners to study the interlinkage or spillover among markets with a greater and renewed interest than ever before. Given the degree of openness to trade and investment, it is a well-accepted fact that the national markets are inter-related and increasingly global (John et. al., 1995). Thus, understanding the behavior and dynamics of spillover is essential for investors, portfolio managers as well as policy makers given its implications for pricing of securities in the global market, international portfolio diversification and hedging strategies and financial market stability. In particular, deregulation and market liberalization measures accelerated the growth of Indian capital market by attracting funds from the FIIs and Indian companies which are also raising funds abroad through external commercial borrowings and cross-listing themselves in developed markets. This trend is well evident between the U.S. and Indian capital markets. At present 10 Indian companies have issued American Deposit Receipts (ADRs) and are cross-listed in the U.S. exchanges. Moreover, as per the Economic Survey 2003-04, the U.S. is the largest trading partner of India having 11.6 percentage of total trade during 2003-04 and the second largest FDI provider to India during 2003-04.

From the perspective of integrated global capital systems; numerous empirical studies have been conducted employing some of the popular econometric techniques such as Vector Autoregression (VAR), cointegration and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH).[1] However, a careful perusal of these studies leads us to arrive at two broad conclusions. *First,* most of the studies employ statistical models which are subject to parametric restrictions and specification error. *Second*, these studies largely examine the relation among the developed markets but a study in the

[1] Some of the notable studies include that of Schollhammer and Sand (1985), Goodhart (1988), Eun and Sangdal (1989), Furstenberg and Jeon (1989), King and Wadhwani (1990), Hamao et al (1990), Arshanapalli and Doukas (1993), Lin and Ito (1994), Karolyi (1995), Masih and Masish (1997), Baig and Goldfajn (1999) Ng (2000), Kumar and Mukhopadaya (2002).

context of developed vis-à-vis developing markets might provide different and useful insights. The present study is primarily motivated by the observations made just above regarding the past studies and involves a different method to test spillover effects based on wavelet analysis. As spillovers are concerned with the transmission of any unanticipated shocks or innovations origination from one stock market to other markets, one first needs to extract such ‘news’ or ‘innovations’ from stock markets. And the fine scale wavelet coefficients are good at representing the high frequency fluctuations by decomposing the time series into various orthogonal components. Thus, the study proposes to use reconstructed return series from the finest scale coefficients of discrete wavelet transform. The literature in this regard is absolutely scarce with one exception. For instance, Lee (2004), using wavelet techniques found strong evidence for price as well as volatility spillover effects across international stock markets, in particular, from the U.S. stock market to the Korean counterpart but not vice versa.

In addition to the above motivating methodological factor, other features which inspire us in examination of the short run dynamics of stock returns and volatility between the NASDAQ Composite Index and the BSE Sensex are given below. First, the exchanges do not have overlapping trading hours and hence the case of spillover can be clearly examined. Second, a quick examination of movements of the BSE Sensex and the NASDAQ Composite Index, during the study period under consideration, suggests that there exists a substantial degree of interdependence. (see figure 1) Third, official source like Reserve Bank of India (RBI) Annual Report (2002-03) states that “Market sentiment was also affected by the sharp decline in the major international markets…The BSE Sensex declined…major international market indices like the NASDAQ Composite Index and the DJIA.” Similarly, RBI Annual Report 2000-01 says, “The stock market remained generally subdued … large sell offs in global equity markets, particularly, in new economy stocks in the NASDAQ.” With this backdrop, our study makes an attempt to implement the wavelet analysis to explore the likely spillover effects between Indian and the US stock markets.

(insert figure 1)

The remainder of the paper is planned thus; in the next section, we describe the wavelet methodology followed by the data used in this study in section III. Section IV presents the empirical analysis of the spillover effects between Indian and the US market. Section V provides the concluding remarks.

