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Volatility Spillover between Stock and Foreign Exchange Markets: Indian Evidence

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ABSTRACT

The study of volatility spillovers provides useful insights into how information is transmitted from stock market to foreign exchange market and vice versa. This paper explores volatility spillovers between the Indian stock and foreign exchange markets. The results indicate that there exists a bidirectional volatility spillover between the Indian stock market and the foreign exchange market with the exception of S&P CNX NIFTY and S&P CNX 500. The findings of the study also suggest that both the markets move in tandem with each other and there is a long run relationship between these two markets. The results of significant bidirectional volatility spillover suggest that there is an information flow (transmission) between these two markets and both these markets are integrated with each other. Accordingly, financial managers can obtain more insights in the management of their international portfolio affected by these two variables. This should be particularly important to domestic as well as international investors for hedging and diversifying their portfolio.

JEL Classification: G15, C32

Keywords: *Stock market; Foreign exchange market; Volatility spillovers; Information transmission; ARCH; GARCH; EGARCH*

I. INTRODUCTION

The objective of this paper is to examine the relationship and volatility spillovers between Indian stock and foreign exchange markets. Internationalization of stock markets, liberalized capital flows, huge foreign investment in Indian equity markets have led stock and foreign exchange markets to be increasingly interdependent. An understanding of the intermarket volatility is important for the pricing of securities within and across the markets for trading and hedging strategies as well as for formulation of regulatory policies in an emerging market like India that is rapidly getting integrated into the global economy.

Several financial as well as currency crises across emerging markets around the globe and the advent of floating exchange rate led the academicians as well as practitioners to have a re-look into the nature of volatility spillovers between stock and foreign exchange markets that have seen large correlated movements resulting in market contagion. It has been observed that exchange rate has been used to explain the behavior of stock prices on the assumption that corporate earnings tend to respond to fluctuations in exchange rate [Kim (2003)]. This issue attracted a plethora of regulatory implications as well, whereby institutional restrictions were set up to mitigate the volatility spillover [Roll (1989)]. Besides, international diversification and cross-market return correlations have led these markets to be increasingly interdependent. To understand the risk-return tradeoff of international diversification and, therefore, management of multi currency equity portfolios, it is important to analyze the interaction between the exchange rate risk and stock price. With significant rise in cross border equity investments and, in particular, investments in emerging markets like India, this has become a critical issue for fund managers, especially in the domain of pricing of securities in the global market, international portfolio diversification, and hedging strategies. Moreover, continuous economic globalization and integration of Indian financial Markets with world financial markets, especially fueled by the development of information technology, increases the international transmission of returns and volatilities among financial markets. A competent knowledge of the volatility spillover effect between the stock and foreign exchange markets, and consequently the degree of their integration, will potentially expand the information set available to international as well as domestic investors, multinational corporations, and policy makers for decision making.

The existing research generally supports the existence of interdependence in return and volatility of stock and foreign exchange markets. However, it is very much centered on the developed markets. No such attempts have been made so far to examine the volatility spillover between the stock and foreign exchange markets in Indian context except for Apte's 2001 study. By using the data from January 2, 1991 to April 24, 2000, Apte (2001) investigates the relationship between the volatility of the stock market and the nominal exchange rate of India. The study suggests that there appears to be a spillover from the foreign exchange market to the stock market, but the reverse is not true. The main limitation of Apte's study is the fact that during the early part of the data series, there are sometimes long gaps due to the stock markets having been closed for several days at a stretch. Also, despite the fact that National Stock Exchange (NSE) started its security trading only in 1994, Apte's data period begins from January 1991 by simulating the previous data points based on post data points.

We differentiate our study from the previous study in several ways. Firstly, we use a larger sample period by analyzing data from 4th January 1993 to 31st December 2003. Time period beyond 2000 is extremely relevant in the Indian context due to the huge inflows of foreign institutional investment into Indian equity market has taken a significant momentum only after the year 2000. Foreign institutional net investment in the Indian stock market was $1,461.4 million in 2000 and almost doubled to $2,807.3 in 2001 and reached $6,594.6 in 2003. Secondly, we consider four indices—SENSEX[1], BSE-100[2], S&P CNX NIFTY-50[3], and S&P CNX-500[4] to represent the Indian stock market, whereas the previous study (Apte, 2001) considered SENSEX and NIFTY-50 only.

Finally, we study volatility spillovers in two different ways. Firstly, we generate the volatility series for both the markets to evaluate the long run relationship by employing both GARCH and EGARCH methodology. Secondly, we extract the shock emanating from one market and introduce it in the volatility equation of the other market to examine the issue of volatility spillovers. It also addresses whether the volatility spillover effect is asymmetric, i.e., whether ‘good’ and ‘bad’ news from the stock market has a different impact on the exchange rates and vice versa.

