Volatility Spillovers across Developed/Developing Markets: The Case of India

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Abstract

The present research paper investigates the daily volatility spillovers between Standard and Poor's 500, Nikkei, and India's Nifty index between the time period from 2000 - 2009. We find that the price series exhibit nonlinear dependencies, inconsistent with chaotic structure. Bivariate GARCH estimations with volume controls indicate multi-directional spillovers. Finding evidence of asymmetric market responses to shocks, we propose and estimate asymmetric bivariate EGARCH models. We find transmissions to be asymmetric whereby positive and negative shocks have an unequal impact on the volatility of the other market. While the relationship between the developed markets is strong, the influence of the less developed Indian market is also apparent.

Keywords: **volatility, bivariate GARCH, chaos, nonlinearities**
JEL Classification : G00, G14, G15

The developed financial markets have witnessed increasing integration. Events of the decade of 2000, as well as financial turmoil in Ireland, Greece, Portugal, and Spain among others, demonstrate how developed economies of even small size can play a significant role in transmitting banking and equity market instability across nations. While researchers have gone to great lengths to investigate the channels of contagion and shock transmission among well established markets, less is known about the day-to-day influence of fast emerging markets such as those of China and India. There are some obvious ramifications of the findings of such research. For instance, if a particular country is determined to be a source of economically important market transmission, policy makers might consider preemptive steps to contain the effects of contagion. More generally, evidence of spillovers would offer an understanding of the degree of openness and economic co-reliance of countries. Moreover, since banking codependence is widely thought of as a source of market contagion, there remains the question of how quickly and to what degree the banking/financial deregulation in a transition economy makes it a source and draw of global financial stress.

The purpose of this paper is to investigate the volatility spillovers between the U.S., Japanese, and Indian stock markets. For this purpose, we examined the daily prices of the Standard and Poor's 500, Nikkei, and Nifty index futures contracts over the time period from 2000 to 2009. The assessment of the feedback between the three countries will provide an opportunity of a comparative analysis of spillovers between developed/developed and developed/developing markets. An incidental ,though important, contribution of the paper is the examination of the possibly nonlinear, chaotic, and asymmetric nature of the price dynamics following information arrival *within* each of the three markets.

Three issues motivate the paper. Foremost, investigating the role of the Indian market in context of its relationship to developing markets will be of obvious interest to academic and policy makers given the ongoing liberalization of

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the financial sector in transition economies such as China, Russia, and India, among others. The impact of many of the important banking reforms in India were felt in the 2000s, the decade of our analysis[1]. Second, the behavior of markets in recent years has triggered curiosity in the underlying dynamics of prices. For instance, the study of chaotic behavior may shed some light on the nature of latent nonlinearities. A comparison of the price dynamics of the developed markets and India would offer insights into possible differences of price behavior and discovery. Third, investigating volatility spillovers, asymmetric reactions to positive and negative news, economic shocks, and approaches to modeling these behaviors are of interest to capital market players and policy makers.

We found evidence that stock index price series exhibit nonlinear dependencies that are inconsistent with chaotic structure. We propose and estimate a set of bivariate GARCH (1,1) models to ascertain the flow of information between prices. The estimates indicate that the volatility spills in both directions, i.e., there is feedback between markets once models take trading volume into account. We also found evidence of asymmetric market responses to negative and positive shocks. We propose and estimate asymmetric bivariate EGARCH models for the price pairs. The findings suggest that the shock transmissions are asymmetric with negative shocks inducing larger moves than positive ones, no matter where they occur.

Related Research

The research on financial contagion may be divided along two lines of inquiry. One path centers on the domestic transmission of asset prices. A notable paper focusing on comovements among domestic asset prices was written by Bernanke and Kuttner (2005). These papers suggest that asset prices in general are positively correlated and respond to monetary policy and changes in economic fundamentals. Another line of research has focused on analyzing international contagion and comovements among asset prices, interest rates, and exchange rates, among other financial variables. We limit our review of the literature to the latter.

Contagion and financial interdependence have been a focus of attention of many researchers in the last three decades. Taken together, the results from various studies suggest temporally increasing cross market correlations. Moreover, there appears to be an important role for the interdependence of banking in international financial market contagion. Earlier studies include research on “meteor showers” and on equity markets time-varying correlations. Ehrmann, Fratzscher, and Rigoban (2005) investigated financial transmission between money, bond markets, equity markets, and exchange rates between the U.S. and Europe and found significant spillovers between similar assets which are magnified during recessions.

A limited number of studies have examined contagion among developing countries and between developed and developing countries. Bekaert, Campbell, and Ng (2005) took an asset pricing approach combined with GARCH modeling of equity returns to study Europe, Southeast Asia, and Latin America. Their findings indicate that contagion and shock transmission may be absent in Central and Latin American markets, while Asian markets are susceptible to regional and global shocks. Dungey, Fry, González-Hermosillo, and Martin (2006) examined volatility in world bond markets for the period of post - Russian bond default in August 1998 and the long term capital management recapitalization announcement. They found that both emerging and developed markets were susceptible to contagion during that period.

Methodology

We first analyzed the prices for stationarity and non-linearities. We were particularly concerned with detecting the sources of nonlinearities in returns. To test for chaotic behavior, we applied the Brock, Dechert, and Scheinkman's (1987) test (BDS) and correlation dimension tests of chaos. Finding nonlinearities but no chaos, we estimated autoregressive GARCH (1,1) models of variances for the three future index series and showed evidence that volatility spillovers occur across prices.

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[1] For instance, according to the Reserve Bank of India, between 1994-2000, twenty large foreign banks entered the Indian market. Prior to that, the major Indian banks were nationalized in order to achieve two objectives, **i)** rapid, but controlled expansion, **ii)** channeling of credit in line with India's five-year plan. Liberalization of the financial sector resulted in rapid foreign investments. For example, FDI growth rates were 145% in 2006 and 47% in 2007 respectively. In 2010, FDI in India was $175 billion, and Indian Direct Investment abroad was $79 billion.