2. WAVELET ANALYSIS

By design, the usefulness of wavelets is its ability to localize data in time-scale space. At high scales (shorter time intervals), the wavelet has a small time support and is thus, better able to focus on short lived and strong transients like discontinuities, ruptures and singularities. At low scales (longer time intervals), the wavelet's time support is large, making it suited for identifying long periodic features. At low scales, the wavelet characterizes the data's coarse structure i.e. its long-run trend and pattern. By gradually increasing the scale, the wavelet begins to reveal more and more of the data details, zooming in on its behavior at a point in time. Wavelet filter provides insight into the dynamics of financial time series beyond that of current methodology. It is important to realize that financial time series may not need to follow the same relationship as a function of time horizon (scale). Hence, a transform that decomposes a process into different time horizons is appealing and identifies local and global dynamic properties of a process at these time scales.

Wavelet analysis is characterized by a wavelet. A wavelet is a small wave, which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary or time varying phenomenon. It still has the oscillating wave like characteristic (as Fourier analysis) but also has the ability to allow simultaneous time and frequency analysis with a flexible mathematical foundation. Readers are referred to Chui (1992) for a thorough review of wavelet analysis and Daubechies (1992) for further technical details. The most interesting reference for application of wavelets in economics and finance has been Gencay et al. (2002). There are two types of wavelets defined on different normalization and orthogonalization rules, namely, father wavelets φ (scaling function) and mother wavelets ψ (wavelets). The father wavelet integrates to a constant and the mother wavelet integrates to zero:

$$\int \varphi(t)dt = A$$
$$\int \psi(t)dt = 0$$

Precisely, father wavelets are used for representing the low frequency, smooth components of the data. The mother wavelets extract the high frequency detail components of the data. Broadly speaking, father wavelets are used to for representing the trend components and the deviations from trend are by mother wavelets.

The wavelets and scaling functions at different scales are given by

$$\varphi_{j,k}(t) = 2^{-j/2}\varphi\left(2^{-j}t - k\right) = 2^{-j/2}\varphi\left(\frac{t - 2^{j}k}{2^{j}}\right) \qquad \ldots(1)$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(2^{-j}t - k\right) = 2^{-j/2}\psi\left(\frac{t - 2^{j}k}{2^{j}}\right) \qquad \ldots(2)$$

where 2^j is called as the scale parameter or dilation factor and the translation parameter 2^jk refers to the location factor. Here, the larger the index j, the larger the scale parameter 2^j, and hence the functions get shorter and more spread out. Similarly, as the functions get wider, the corresponding translation parameter becomes larger.

Given this family of basis functions, any function $f(t)$ in $L^2(R)$ can be represented by

$$f(t) = \sum_k c_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots\ldots + \sum_k d_{1,k}\psi_{1,k}(t). \qquad \ldots(3)$$

The coefficients in the above expansion are given by the projections

$$c_J(k) = \langle f(t), \varphi_{J,k}(t)\rangle = \int f(t)\varphi_{J,k}(t)dt \qquad \ldots(4)$$

and

$$d_j(k) = \langle f(t), \psi_{j,k}(t)\rangle = \int f(t)\psi_{j,k}(t)dt \qquad \ldots(5)$$

where the $c_{J,k}$ are the coefficients for the father wavelets at the maximal scale, 2^J, known as the "smooth coefficients or scaling coefficients". The $d_{j,k}$ are the detail coefficients obtained from the mother wavelets at all scales from 1 to J, the maximal scale.

Alternatively, $f(t)$ can also be represented as

$$f(t) = C_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_1(t) \qquad (6)$$

where $C_J = \sum_k C_{J,k}\phi_{J,k}(t)$ and $D_J = \sum_k d_{j,k}\psi_{j,k}(t),\ j = 1,\ldots.,k$. As each terms in the above equation represents components of the signal $f(t)$ at different resolutions, it is called a multiresolution decomposition.