This paper has six sections. Section II presents a review of previous studies regarding the volatility spillovers between stock and foreign exchange markets. Section III outlines the ARCH school of models that we use to examine the volatility spillovers between the two markets. Section IV reports the description of the variables. Section V presents the empirical results followed by the concluding remarks in Section VI.

II. LITERATURE REVIEW

The behavior of volatility of stock market has been extensively studied using the ARCH-GARCH framework pioneered by Engel (1982) and further developed by Bollerslev (1986), Nelson (1991) and others. The literature on volatility spillover can be broadly categorized into two groups. The first group of studies focuses on return series or errors from modeling return series and the relationship of returns across markets. For instance, Eun and Shim (1989) show that about 26 percent of the error variance of stock market returns can be explained by innovations in other stock markets, and, not surprisingly, report that the US market is the most influential stock market. The second group of research directly examines volatility. In an investigation of the crash of October 1987, King and Wadhwani (1990) study shows transmission of price information across markets through volatility innovations even when the information is market specific. They argue that there is a ‘contagion’ effect across markets whereby markets overreact to the events of another market irrespective of the economic value of the information.

Chiang, Yang, and Wang (2000) study points out that national stock returns in Asian countries are positively related to the value of the national currency. Similarly, Sabri (2004) evaluates features of emerging stock markets, in order to point out the most associated indicators of increasing stock return volatility and instability of emerging markets. The study shows that stock trading volume and currency exchange rate respectively represent the highest positive correlation to the emerging stock price changes. Research on volatility spillovers is not limited to stock market only. Similar tests have been conducted in other markets such as foreign exchange, cash and future markets.

Brailsford (1996) examines the issue of volatility spillovers between the Australian and New Zealand equity markets. The results indicate that volatility in the Australian market influences the subsequent conditional volatility of the New Zealand market. Similarly, conditional volatility in the Australian market appears to be influenced by volatility in the New Zealand market. Baele (2005) examines the magnitude and time varying nature of volatility spillovers from the aggregate European (EU) and U.S. market to 13 local European equity markets.

Kanas (2000) investigates the interdependence of stock returns and exchange rate changes within the same economy by considering the six industrialized countries--US, UK, Japan, Germany, France and Canada. The study concludes: (i) there is cointegration between stock prices and exchange rates; (ii) there is evidence of spillover from stock returns to exchange rate changes for all countries except Germany; (iii) the spillovers from stock returns to exchange rate changes are symmetric in nature; (iv) volatility spillovers from exchange rate changes to stock returns are insignificant for all the countries; (v) the correlation coefficient between the EGARCH filtered stock returns and exchange rate changes is negative and significant for all the countries, which indicates a significant contemporaneous relationship between stock returns and exchange rate changes.

Bodart and Reding (2001) show that exchange rates have a significant effect on expected industry stock returns and on their volatility, though the magnitude of this effect is quite small. The study also concludes that the importance of the exchange rate spillovers is influenced by the exchange rate regime, the magnitude, and the direction of exchange rate shocks.

Fang and Miller (2002) investigate empirically the effects of daily currency depreciation on Korean stock market returns during the Korean financial turmoil of 1997 to 2000. The study finds: (i) there exists a bi-directional causality between the Korean foreign exchange market and the Korean stock market; (ii) the level of exchange rate depreciation negatively affects stock market returns; exchange rate depreciation volatility positively affects stock market returns; and stock market return volatility responds to exchange rate depreciation volatility.

In the light of the above discussion on volatility spillover, this study examines the information flow between the Indian stock and foreign exchange markets. A good understanding of the determinants, which shape the first and second moments of the conditional distribution of stock return as well as exchange rate return, is crucial for efficient portfolio management strategies. Among those determinants, exchange rates have received particular attention due to the importance of currency management strategies in highly integrated financial markets and the implication of exchange rate fluctuations for company profitability [Bodart and et al (2001)].

III. EMPIRICAL METHODOLOGY

In order to analyze the transmission of volatility or volatility spillover effects between the stock and foreign exchange markets, both Generalised Autoregressive Conditionally Heteroscedastic model (GARCH) and Exponential Generalised Autoregressive Conditionally Heteroscedastic model (EGARCH) are taken into consideration. The

GARCH model allows the conditional variance to be dependent upon previous own lags apart from the past innovation. Through GARCH model, it is possible to interpret the current fitted variance as a weighted function of long-term average value information about volatility during the previous period as well as the fitted variance from the model during the previous period.