❖ **Testing for Chaos :** The common tests of chaos were discussed by Adrangi, Chatrath, Dhanda, and Raffiee (2001a) and Adrangi, Chatrath, Kamath, and Raffiee (2001b) . We present them briefly in this paper to inform the reader. There are two tests employed here: **(i)** the Correlation Dimension of Grassberger and Procaccia (1983) and Takens (1984), **(ii)** the BDS statistic of Brock, Dechert, and Scheinkman (1987).

a) Correlation Dimensions : Consider the stationary time series x_t, t =1...T. One imbeds x_t in a m-dimensional space by forming M-histories starting at each date t : $x_t^2 = \{x_t, x_{t+1}\}$,.., $x_t^M = \{x_t, x_{t+1}, {}_{t+2},......,x_{t+M-1}\}$. If the true system is n-dimensional, provided M ≥ 2n+1, the M-histories can help recreate the dynamics of the underlying system, if they exist (Takens, 1984). For a given embedding dimension M and a distance ε , the correlation integral is given by :

$$C^M(\varepsilon) = \lim_{T\to\infty}\{\text{the number of (i, j) for which } \left\| x_i^M - x_j^M \right\| \le \varepsilon\} / T^2 \quad (1)$$

where || || is the distance induced by the norm. For small values of ε, one has $C^M(\varepsilon) \sim \varepsilon^D$ where D is the dimension of the system (see Grassberger and Procaccia, 1983). The correlation dimension in embedding dimension M is given by:

$$D^M = \lim_{\varepsilon\to 0}\lim_{T\to 0}\{\ln C^M(\varepsilon) / \ln \varepsilon\} \quad (2)$$

and the correlation dimension is itself given by :

$$D = \lim_{M\to 0} \ln D^M \quad (3)$$

We estimate the statistic :

$$SC^M = \frac{\{\ln C^M(\varepsilon_i) - \ln C^M(\varepsilon_{i-1})\}}{\{\ln(\varepsilon_i) - \ln(\varepsilon_{i-1})\}} \quad (4)$$

for various levels of M (e.g., Brock and Sayers, 1988). The SC^M statistic is a local estimate of the slope of the C^M versus e function. Following Frank and Stengos (1989), we take the average of the three highest values of SC^M for each embedding dimension.

b) BDS Statistics : Brock et al., (1987) employed the correlation integral to obtain a statistical test that has been shown to have a strong power in detecting various types of nonlinearity as well as deterministic chaos. BDS show that if x_t is (i.i.d) with a nondegenerate distribution :

$$C^M(\varepsilon) \rightarrow C^1(\varepsilon)^M, \text{ as } T \rightarrow \text{infinity} \quad (5)$$

for fixed M and ε . Employing this property, BDS shows the statistics :

$$W^M(\varepsilon) = \sqrt{T}\,\{[C^M(\varepsilon) - C^1(\varepsilon)^M] / \sigma^M(\varepsilon)\} \quad (6)$$

where σ^M, the standard deviation of [·], has a limiting standard normal distribution under the null hypothesis of IID. W^M is termed the BDS statistic. Nonlinearity will be established if W^M is significant for a stationary series void of linear dependence. The absence of chaos will be suggested if it is demonstrated that the nonlinear structure arises from a known non-deterministic system.

Data and Summary Statistics

We employ daily nearby equity index futures prices, volume, and open interest of Nifty, S&P500, and Nikkei index contracts. The time period of the study covers the period from June 2000 till October 2009. Percentage changes are given by $R_t = (\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the daily closing values.

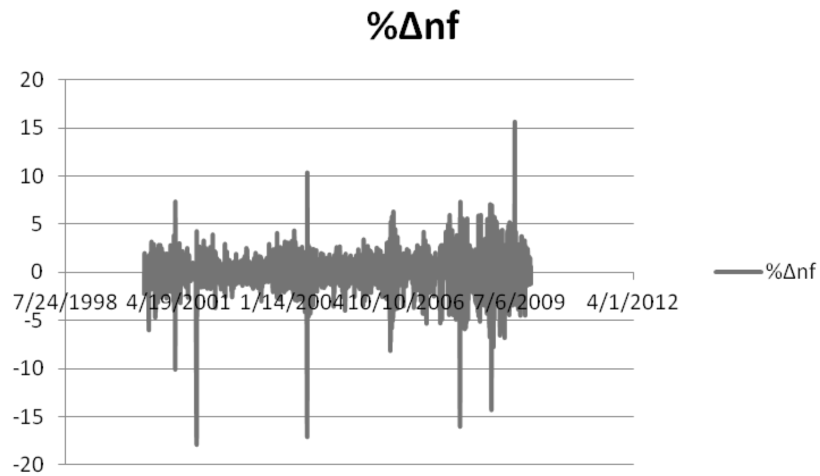
Figures 1- 6 depict the graphs of daily futures prices of Nifty and Nikkei, and S&P500 nearby contracts. These Figures show that prices exhibit mean and covariance nonstationarity. Percentage change in futures prices of the three contracts are mean-stationary, however, may be covariance non-stationary. Graphic evidence of nonstationarity calls for formal statistical tests of stationarities and possible nonlinearities in all three series. We provide the statistical evidence of behavior of these series in the Table 1.