The coarsest scale signal $C_J(t)$ represents a coarse scale smooth approximation to the signal. Adding the detail signal $D_J(t)$ gives a scale 2^{J-1} approximation to the signal, $C_{J-1}(t)$, which is a refinement of the coarsest approximation $C_J(t)$. Further refinement can sequentially be obtained as:

$$C_{j-1}(t) = C_J(t) + D_{j-1}(t) = C_J(t) + D_J(t) + D_{J-1} + \ldots + D_j(t). \qquad \ldots(7)$$

The collection $\{C_J, C_{J-1}, C_{J-2}, \ldots, C_1\}$ provides a set of multiresolution approximations of the signal $f(t)$.

3. DATA

The study makes use of daily data on BSE Sensitive Index and the NASDAQ Composite Index for the period of five years. The study spans over a period of September 1998 to August 2003, thus involving 1228 and 1250 number of data points for the Sensex and the NASDAQ Composite Index respectively[2]. After matching the daily observations between these two stock markets, the number of data points comes down to 1193. Daily open and close quotes of the Sensex and the NASDAQ Composite Index have been downloaded from www.bseindia.com and www.finance.yahoo.com respectively. The indices

[2] These two stock markets are operating in different time zones with different holidays and trading days schedules and hence the difference in number of observations.

downloaded are measured in terms of local currency that avoids the problem of exchange rate risk.

To study the spillovers on nonsynchronous trading environments, a daily (close-to-close) return is divided into a daytime (open-to-close) and an overnight (close (t-1)-to-open) returns have been calculated for both the indices such as Hamao *et al.* (1990), and Lin *et al.* (1994). Since there is a time lag of twelve-and-half hours between the US Eastern Standard Time and Indian Standard Time, current day data set for the BSE is juxtaposed with the data set for the NASDAQ with one period lag. Thus it is possible to study the influence of daytime returns in one market on the overnight return of the other. Notice that we also use close-to-close returns to examine spillovers as in Karolyi (1995). So in this study, we calculate the returns as follows:

Sensex close returns (SCR) = Log (Sensex close on day t / Sensex close on day t-1)*100
Sensex overnight returns (SOR) = Log (Sensex open on day t / Sensex close on day t-1)*100
Sensex daytime returns (SDR) = Log (Sensex close on day t / Sensex open on day t)*100
NASDAQ close returns (NCR) = Log (NASDAQ close on day t / NASDAQ close on day t-1)*100
NASDAQ overnight returns (NOR) = Log (NASDAQ open on day t / NASDAQ close on day t-1)*100
NASDAQ daytime returns (NDR) = Log (NASDAQ close on day t / NASDAQ open on day t)*100

Note that these daily rates of returns on a given calendar day may represent returns realized over different time intervals depending on holiday and trading day schedules. To account for this problem of multiple day returns associated with weekends and holidays, we use the dummy variable (discussed later in empirical section). Finally, to examine the short-run inter linkages between the US and Indian stock markets, we test the effect of the NASDAQ daytime returns and volatility on the Sensex overnight returns and volatility respectively. As mentioned earlier, we also gauge the effect of the NASDAQ close returns and volatility on the Sensex close returns and volatility.

4. EMPIRICAL ANALYSIS

Table 1 presents a range of preliminary descriptive statistics for the daily stock index returns of the BSE Sensitive Index and the NASDAQ Composite Index. The skewness and kurtosis for all the return series indicate the evidence of empirical distributions with heavy tails relative to the normal distribution. Also the results of the ARCH test for the residuals, generated by fitting an ARMA (1,1) model to all the three return series of both the indices, signify the presence of ARCH effect for all the return specifications of both the indices.