In GARCH models, restrictions are to be placed on the parameters to keep the conditional volatility positive. This could create problems from the estimation point of view. One of the primary restrictions of GARCH model is that they enforce a symmetric response of volatility to positive and negative shocks. This arises due to the conditional variance being a function of the magnitudes of the lagged residuals and not their signs.[5] However; it has been argued that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. The EGARCH or Exponential GARCH model was proposed by Nelson (1991) and uses natural log of the conditional variance to address this drawback of GARCH model. Nelson and Cao (1992) argue that the nonnegativity constraints in the linear GARCH model are too restrictive. The GARCH model imposes the nonnegative constraints on the parameters, while there are no restrictions on these parameters in the EGARCH model. EGARCH allows for an explicit testing of volatility spillover without imposing additional restrictions.

The price and volatility spillover effect between the stock and foreign exchange markets and the degree of integration as well as significant interrelationships can be interpreted in at least two ways. First, a causal relationship may exist such that the volatility in one market induces volatility in the other through a lead-lag relationship. This is possible because the trading hours of the two markets are not common. Second, common international factors could influence the volatility in both the markets, thereby giving rise to an apparent causal relationship between the markets.

To model the volatility spillover between the stock and foreign exchange markets, we evaluate different orders of AR-GARCH and AR-EGARCH models. Since AR (1)-GARCH (1, 1) and AR (1)-EGARCH (1, 1) models are well fitted to the stock and exchange rate returns, we use AR (1)-GARCH (1, 1) and the AR (1)-EGARCH (1, 1) models. We examine the volatility spillover in two ways. First, the volatility series generated from the specific model entertained are extracted for both stock returns as well as returns in the foreign exchange market. Then, in order to ascertain the possible existence of co-movement among them we apply Johansen Maximum Likelihood Cointegration (1988) test. Secondly, the residuals are generated from a specific model and for a particular market. These residuals are used as shocks emanating in one market and we introduce them to the volatility equation of the other market. If the coefficient of the same is significant, this confirms the presence of volatility spillover. The AR (1) equation as well as both GARCH (1, 1) and EGARCH (1, 1) spillover equation may be specified as follows:

$$\textbf{AR (1):} \quad y_t = c + \tau y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2) \tag{1}$$

Where y_t is the return of both stock indices as well as exchange rates at time period t, c is the intercept, y_{t-1} is the previous period return at the time period t-1 and ε_t is the white noise error term. Here, return on daily stock prices and exchange rates are a function of previous period returns on stock indices and exchange rates plus an error term.

A. GARCH (1, 1) Spillover Equation

$$h_{t(\text{Stock Indices})} = \omega_0 + \beta_1 \varepsilon_{t-1}^2 + \alpha_1 h_{t-1} + \psi(\text{sqresid}_{\text{erate}}) \tag{2}$$

$$h_{t(\text{Erate})} = \omega_0 + \beta_1 \varepsilon_{t-1}^2 + \alpha_1 h_{t-1} + \psi(\text{sqresid}_{\text{stock indices}}) \tag{3}$$

where $\omega_0 > 0$, $\beta_1 \geq 0$, $\alpha_1 \geq 0$. In both Equations (2) and (3), h_t is the conditional variance of both stock indices and exchange rates respectively, which is a function of mean ω_0. News about volatility from the previous period is measured as the lag of the squared residual from the mean equation (ε_{t-1}^2), last period's forecast variance (h_{t-1}) and the squared residual of exchange rate and stock indices, respectively in both the above equations.

In the GARCH (1,1) spillover equation, we use the squared residual of another market (ψ) instead of residual on their level, which is used as a proxy for shock in other markets, because in case of GARCH, we make sure that volatility is positive.

B. EGARCH (1, 1) Spillover Equation

$$\ln h_{t(\text{Stock Indices})} = \omega_0 + \beta_1 \ln h_{t-1} + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \phi \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \psi(\text{resid}_{\text{erate}}) \tag{4}$$

$$\ln h_{t(\text{Erate})} = \omega_0 + \beta_1 \ln h_{t-1} + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \phi \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \psi(\text{resid}_{\text{stock indices}}) \tag{5}$$

The above equations represent the EGARCH (1, 1) model. In these equations, log h_t is the log of variance, which automatically restricts the volatility to be positive. ω_0 is the constant level of volatility. $\beta_1 \ln h_{t-1}$ explains the consistence, because this is a function of volatility. The coefficient α_1 measures reaction of volatility to change in news. We take the residual modulus that measures the relation with respect to positive news. The coefficient ϕ_1 explains the relationship of volatility to both positive and negative news, because we are not taking modulus. The coefficient ψ represents the volatility spillover coefficient. In Equation (4), residuals are generated from the EGARCH model of exchange rate, whereas in Equation (5), residuals are generated from the EGARCH model of stock indices. In the above EGARCH (1, 1) model, only residuals of other markets have been taken into consideration instead of squared residual, since EGARCH, by definition, ensures that volatility is positive.