The R_t series are found to be stationary employing the Augmented Dickey Fuller (ADF) statistics. There are linear and nonlinear dependencies as indicated by the Q and Q^2 statistics, and autoregressive conditional heteroskedasticity

Figure 1: Nifty Nearby Index Futures Prices

Source: Authors' Research

Figure 2: Percentage Change in Nifty Nearby Index Futures Prices

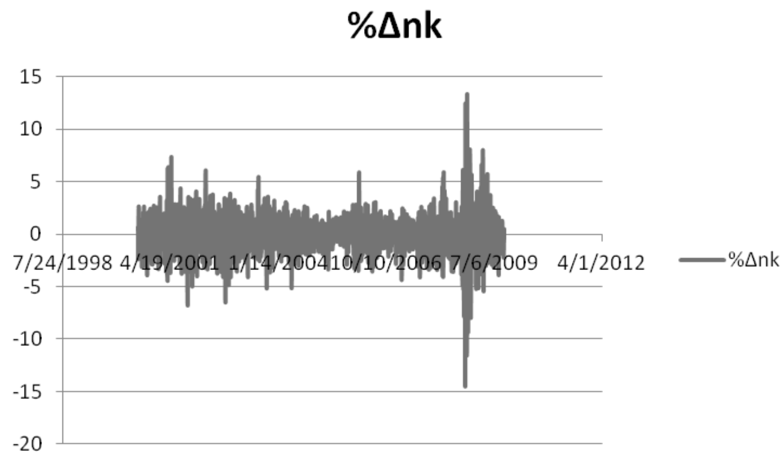


Source: Authors' Research

Figure 3: Nikkei Nearby Index Futures Prices

Source: Authors' Research

Figure 4: Percentage Change in Nikkei Nearby Index Futures Prices

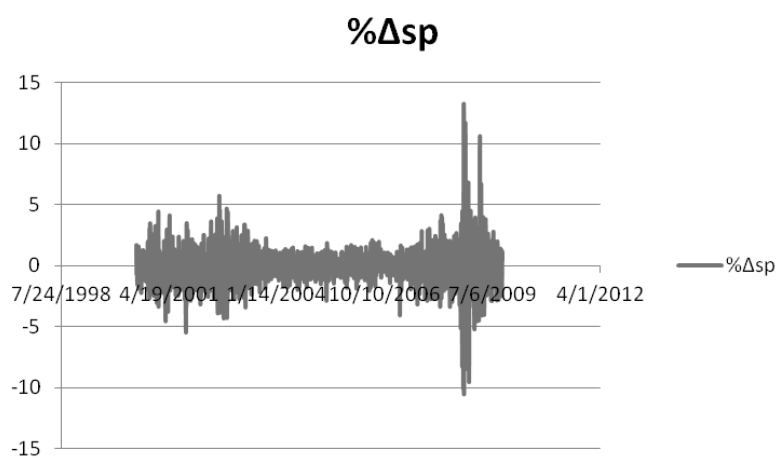


Source: Authors' Research

Figure 5: S&P500 Nearby Index Futures Prices

Source: Authors' Research

Figure 6: Percentage Change in S&P500 Nearby Index Futures Prices



Source: Authors' Research

Table 1 : Diagnostics			
Price Levels			
Interval: 6/2000-10/2009 N= 2440	**NF**	**NK**	**SP**
ADF	-0.421	-1.672	-1.861
ADF_trend	-2.332	-1.726	-1.899
PP	-0.359	-1.760	-1.846
PP_trend	-2.268	-1.817	-1.877
KPPs	5.265[a]	0.903[a]	0.713[b]
KPPs_trend	0.523[a]	0.659[a]	0.612[a]
Q(24)	51770.000[a]	506089.000[a]	50376.000[a]
$Q^2(24)$	50517.000[a]	50502.000[a]	50370.000[a]
LM-ARCH (6)	139.785[a]	425.67[a]	411.594[a]
Percentage Changes			
ADF	-47.050[a]	-20.886[a]	-38.139[a]
ADF_trend	-47.058[a]	-20.881[a]	-38.132[a]
PP	-47.063[a]	-50.662[a]	-51.416[a]
PP_trend	-47.069[a]	-50.652[a]	-51.409 [a]
KPPS	0.188	0.166	0.129
KPPS_trend	0.119	0.162	0.121
Q(24)	41.166[b]	114.66[a]	93.506[a]
$Q^2(24)$	259.420[a]	4549.400[a]	2746.800[a]
LM_ARCH (6)	109.709[a]	648.664[a]	431.724[a]
Summary descriptive statistics for model variables. All variables are in level.			
Mean	29493.87	1249.802	1183.131
Stand Dev	1419.10	290.213	200.264
Skewness	0.687	0.297	-0.105
Kurtosis	-0.739	-2.063	-0.821
J-B	227.644[a]	138.568[a]	66.933[a]
Mean Volume	48039.52	3358.28	48930.08
Mean Open Interest	4096354.000	33801.770	497495.605

Notes: SP, NK, and NF represent S&P500, Nikkei, and Nifty futures prices.

Returns are given by $R_t = \ln(P_t/P_{t-1})\cdot 100$, where P_t represents closing exchange rate on day t. ADF represents the Augmented Dickey Fuller tests (Dickey and Fuller, 1981). The Q(12) and $Q^2(12)$ statistics represent the Ljung-Box (Q) statistics for autocorrelation of the R_t and R_t^2 series respectively. The ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) and is χ^2 distributed with 6 degrees of freedom.

[a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

(ARCH) effects are suggested by the ARCH (6) chi-square statistic. Whether these dynamics are chaotic in origin is the question we turn to next. To capture the linear structure, we estimated the autoregressive models:

$$R_t = \sum_{i=1}^{p} \pi_i R_{t-i} + \varepsilon_t . \qquad (7)$$

The lag length for each series is selected based on the Akaike (1974) criterion. The residual (ε_t) represents the index movements that are purged of linear relationships. The mean equation of the GARCH model is the same as given in the equation (7), while the conditional variance equation of the model is given by :

$$\sigma^2_{i,t} = \beta_i + \gamma_i u^2_{i,t-1} + \varphi_i \sigma^2_{i,t-1} \quad i=1, 3, \qquad (8)$$

where $\sigma^2_{i,t}$ is the conditional variance, $u_{i,t-1}$ is the lagged innovations, and $\sigma^2_{i,t-1}$ is the lagged conditional volatility.