(insert table 1)

Figure 2 shows the wavelet decompositions of the stock returns of the Sensex and the NASDAQ by using Haar wavelets. Both the Haar and Symlet 8 wavelets are used in this study.[3] Although the Haar wavelet has good properties such as simplicity, orthonormality and compact support, the Symlet 8 wavelet is a better approximation to an ideal band pass filter with symmetric properties. The wavelet decomposition results are arranged into level 1 to level 5, where the last one represents the low pass coefficients of level 5. As discussed earlier initial level or fine scale coefficients filter out the high frequency fluctuations by looking at the adjacent differences in the data series. As we go further, the higher levels of wavelet coefficients become smooth and represent the low frequency fluctuations in the series. The highly volatile movements in stock returns are clearly depicted in high frequency fluctuations as shown in d_1 and d_2. This analysis clearly indicates the usefulness of the time-scale decompositions and multi-scale nature of the wavelets. In the stock market, there are traders who take a very long-term view and consequently concentrate on what are termed ‘market fundamentals’; these traders ignore short-term phenomena. For them, the high level or coarse scale wavelet coefficients are very useful and they are more concerned about the same. 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 path. Their decisions have a time horizon of a few months to a year; so they are interested in middle level wavelet decompositions of the return series. And yet for some other traders in the market, a day is a long time and consequently concentrate on day-by-day fluctuations. Therefore, low level or fine scale wavelet coefficients of return series are more useful for them in stock market.

[3] The Symlet 8 wavelet decomposition graphs are not presented here but will be available on request.

(insert figure 2(A) and 2(B))

As discussed earlier, to examine the spillovers between two stock markets, we need to relate the high frequency fluctuations in stock returns i.e., the abnormal stock returns that are not predicted on the basis of all information reflected in past returns. As the fine scale wavelet coefficients are good at representing the high frequency fluctuations, we use the reconstructed return series from the finest scale (d_1) of wavelet decompositions. Table 2 provides the summary statistics for the reconstructed stock returns. The most interesting finding is that the mean is zero in case of the Haar wavelet and very near to zero in case of the Symlet wavelet. Though all measures of dispersion are indicative of evidence against normal distribution but they are lesser in extent than the original returns. All the series are of stationary in nature as evident from the Augmented Dickey-Fuller (ADF) test at 5% and 1% levels of significance.

(insert table 2)

Table 3 reports the pair wise correlations of the wavelet returns of the Sensex and the NASDAQ. The correlations of the wavelet returns reflect the degree to which new information producing an abnormal return in one market is shared by the other market. Broadly speaking, the correlations between overnight returns and daytime returns pairs are higher than the other pairs. However, the pair wise correlations between daytime returns are very low and show wrong signs. The correlations between close-to-close returns between two markets show a little better performance than daytime returns correlations.

(insert table 3 and 4)

The correlation between two series does not indicate any causation. So we use Granger (1969) test to examine the causality between the Sensex and the NASDAQ Composite Index. Table 4 reports that the F-statistics is significant in two cases. First, the past values of the NASDAQ daytime returns help to predict current changes in the Sensex overnight returns but not the other way round. Second, there is also causality from the NASDAQ close-to-close returns to the Sensex close-to-close returns. This suggests a unidirectional causality running from the NASDAQ returns to the Sensex returns. Given this preliminary analysis of correlations and the Granger causality, we decide to use two pairs for further regression analysis. The regression analysis pairs are the NASDAQ daytime returns (t-1) fluctuations on the Sensex overnight returns (t) and the NASDAQ close-to-close returns (t-1) fluctuations on the Sensex close-to-close returns (t).

Table 5 provides the coefficient estimates from a sequence of least squares regressions using finest scale returns obtained from wavelet decompositions. The pairs of regression analysis have been fixed keeping in mind that if one stock market is causally prior to other market, the price movements of the influential market should affect subsequent price changes in other market but is not affected by price movements of other market in earlier period which is again supported by Granger causality test. Note that these daily rates of returns on a given calendar day may represent returns realized over different time intervals depending on holiday and trading day schedules. To account for this problem of multiple day returns associated with weekends and holidays, we use the multiple day return dummy in our regression analysis.