IV. DESCRIPTION OF THE VARIABLES AND DATA POINTS

The current study is based on the daily closing return values of four broad based indices - Bombay Stock Exchange Sensitive index (BSE), BSE National index of 100 scrips traded in five major stock markets in India, S&P CNX Nifty and S&P CNX 500 and the daily closing prices of exchange rate of Indian rupee per U.S. dollar. Data do not include dividends, as the data on daily observations on dividends are not available. The daily data covers the period from 4th January 1993 to 31st December 2003 in the case of BSE indices with a total of 2557 observations. For the NSE indices, we use daily data for the period 3rd June 1996 to 31st December 2003, with a total of 1818 observations. The daily data of bilateral nominal exchange rates of INR/US$ covers the period from 4th January 1993 to 31st December 2003 in case of BSE indices and 3rd June 1996 to 31st December 2003 in case of NSE indices, respectively. The data of stock indices are collected from BSE and NSE web sites and the data on exchange rate is collected from pacific FX database. The study does not find any break (Chow & Perron Break Test) within the sample period, hence sub-sampling is not relevant in this context. Moreover, the stock market operates for five days whereas foreign exchange market operates for six days in a week. Therefore, in order to arrive at the common data points in which both stock price and exchange rate data points are available, we consider homogeneous time frame for the sample period.

V. EMPIRICAL ANALYSIS

To analyze the volatility spillovers between the Indian stock market and the foreign exchange market, the data are converted into continuously compounded rate of return (R_t) by taking the first difference of the log prices i.e. $R_t = 100{*}\ln(P_t / P_{t-1})$. The volatility models that we estimate in this section are intended to capture the conditional variance of the stochastic components of the returns. The summary statistics of the variables used in this study are presented in Table 1.

Table 1
Summary statistics of daily closing returns on the BSE and NSE indices and their respective exchange rates

Variables	Mean	SD	SK	Kurtosis	J-B	ADF
Sensex	0.032	1.674	-0.112	5.727	797.7021 (0.01)	-22.140 (4)
BSE 100	0.037	1.650	-0.158	6.189	1093.806 (0.01)	-21.304 (4)
Exchange Rate (For Sensex and BSE 100)	0.017	0.342	10.556	311.45	10184610 (0.01)	-22.281 (4)
Nifty	0.029	1.662	-0.030	6.173	762.711 (0.01)	-18.394 (4)
S&P 500	0.037	1.704	-0.202	5.959	671.925 (0.01)	-17.816 (4)
Exchange Rate (For Nifty and S&P 500)	0.014	0.217	0.110	29.317	52441.20 (0.01)	-17.767 (4)

Note: Figures in the parentheses show the significance level. SD and SK are the Standard Deviation and Skewness, respectively. The MacKinnon critical values for ADF test of BSE indices and their respective Exchange Rates at 1%, 5% and 10% significance level are -3.9671, -3.4142, -3.1288 (with trend and intercept) respectively. The MacKinnon critical values for ADF test of NSE indices and their respective Exchange Rates at 1%, 5% and 10% significance level are -3.9684, -3.4148, -3.1292 (with trend and intercept) respectively.

The stock indices and their respective exchange rates have very small positive daily rate of return. The kurtosis coefficient, a measure of thickness of the tail of the distribution, is quite high in the case of all the variables. A Gaussian (normal) distribution has kurtosis equal to three, and, hence, this implies that the assumption of Gaussianity cannot be made for the distribution of the concerned variables. This finding is further strengthened by Jarque-Bera test for normality which in our case yields very high values much greater than for a normal distribution and, therefore, we reject the null hypothesis of normality at any conventional confidence levels. We also use Augmented Dickey Fuller (ADF) test (both with trend and intercept) to check the stationarity property of the concerned variables and their order of integration from the ADF test; the results show that the null hypothesis of unit root is rejected for all the variables at their return level. Hence, it can be concluded that they are stationary and integrated of order 1, I(1).

We begin our empirical analysis with an autoregressive model of order one, AR(1). This is carried out primarily to eliminate the first-degree autocorrelation among the returns, which makes the data amenable for further analysis. We present the results due to fitted AR (1) model to respective return series in Table 2, which shows that the AR (1) coefficients for BSE Sensitive index, National index, NSE S&P CNX Nifty, S&P CNX Nifty 500 and the corresponding exchange rates with these indices are highly significant.