Empirical Findings

a) Correlation Dimension Estimates : The Table 2 reports the Correlation Dimension (SC^M) estimates for the returns and logistic series. The values of the correlation dimension for chaotic series and its filtered version shown in the first

Table 2 : Correlation Dimension Estimates

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
SP AR(1)	2.466	4.051	5.399	6.695
NK AR(1)	3.267	5.570	7.338	9.095
NF AR(1)	2.696	4.584	6.230	7.760
SP GAR(1,1)	3.887	7.875	11.302	14.374
NK GAR(1,1)	4.139	8.322	10.509	11.444
NF GAR(1,1)	3.381	6.561	9.621	12.624

Notes: SP AR(1), NK AR(1), and NF AR(1) represent AR(1) model residuals fitted to S&P500, Nikkei, and Nifty futures prices. The Table reports SCM statistics for the Logistic series (w=3.750, n=2000), daily percentage changes in futures prices over four embedding dimensions: 5, 10, 15, 20. AR(1) represents autoregressive order one residuals. GAR (1,1) represents standardized residuals from a AR1- GARCH(1,1) model.

Source: Compiled by the Authors

Table 3 : BDS Statistics for AR(1) Residuals

	M			
ε/σ	2	3	4	5
SP AR(1)				
0.50	9.1193	15.034	19.784	25.175
1.00	10.850	16.155	19.518	23.211
1.50	12.310	16.692	18.985	21.281
2.00	13.544	17.608	19.634	21.229
NK AR(1)				
0.50	7.4547	9.9987	13.018	16.871
1.00	8.2569	10.557	12.486	15.002
1.50	10.019	12.138	13.429	17.970
2.00	13.106	15.241	16.245	17.212
NF AR(1)				
0.50	13.144	17.748	21.720	26.682
1.00	14.169	17.897	21.148	24.593
1.50	13.890	16.240	18.951	21.382
2.00	12.833	14.656	17.061	18.999

Notes: SP AR(1), NK AR(1), and NF AR(1) represent AR(1) model residuals fitted to S&P500, Nikkei, and Nifty futures prices. The figures are BDS statistics for the AR(p).

Source: Compiled by the Authors

Table 4 : BDS Statistics for GARCH (1,1) Standardized Residuals				
	M			
ε /σ	2	3	4	5
SP_gar11				
0.50	-2.474	-0.443	0.129	0.443
1.00	-2.785	-1.048	-0.767	0.005
1.50	-2.593	-1.335	-1.222	-0.413
2.00	2.183	-1.439	-1.359	-0.593
NK_gar11				
0.50	-1.705	-1.578	-0.876	0.329
1.00	-1.866	-1.932	-1.678	-1.127
1.50	-1.892	-2.148	-2.063	-1.569
2.00	-1.646	-2.057	-2.077	-1.622
NF_gar11				
0.50	0.475	0.531	1.384	2.128
1.00	0.402	0.331	0.808	1.700
1.50	0.023	-0.339	0.275	1.203
2.00	-0.072	-0.699	0.032	0.703

Notes: SP_ gar (1,1), NK_ gar (1,1), and NF _gar (1,1) represent standardized residuals of GARCH (1,1) models fitted to S&P500, Nikkei, and Nifty futures prices. The figures are BDS statistics for the standardized residuals from GARCH (1,1) models. The BDS statistics are evaluated against critical values obtained from Monte Carlo simulations.

Source: Compiled by the Authors

two rows of the Table do not show an explosive trend. For instance, SC^M estimates for the logistic map stay around one as the embedding dimension rises. Furthermore, the estimates for the logistic series are insensitive to AR transformations, consistent with chaotic behavior. For the return series, SC^M estimates show inconsistent behavior with chaotic structures. For instance, the SC^M does not settle. The estimates for the AR transformation do not change results much, but are mostly larger and do not settle with increasing of the embedding dimension. These initial indicators suggest that the series under consideration are not chaotic.

b) BDS Test Results : The Tables 3 and 4 report the BDS statistics (Brock et al.,1987) for [AR(p)] series, and standardized residuals ($\varepsilon/\sqrt{h}$) from the GARCH (1,1) models, respectively. The critical values for the BDS statistics are reported in Adrangi et al. (2001a, b). The BDS statistics strongly reject the null of no nonlinearity in the [AR(1)] errors for all of the return series. However, BDS statistics for the standardized residuals from the GARCH-type models are mostly insignificant at the 1 and 5 percent levels. On the whole, the results provide compelling evidence that the nonlinear dependencies in the series arise from GARCH-type effects, rather than from a complex, chaotic structure. From the BDS statistics presented in the Table 4, it is apparent that the variations of the GARCH model may explain the nonlinearities.

c) Bivariate GARCH Models : Ross (1989) argues that volatility may be regarded as a measure of information flow. Thus, if information arrives first in one market, one should see a volatility spillover from that market to others. To model the relationship between the returns while accounting for the GARCH effects, we estimate three VAR models in a bivariate GARCH context:

$$R_{it} = \alpha_i + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + u_{i,t} \quad \text{i, j=1, 2,} \qquad (9)$$

where the variance is given by :

$$\sigma^2_{i,t} = \beta_i + \gamma_i u^2_{i,t-1} + \varphi_i \sigma^2_{t-1} \quad \text{i=1, 2.}$$

Theory suggests that trader behavior in financial assets will induce time-varying and persisting volatility (Kyle 1985), and there is sufficient evidence that many financial series exhibit such patterns e.g., Shiller (1979), Weiss (1984), and Engle, Ng, and Rothschild (1990).