(insert table 5)

To see if the NASDAQ market movements explain the Sensex prices, we estimate the regressions where the NASDAQ wavelet returns of one-day lag enter as the independent variable. The estimates of the slope coefficient of the NASDAQ daytime returns turn out to be significant at 5 and 1 percent significance levels in case of Haar and Symlet wavelets respectively. However, the significance of the slope coefficients from Haar and symlet wavelets differs in case of the NASDAQ close-to-close returns. There is significant evidence of spillover effects from the NASDAQ close-to-close returns to the Sensex close-to-close returns in case of Symlet wavelet, but it is not the case with Haar wavelet. Thus, it is found from these results that the innovations in the NASDAQ spillover to BSE. Again, this is in agreement with the earlier findings that innovations in the U.S. stock markets are transmitted to other markets. Since strong evidences are found that Indian stock markets are influenced by the U.S. stock markets in both the cases of close-to-close and open-to-close returns, the information generated in the U.S. market may be used to trade profitably in India.

(insert table 6)

In this section, we examine the impact of unexpected movements in stock price volatility in the U.S. market on its Indian counterpart. In spillover literature, GARCH-type models have been used to explain the movements in volatility by estimating conditional variance. But in this study, we use wavelet decompositions to derive such unexpected changes in stock price volatility. It may be noted that we have used the GARCH model to estimate the conditional volatility during the study period (see appendix for details on the GARCH model employed).[4] Based on the way similar to price spillovers, we estimate the regression coefficients using finest scale wavelet volatility series obtained from wavelet decompositions.[5] Since the multiple day return dummy is used in GARCH model while extracting conditional volatility series, it is not incorporated in regression analysis of volatility spillovers. As shown in Table 6, the coefficients of the least square regressions in all cases are not significant. Such a finding of no volatility spillover effects from the U.S. stock market to its Indian counterpart is in line with the earlier findings that unexpected changes in stock price volatility in the U.S. market do not lead to subsequent changes in volatility in India (Choudhry, 2004; Kaur, 2004). However, this is not consistent with the studies undertaken by Kumar and Mukhopadyay (2002) who have

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[4] The GARCH results are suppressed here due to the space constraint. The results, however, can be obtained from the author upon request.

[5] Wavelet decomposition analysis of conditional variance series is not reported here and can be obtained from the corresponding author on request.

reported significant and one way volatility spillover from the NASDAQ to the National Stock Exchange (NSE). This could be partly due to the fact that while they have considered the NSE Nifty Index, we have used the BSE Sensex. If the volatility spillover existed at the aggregate market level, it should have got reflections at the BSE Sensex also. This is due to the fact that almost all the Sensex stocks are and have been part of the NSE Nifty portfolio but not vice-versa. This might also be due to the fact that information from the U.S. market are efficiently and uniformly reflected in the price series but do not act as the source of volatility in Indian stock markets. However, more research is required to unravel the true nature of the 'volatility spillover effect' between the U.S. and Indian stock markets.

5. CONCLUDING REMARKS

This paper has attempted to examine the price and volatility spillovers between the U.S. and Indian stock markets. By relating the high-frequency fluctuations in stock returns, obtained from wavelet decompositions, we examine spillover effects of innovations between these stock markets. The price spillover effect is unidirectional from the U.S. market to its Indian counterpart as evidenced from the Granger causality and the regression analysis of returns. But there is insufficient evidence to find any volatility spillover effect between these two markets from regression analysis of wavelet returns. In particular, we find the price spillover effect from the NASDAQ daytime returns to the Sensex overnight returns. Second, the NASDAQ close-to-close returns also have an impact on the Sensex close-to-close returns as evidenced from the Symlet 8 wavelet returns. However, there is no empirical support regarding the transmission of stock price volatility between these two markets. Finally, it is suggested that while there is significant price spillover effects between the U.S. and Indian stock markets, the study falls short of supporting the volatility spillover effect.