The statistics in the Table 1 indicate that the most basic GARCH model effectively captures the nonlinearities in returns. Standardized residuals exhibit relatively smaller kurtosis, further evidence of a superior fit to the data (Hsieh,1989). To be able to investigate the volatility spillovers and information arrival, we propose the VAR framework that also controls the likely variance and covariance persistence. The following equations are estimated e.g., Hamao, Masulis, and Ng (1990) ; Chan, Chan, and Karolyi (1991) ; and Chatrath and Song (1998):

$$\sigma^2_{1,t} = \alpha_0 + \alpha_1\sigma^2_{1,t-1} + \alpha_2\varepsilon^2_{1,t-1} + \alpha_3\varepsilon^2_{2,t-1} \quad (10)$$

$$\sigma^2_{2,t} = \beta_0 + \beta_1\sigma^2_{2,t-1} + \beta_2\varepsilon^2_{2,t-1} + \beta_3\varepsilon^2_{1,t-1} \quad (11)$$

and

$$\sigma_{12,t} = \gamma_0 + \gamma_1\sigma_{12,t-1} + \gamma_2\varepsilon_{1,t-1}\varepsilon_{2,t-1} \quad (12)$$

assuming

$$\begin{pmatrix} \hat{\varepsilon}_{1,t} \\ \hat{\varepsilon}_{2,t} \end{pmatrix} \mid \Omega_{t-1}\_Studentt\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{1,t} & \sigma_{1,2,t} \\ \sigma_{1,2,t} & \sigma^2_{2,t} \end{pmatrix}, \Theta \right)$$

$\sigma_{12,t}$ represents the conditional covariance given by an autoregressive linear function of the cross product in the past squared errors and Θ is the inverse of the degrees of freedom in the Student t distribution, and the conditional correlation,

$$\rho_{12,t} = \sigma_{1,2,t}\,(\sigma_{2,t}\sigma_{1,t})^{-\frac{1}{2}}$$

is allowed to vary over time.

The parameters α_2 and β_2 in (10) and (11) are the measures of volatility, with a large value indicating that the conditional variance remains elevated for extended periods of time following return shocks. The parameters α_3 and β_3 are intended to capture the volatility spillovers between markets. For instance, $\alpha_3>0$ and $\beta_3=0$ would be consistent with the hypothesis that the volatility spills over from the first futures prices to the other, and not *vice versa*. The nonlinear optimization methodology BHHH (Brendt, Hall, B.H., Hall, R.E.,& Hausman, 1974) is deployed.

The Tables 5 and 6 present the results of bivariate GARCH model. Most model coefficients are statistically significant at commonly expected levels of significance. In all cases, the conditional variances are sensitive to past volatilities in the market. The coefficients of the lagged squared residuals of the equations (α_3) are all positive and statistically significant. The implication is that volatility spillovers from one series to another are beyond being random. The spillover of volatility in this manner suggests that future S&P and Nikkei future price movements inform Nifty market and its movements.

The shock transmission between market pairs seems to occur from Nikkei and S&P futures into the Nifty future markets as shown by the significance of the inter-market shock term. This may be plausible as Nikkei and S&P markets attract more global attention and interest than the Nifty futures contracts. However, contract volumes and open interest may also be responsible for the direction of shock transmission. In order to verify this hypothesis, we re-estimate the bivariate GARCH models of the Table, explicitly including volume indicators, i.e., daily futures contracts volume of trade and open interest on each day. The Tables 7 and 8 report the re-estimated findings.

Volume and open interest in all cases are statistically significant. Once the volume affect is accounted for, the past inter-market shocks appear to be transmitted in both directions, shown by the statistical significance of the inter-market shock terms in Tables 7 and 8. This finding is significant in that it shows the shocks to each market are transmitted in a day once volume effects are accounted for.

The evidence of asymmetric information arrival and statistical significance of size and sign bias tests are clues that the volatility transmission may follow an asymmetric process. To account for asymmetric shock responses, we estimate the bivariate EGARCH models that can assess the asymmetric volatility response within and across markets.

Table 5 : Bivariate GARCH Model with Cross Contract Volatility Spillovers S&P500 and Nifty

$$\sigma^2_{1,t} = \alpha_0 + \alpha_1\sigma^2_{1,t-1} + \alpha_2\varepsilon^2_{1,t-1} + \alpha_3\varepsilon^2_{2,t-1} \qquad (10)$$

$$\sigma^2_{2,t} = \beta_0 + \beta_1\sigma^2_{2,t-1} + \beta_2\varepsilon^2_{2,t-1} + \beta_3\varepsilon^2_{2,t-1} \qquad (11)$$

and

$$\sigma_{12,t} = \gamma_0 + \gamma_1\sigma_{12,t-1} + \gamma_2\varepsilon_{1,t-1}\varepsilon_{2,t-1} \qquad (12)$$

Mean Equation	**SP**	**Nifty**
Intercept	0.026[b]	0.094 [b]
	(0.020)	(0.038)
Own Lagged	-0.079[a]	0.236 [a]
	(0.023)	(0.026)
Cross Lagged	-0.012	0.029 [a]
	(0.012)	(0.020)
Variance Equation	**SP**	**Nifty**
Intercept	0.0159[a]	0.189[a]
	(0.003)	(0.023)
Lagged Conditional Variance	0.914[a]	0.697[a]
	(0.0009)	(0.016)
Lagged Own Shocks	0.075[a]	0.191[a]
	(0.009)	(0.013)
Intermarket Lagged Shock	0.0001	0.153[a]
	(0.0007)	(0.012)
Ho: Intermarket lagged shocks are equal		**χ^2 =332.967 [a]**
Conditional Covariance Equation		
Intercept	0.012[a]	
	(0.005)	
Lagged Conditional Covariance	0.907 [a]	
	(0.021)	
Product of Lagged Residuals	0.043 [a]	
	(0.012)	
Diagnostics on Standardized residuals		
Q(12), ε_t/σ	43.595[a]	192.176 [a]
Q(24), ε_t/σ	49.120[a]	236.638 [a]
Q^2(12), ε_t^2/σ	1437.258[a]	857.139[a]
Q^2(24), ε_t^2/σ	2557.373[a]	1237.932[a]
Q(12), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	224.108 [a]	
Q(24), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	411.940 [a]	
System Log Likelihood	-4585.068	
Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	18.617[a]	11.005[a]
Size bias	-13.160[a]	-17.505[a]
Joint sign and size bias (χ^2)	444.371[a]	372.77[a]

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it}/\sqrt{\sigma_{it}}$) and their squared values. The sign and size bias tests show whether asymmetric model may be appropriate (see Engle & Ng , 1993).