Appendix

As it is already outlined above, the study intends to estimate the conditional volatility in a GARCH setup, instead of using squared return as the proxy for volatility. In this study we have consistently used the ARMA (1,1) – GARCH (1,1) model to explain the volatility dynamics.[6] The specifications for our study is as thus:

$$R_t = a_0 + a_1 R_{t-1} + b_1 \varepsilon_{t-1} + \delta D_1 + u_t \qquad \text{(A1)}$$

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1} \qquad \text{(A2)}$$

where, $\omega > 0$, $\alpha \geq \beta$, ≥ 0 and D_1 is the multiple day return dummy.

The first equation shows the ARMA (1,1) specification for the return series whereas GARCH (1,1) volatility specification is given by the second equation. The non-negativity constraints are quite important, as they are required to be met in order to ensure positivety of variance. Besides, the sum of parameters ($\alpha+\beta$) must be less than unity as the volatility is found to be mean reverting in nature which in other words ensures the stability of the model. The GARCH (1,1) model is estimated by using BHHH algorithm and the estimated GARCH models for both the indices are found to obey the coefficient restrictions as well as the sum of ($\alpha+\beta$) is less than unity in all the cases. Besides, we also carry out the LM test on squared residuals after fitting the GARCH model and the result evidences presence of no ARCH effect in the GARCH residuals, which highlights on the adequacy of the fitted model. We use thus fitted GARCH model to extract the conditional volatility series for both the indices as well as for all the variants of return specification, which are used as the estimated volatility for further wavelet analysis.

[6] GARCH (1,1) has been found as the most parsimonious as well as adequate representation of volatility dynamics.

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Table 1: Summary Statistics of Daily Returns on BSE Sensex and NASDAQ Composite Index

Summary Statistics	SOR	SDR	SCR	NOR	NDR	NCR
Mean	0.082	-0.068	0.014	0.049	-0.043	0.005
Standard Deviation	0.499	0.675	0.745	0.539	0.894	1.027
Skewness	-2.737**	-0.275**	-0.420**	-1.164**	0.357**	0.113**
Kurtosis	43.272*	5.188*	7.378*	15.805*	6.158*	4.488*
Raw Return Correlation						
Lag 1	0.087***	-0.040	0.058**	-0.102*	-0.046	0.011*
Lag 2	0.063**	0.011	0.014**	-0.107*	-0.078*	-0.042**
LB (6)	24.331*	18.149*	11.643***	22.708*	15.246*	6.454
LB (12)	63.286*	27.544*	17.139	49.861*	38.786*	24.686*
ARCH (4) LM test	23.065*	158.029*	45.064*	21.515*	67.551*	60.484*

Note: SOR = Sensex overnight return, SDR = Sensex daytime return, SCR = Sensex close return, NOR = NASDAQ overnight return, NDR = NASDAQ daytime return, NCR = NASDAQ close return.

1. *, ** and *** represent the level of significance at 1%, 5% and 10% respectively.
2. LB (k) represents the Ljung-Box test statistics for serial correlation at ‘k’ lags.
3. LM statistics represents the Lagrange Multiplier test, with the null hypothesis that ‘ARCH effects are not present in the first 4 lags’.
4. LM test is done for residuals generated after fitting an ARMA (1,1) model to the return series

Table 2: Summary Statistics of Returns Reconstructed using Wavelets

Haar					
	Mean	Std. Dev.	Skewness	Kurtosis	ADF Statistic
SOR	0.0000	0.3368	0.0000	27.0338	-25.5081
SDR	0.0000	0.4879	0.0000	7.0702	-25.4670
SCR	0.0000	0.5146	0.0000	7.0158	-25.7277
NOR	0.0000	0.4083	0.0000	11.1129	-24.2653
NDR	0.0000	0.6574	0.0000	9.1414	-28.0016
NCR	0.0000	0.7298	0.0000	5.7253	-27.8430
Symlet 8					
SOR	0.0000	0.3403	-1.4323	30.8914	-48.1300
SDR	0.0005	0.4826	0.3088	7.1730	-48.3933
SCR	0.0006	0.5159	-0.0740	7.2705	-49.3162
NOR	0.0000	0.4108	-0.7301	15.1950	-47.0262
NDR	0.0006	0.6681	0.5750	9.4772	-47.7922
NCR	0.0006	0.7294	0.4358	5.9850	-46.6272

Note: SOR = Sensex overnight return, SDR = Sensex daytime return, SCR = Sensex close return, NOR = NASDAQ overnight return, NDR = NASDAQ daytime return, NCR = NASDAQ close return. The critical values for ADF unit root test at 1%, and 5% levels are -3.51 and -2.89 respectively.