[a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

Table 6 : Bivariate GARCH Model with Cross Contract Volatility Spillovers S&P500 and Nifty

Mean Equation	SP	Nifty
Intercept	0.026[b]	0.069 [b]
	(0.020)	(0.038)
Own Lagged	-0.065[a]	0.236 [a]
	(0.023)	(0.026)
Cross Lagged	-0.032	0.029 [a]
	(0.012)	(0.020)
Variance Equation	**SP**	**Nifty**
Intercept	0.040[a]	0.543[a]
	(0.012)	(0.057)
Lagged Conditional Variance	0.975[a]	0.806[a]
	(0.002)	(0.019)
Lagged Own Shocks	0.009[a]	-0.003[a]
	(0.0007)	(0.0005)
Intermarket Lagged Shock	0.0002	0.068[a]
	(0.0003)	(0.008)
Volume	0.01E-3 [a]	0.007E-3[a]
	(0.04E-4)	(0.01E-3)
Open Interest	-0.01E-3 [a]	-0.01E-4 [a]
	(0.03E-4)	(0.012E-5)
Ho: Intermarket lagged shocks are equal	**χ^2=75.279**	
Conditional Covariance Equation		
Intercept	0.080[a]	
	(0.016)	
Lagged Conditional Covariance	0.927[a]	
	(0.044)	
Product of Lagged Residuals	-0.032[a]	
	(0.001)	
Diagnostics on Standardized residuals		
Q(12), ε_t/σ	23.076[a]	147.037[a]
Q(24), ε_t/σ	27.374	163.887[a]
$Q^2(12)$, ε_t^2/σ	628.244[a]	126.520[a]
$Q^2(24)$, ε_t^2/σ	791.828[a]	138.688[a]
Q(12), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	37.788 [a]	
Q(24), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	83.058 [a]	
System Log Likelihood	-3956.137	
Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	2.729[a]	2.340[b]
Size bias	-7.133[a]	-9.029[c]
Joint sign and size bias (χ^2)	55.087[a]	96.742[a]

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it}/\sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng, 1993).

[a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

Table 7 : Bivariate GARCH Model With Volatility Spillovers Nikkei and Nifty futures prices

Mean Equation	**Nikkei**	**Nifty**
Intercept	-0.013	0.123[a]
	(0.029)	(0.038)
Own Lagged	-0.106[a]	0.052 [b]
	(0.020)	(0.021)
Cross Lagged	-0.015	0.048 [b]
	(0.016)	(0.023)
Variance Equation	**Nikkei**	**Nifty**
Intercept	0.066[a]	4.814 [a]
	(0.012)	(0.262)
Lagged Conditional Variance	0.908 [a]	-0.477 [a]
	(0.011)	(0.082)
Lagged Own Shocks	0.056 [a]	0.007 [a]
	(0.007)	(0.001)
Intermarket Lagged Shock	0.002	-0.012 [a]
	(0.002)	(0.0006)
Ho: Intermarket lagged shocks are equal	**χ^2= 284.449[a]**	
Conditional Covariance Equation		
Intercept	0.739 [a]	
	(0.145)	
Lagged Conditional Covariance	0.022	
	(0.175)	
Product of Lagged Residuals	0.036 [a]	
	(0.003)	
Diagnostics on Standardized residuals		
Q (12), ε_t/σ	17.090[b]	44.989[a]
Q (24), ε_t/σ	26.212	62.704[a]
Q^2(12), ε_t^2/σ	45.682[a]	227.676[a]
Q^2(24), ε_t^2/σ	65.176 [a]	289.354[a]
Q(12), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	103.480 [a]	
Q(24), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	184.742 [a]	
Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	3.087[a]	3.203[a]
Size bias	-1.447	-9.533[a]
Joint sign and size bias (χ^2)	10.486[a]	102.323 [a]
System Log Likelihood	-4544.199	

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it}/\sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng , 1993).

[a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

Table 8 : Bivariate GARCH Model With Volatility Spillovers Nikkei and Nifty futures prices Including Contract Volume and Open Interest

Mean Equation	**Nikkei**	**Nifty**
Intercept	-0.021	0.0197 [a]
	(0.032)	(0.041)
Own Lagged	-0.073 [a]	0.053 [a]
	(0.014)	(0.011)
Cross Lagged	-0.008	0.045 [a]
	(0.017)	(0.019)
Variance Equation	**Nikkei**	**Nifty**
Intercept	-0.964 [a]	0.0195 [a]
	(0.109)	(0.026)
Lagged Conditional Variance	0.592 [a]	0.921 [a]
	(0.0411)	(0.009)
Lagged Own Shocks	-0.006 [a]	0.045 [a]
	(0.001)	(0.0006)
Intermarket Lagged Shock	0.0633 [a]	0.006 [a]
	(0.008)	(0.002)
Volume	0.001E-2 [a]	0.003-E-3 [a]
	(0.003E-3)	(0.001E-3)
Open Interest	-0.006E-3 [a]	-0.001E-3 [a]
	(0.001E-3)	(0.002E-4)
Ho: Intermarket lagged shocks are equal	**χ^2= 60.968**	
Conditional Covariance Equation		
Intercept	0.986 [a]	
	(0.042)	
Lagged Conditional Covariance	-0.486 [a]	
	(0.036)	
Product of Lagged Residuals	0.064 [a]	
	(0.006)	
Diagnostics on Standardized residuals		
Q (12), ε_t/σ	27.718[a]	23.027[a]
Q (12), ε_t/σ	44.494[a]	34.075[b]
$Q^2(12)$, ε_t^2/σ	1316.307[a]	80.493 [a]
$Q^2(12)$, ε_t^2/σ	1807.538 [a]	85.595 [a]
Q(12), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	128.468 [a]	
Q(24), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	225.721 [a]	
Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	2.8332[a]	3.064 [a]
Size bias	-8.884 [a]	-9.449 [a]
Joint sign and size bias (χ^2)	95.740[a]	92.184 [a]
System Log Likelihood	-4599.894	

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it}/\sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng , 1993). [a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

The model is an extension of the univariate EGARCH model of Nelson (1991). Koutmos (1999), Cheung and Ng (1992), among others have documented this pattern of asymmetric volatility transmission in financial markets. We estimate the EGARCH model:

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + \varepsilon_{i,t} \quad \text{i, j = 1,2} \tag{13}$$

$$Ln\,(\sigma^2_{i,t}) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij}\varphi_j\,(z_{j,t-1}) + \gamma_i \ln(\sigma^2_{i,t-1}) \qquad \text{i,j = 1,2} \tag{14}$$

$$\varphi_j\,(z_{j,t-1}) = (|z_{j,t-1}| - E\,(|z_{j,t-1}|) + \delta_j z_{j,t-1}) \qquad \text{i,j= 1,2} \tag{15}$$

Where,

$$z_{j,t} = (|u_{j,t} / \sigma_{j,t}| - \sqrt{2/\pi}) + \delta_j u_{jt} / \sigma_{j,t}$$

and,

$$\sigma_{i,j,t} = \rho_{i,j}\, \sigma_{i,t}\, \sigma_{j,t} \qquad \text{i, j = 1,2,} \tag{16}$$

where $z_{i,t} = \varepsilon_{it} / \sigma^2_{i,t}$ is the standardized innovations of market i at time t. Volatility persistence is measured by γ. Nelson (1991) notes that $\gamma_i < 1$ indicates that the unconditional volatility is finite and measurable, while $\gamma_i = 1$ signals a non-stationary and unconditional volatility that is not well-defined. We use a combination of the simplex method and the Broyden - Fletcher - Goldfarb - Shanno (BFGS) algorithm to maximize the likelihood function, $L(\Omega)$.

The Table 9 reports the estimation results of the equations (13)-(16) for the S&P 500 and Nifty futures price indices. In both equations, δ_1 and δ_2 are negative. Coupled with positive β_{12} and β_{21}, these findings show that volatility transmission across markets is asymmetric. Negative shocks in each market result in elevated conditional volatility in the other and there is feedback in a similar manner. Statistically significant $\delta_j < 0$ shows the presence of asymmetric volatility effects in each market. Thus, negative shocks in each market lead to higher volatility than positive innovations. The size effects (the degree of asymmetry) as measured by $|-1+\delta_j|/(1+\delta_j)$ are 11.5 and 2.25 respectively for S&P 500 and Nifty, indicating that asymmetric shock effects in Nifty market are far less than those for S&P500. The unconditional volatility in both the cases is finite as indicated by γ_1 and $\gamma_2 < 1$.   Insignificant sign and size bias tests reinforce the statistical validity of the Asymmetric model.

The Table 10 reports the estimation results of the equations (13)-(15) for the Nikkei and Nifty futures. In both the equations, negative δ_1 and $\delta_1$coupled with positive β_{12} and β_{21}, show that volatility transmission across markets is asymmetric. Negative shocks in each market results in elevated conditional volatility in the other and there is feedback in a similar manner. Statistically significant $\delta_j < 0$ shows the presence of asymmetric volatility effects in each market. Thus, negative shocks in each market lead to higher volatility than positive innovations. The size effects as measured by $|-1+\delta_j|/(1+\delta_j)$ are 2.68 and 16.24 respectively for Nikkei and Nifty, indicating that asymmetric shock effects of negative shocks (innovations) in the Nifty market are far greater than those for Nikkei.

To summarize the impact of negative and positive shock transmission among markets, we use the estimated δ_j and β_{ij} coefficients. For instance, a one unit negative shock to market j affects the conditional volatility in market i by $(-1+\delta_j)^*\ (\beta_{ij}\ )$. The Table 11 summarizes these effects for a one unit positive and negative shock from market i on the percentage change in volatility of market j. The notable conclusions are as follows. First, the shock transmission is asymmetric. For instance, in all cases, positive shocks to the S&P500 futures have a smaller percentage impact on S&P 500 and Nifty relative to negative shocks of the same size. Volatility reaction in all markets to own negative innovations and cross market negative innovations is much larger in all markets. Second, negative shocks to Nifty futures markets show a significant impact on the volatility of S&P500 and Nikkei. Finally, the Nifty futures market volatility is more responsive to direct shocks to the Nifty futures market than to the S&P500 or Nikkei markets. The volatility response of the Nifty futures is about twice as large in response to the Nikkei futures shocks than to the S&P500 futures shocks.