Table 3: Pair Wise Correlations of Returns Reconstructed using Wavelets

	Haar	Symlet 8
SOR-NDR (1)	0.1493	0.2815
NOR-SDR	0.1843	0.1727
SDR-NDR (1)	-0.0116	-0.0234
NDR-SDR	-0.0289	0.0201
SCR-NCR (1)	0.0414	0.1026
NCR-SCR	-0.0326	-0.0213

Note: SOR = Sensex overnight return, SDR = Sensex daytime return, SCR = Sensex close return, NOR = NASDAQ overnight return, NDR = NASDAQ daytime return, NCR = NASDAQ close return. (1) represents returns at one period lag.

Table 4: Granger Causality Tests of Returns Reconstructed using Wavelets

		Haar		Symlet 8	
Cause	Effect	F-statistic	P-value	F-statistic	P-value
NDR (1)	SOR	5.2807	0.0000	12.1730	0.0000
SDR	NOR	0.4738	0.8282	1.6867	0.1207
NDR (1)	SDR	1.3321	0.2396	0.8579	0.5253
SDR	NDR	1.3155	0.2470	0.4945	0.8127
NCR (1)	SCR	1.2916	0.2579	3.0232	0.0061
SCR	NCR	0.2849	0.9443	0.9678	0.4458

Note: SOR = Sensex overnight return, SDR = Sensex daytime return, SCR = Sensex close return, NOR = NASDAQ overnight return, NDR = NASDAQ daytime return, NCR = NASDAQ close return. (1) represents returns at one period lag.

Table 5: Regression Results of Returns Reconstructed using Wavelets

	Haar		Symlet 8	
	SOR	SCR	SOR	SCR
NDR (1)	0.0262 (0.0570)		0.1049 (0.0000)	
NCR (1)		0.0090 (0.5920)		0.0538 (0.0129)
Dummy	0.0723 (0.0001)	0.0295 (0.3322)	0.0449 (0.0064)	0.0491 (0.0599)
R-squared	0.2653	0.2441	0.4053	0.3528
D-W Statistic	2.3162	2.3318	2.3129	2.3975

Note: SOR = Sensex overnight return, SDR = Sensex daytime return, SCR = Sensex close return, NOR = NASDAQ overnight return, NDR = NASDAQ daytime return, NCR = NASDAQ close return. (1) represents returns at one period lag and figures in parentheses represent P-values. D-W statistic represents Durbin-Watson Statistic.

Table 6: Regression Results of Volatility Reconstructed using Wavelets

	Haar		Symlet 8	
	SORVOLT	SCRVOLT	SORVOLT	SCRVOLT
NDRVOLT (1)	-0.0810 (0.8007)		0.2292 (0.4586)	
NCRVOLT (1)		0.0056 (0.7936)		0.1021 (0.2304)
R-squared	0.1599	0.1875	0.2118	0.2059
D-W Statistic	2.3426	2.3319	2.3049	2.3928

Note: SORVOLT = Sensex overnight return volatility, SCRVOLT = Sensex close return volatility, NDRVOLT = NASDAQ daytime return volatility, NCRVOLT = NASDAQ close return volatility. (1) represents returns at one period lag and figures in parentheses represent P-values. D-W statistic represents Durbin-Watson Statistic.

Figure 1: BSE Sensex vs. NASDAQ Composite Index

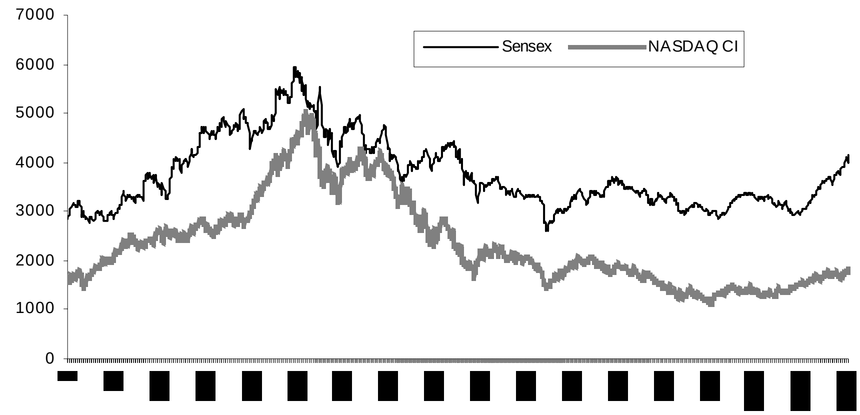

Figure 2 (A) : Wavelet Decompositions of Sensex Returns Series

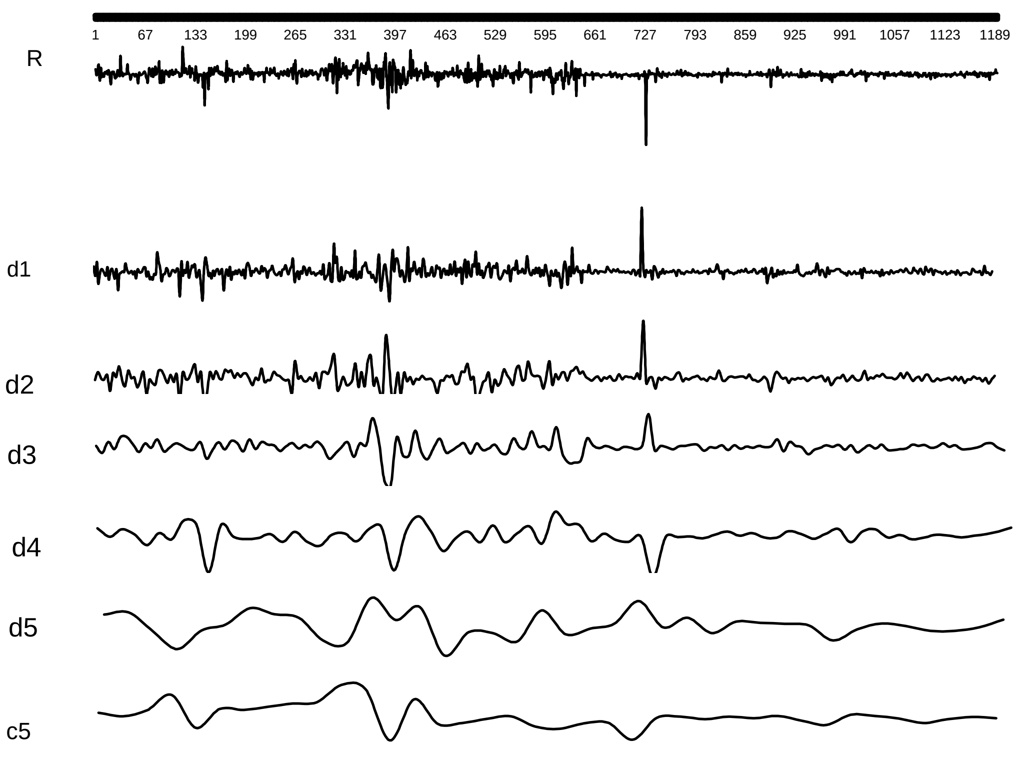

Figure 2 (B) : Wavelet Decompositions of NASDAQ Composite Returns Series