Summary and Conclusions

The present paper investigates the volatility spillovers between Standard and Poors 500, Nikkei, and Nifty (India)

Table 9 : Bivariate Asymmetric VAR- EGARCH Model With Volatility Spillovers S&P500 and Nifty futures prices

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,\, t-1} + \mu_{i,t} \quad \text{i,j=1,2}$$

$$Ln\,(\sigma^2_{i,t}) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij}\, \varphi_j\, (z_{j,\, t-1}) + \gamma_i \ln\,(\sigma^2_{i,t-1}) \qquad \text{i, j = 1,2}$$

$$\varphi_j\,(z_{j,\, t-1}) = (|z_{j,\, t-1}| - E\,(|z_{j,\, t-1}|) + \delta_j z_{j,t-1}) \qquad \text{i, j=1, 2}$$

Mean Equations		
	SP	Nifty
Intercept α_{10}, α_{20}	-0.015	0.132[a]
	(0.016)	(0.026)
Lagged Return SP α_{11}, α_{21}	-0.064[a]	0.237[a]
	(0.019)	(0.026)
Lagged Return NF α_{12}, α_{22}	-0.0001	0.029
	(0.012)	(0.020)
Variance Equation	**SP**	**Nifty**
Intercept β_{10}, β_{20}	0.006[b]	0.093[a]
	(0.003)	(0.014)
Asymmetric Effect β_{11}, β_{21}	0.086 [a]	0.131 [a]
	(0.012)	(0.019)
Asymmetric Effect β_{12}, β_{22}	0.030 [a]	0.239 [a]
	(0.008)	(0.025)
Lagged stand. Shock δ_1 δ_2	-0.784 [a]	-0.384 [a]
	(0.209)	(0.086)
Lagged Conditional Variance γ_1 γ_2	0.981[a]	0.913 [a]
	(0.002)	(0.012)
Diagnostics on Standardized residuals		
Q (12), ε_t/σ	20.281[a]	26.023[a]
Q (24), ε_t/σ	23.691	41.194[a]
Q^2 (12), ε_t^2/σ	31.530[a]	1.171
Q^2 (24), ε_t^2/σ	38.379[a]	3.757
Q(12), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	5.147	
Q(24), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	23.746	
Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	1.306	-0.083
Size bias	0.460	-0.804
Joint sign and size bias (χ^2)	15.497[a]	2.734
System Log Likelihood	-7452.40	

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it}/\sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng , 1993). [a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

Table 10 : Bivariate Asymmetric VAR-EGARCH Model With Volatility Spillovers Nikkei and Nifty futures prices

$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + u_{i,t}$ i,j=1,2

$Ln\,(\sigma^2_{i,t}) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij}\varphi_j\,(z_{j,t-1}) + \gamma_i \ln\,(\sigma^2_{i,t-1})$ i,j = 1,2

$\varphi_j\,(z_{j,t-1}) = (|z_{j,t-1}| - E\,(|z_{j,t-1}|) + \delta_j z_{j,t-1})$

Mean Equation		
	Nikkei	**Nifty**
Intercept α_{10}, α_{20}	-0.006[a]	0.123[a]
	(0.027)	(0.030)
Lagged Return NK α_{10}, α_{20}	-0.094[a]	0.051[b]
	(0.019)	(0.021)
Lagged Return NF α_{10}, α_{20}	0.028	0.047[b]
	(0.018)	(0.022)
Variance Equation	**Nikkei**	**Nifty**
Intercept β_{10}, β_{20}	0.036[a]	0.097[a]
	(0.006)	(0.014)
Asymmetric Effect β_{11}, β_{21}	0.144[a]	0.133[a]
	(0.018)	(0.022)
Asymmetric Effect β_{12}, β_{22}	0.039[a]	0.178[a]
	(0.011)	(0.023)
Lagged stand. Shock δ_1 δ_2	-0.457[a]	-0.884[a]
	(0.091)	(0.118)
Lagged Conditional Variance γ_1 γ_2	0.960[a]	0.909[a]
	(0.006)	(0.012)
Diagnostics on Standardized residuals		
Q (12), ε_t/σ	14.272[c]	28.810[a]
Q (24), ε_t/σ	23.616	41.967[a]
Q^2 (12), ε_t^2/σ	30.634[a]	0.477
Q^2 (24), ε_t^2/σ	45.314[a]	1.540
Q (12), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	5.236	
Q (24), $\varepsilon_{it}\varepsilon_{it}/\sigma_i\sigma_j$	20.859	
Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	1.238	1.168
Size bias	0.453	-0.496
Joint sign and size bias (χ^2)	4.529	1.401
System Log Likelihood	-6345.30	

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it}/\sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng, 1993).

[a, b,] and [c] represent significance at .01, .05, and .10 levels respectively.

Source: Compiled by the Authors

Table 11 : Impact of Cross Market Shocks on the Percentage Change in Volatility		
Shock Origin (t-1)	**S&P500**	**Nifty**
S&P500 (+)	0.0186	0.0185
S&P500(-)	0.1534	0.0415
Nifty (+)	0.0283	0.1472
Nifty (-)	0.2337	0.3308
	Nikkei	**Nifty**
Nikkei (+)	0.0782	0.0045
Nikkei (-)	0.2098	0.0735
Nifty (+)	0.1792	0.0207
Nifty (-)	0.4808	0.3354
Source: Compiled by the Authors		

index futures contracts in the context of possible nonlinear relationships in contract prices. An important contribution of this paper is exploring nonlinearities and nonlinear dynamics in a framework of asymmetric shocks to markets and information arrival. Several issues motivated the paper. Foremost, investigating the intermarket dynamics among the developed and emerging markets is increasingly important, given the ongoing banking/financial liberalization in the latter. Investigating volatility spillovers and potentially asymmetric reactions to positive and negative shocks emanating in various markets inform the capital market players and political policy makers. Furthermore, questions on market behavior following the liberalization of the banking sector in a transition economy such as India are important as other countries also consider globalization of their financial sector.

Our findings point to a strong evidence that futures price series exhibit nonlinear dependence. We offer bivariate VAR- GARCH (1,1) and VAR-EGARCH processes that best explain the nonlinearities in the daily futures prices. Bivariate EGARCH models show that the volatility spills in both directions, i.e, there is bivariate feedback between futures contracts once models take volume variables into account. We also find evidence of asymmetric market responses to negative and positive shocks. Whereas, it is not surprising that the Indian market responds to shocks in the developed markets, it is noteworthy that shocks in the Indian market have induced a response in the developed markets in recent years.

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