After fitting the AR (1) model, we test for the presence of autocorrelation among the residuals as well as squared residuals from the fitted model. The results from Ljung Box Q statistics, which are used to test the null hypothesis of 'No Autocorrelation' against the alternative of existence of autocorrelation, are reported in Table 2. From the results, it is inferred that the null hypothesis is not rejected in case of residuals, whereas it is strongly rejected in case of squared residuals. Prima facie this creates the case to apply GARCH models. In order to confirm the presence of ARCH effect in the data we go for a Lagrange Multiplier (LM) Test and the results show that the null hypothesis of 'No ARCH Effect' is strongly rejected in case of all the concerned variables.

Table 3 presents the estimation results of AR (1)-GARCH (1, 1) as well as that of AR (1)-EGARCH (1, 1) model. We use the GARCH and EGARCH models of order (1, 1) because this order has been found to provide the most parsimonious representation of ARCH class of models and, at the same time, the acceptability of the order has been strongly proved empirically. The results presented in Table 3 show that all the coefficients of GARCH equation for sensitive index obey the restrictions inherent in the model in terms of their signs as well as magnitude. The first panel shows the spillover explained through the use of GARCH models where the residuals have been extracted after estimating the GARCH for each of the markets and the same has been used as a shock (as a proxy for volatility) spilling over to the other market. With reference to Equations 1 to 5, the coefficient ψ represents the volatility spillover parameter. In the case of GARCH model, we are using squared residuals instead of residuals on their level in order to ensure positivity in variance or volatility. This is, however, not the case for EGARCH model as the definition of the model ensures variance to be positive. The results in Table 3 show that volatility spillover parameter is significant in case of both the markets and for both the models, which leads us to conclude that there exists bi-directional volatility spillover between stock market and foreign exchange market. Checking for autocorrelation as well as ARCH effect in the residuals and squared residuals also validates the estimation of the models. The results show non-existence of the same among the residuals after estimating GARCH and EGARCH models.

Table 2
AR (1) model fitted to the data

	Constant	AR(1)	Q(8)[5]	$Q^2(8)$[6]	LM[7]
Sensex	0.033	0.103	8.817	225.87	94.53
	(0.36)	(0.01)	(0.226)	(0.01)	(0.01)
BSE 100	0.039	0.129	8.1309	397.09	171.18
	(0.29)	(0.01)	(0.321)	(0.01)	(0.01)
Nifty	0.029	0.056	7.681	134.79	64.097
	(0.479)	(0.01)	(0.36)	(0.01)	(0.01)
S&P 500	0.037	0.104	8.975	266.04	108.55
	(0.39)	(0.01)	(0.25)	(0.01)	(0.01)
Exchange Rate (Sensex)[1]	0.017	-0.095	8.817	225.87	94.534
	(0.01)	(0.01)	(0.22)	(0.01)	(0.01)
Exchange Rate (BSE 100)[2]	0.017	-0.095	7.305	12.305	94.124
	(0.01)	(0.01)	(0.47)	(0.09)	(0.01)
Exchange Rate (Nifty)[3]	0.014	-0.097	3.832	139.97	91.142
	(0.01)	(0.01)	(0.14)	(0.01)	(0.01)
Exchange Rate (S&P 500)[4]	0.014	-0.113	3.539	166.53	91.943
	(0.01)	(0.01)	(0.89)	(0.01)	(0.01)

[1,2,3,4] represent the exchange rate after the dates being matched with corresponding indexes.
[5] represents L-Jung Box Q statistics for the residuals from AR (1) model.
[6] represents L-Jung Box Q statistics for the squared residuals from AR (1) model.
[7] represents Lagrange Multiplier statistics to test for the presence of ARCH effect in the residuals from AR (1) model.

Table 3
Volatility spillover: sensitive index (SENSEX)

Coefficients[1]	AR(1) – GARCH (1,1)		AR(1) – EGARCH (1,1)	
	Sensex→Exchange rate	Exchange rate → Sensex	Sensex→Exchange rate	Exchange rate → Sensex
c	0.062	0.0007	0.033	0.002
	(0.06)	(0.45)	(0.34)	(0.04)
τ	0.135	-0.092	0.152	-0.157
	(0.01)	(0.01)	(0.01)	(0.01)
ω_0	0.114	0.0001	-0.129	-0.722
	(0.01)	(0.01)	(0.01)	(0.01)
β_1	0.102	0.749	0.020	0.556
	(0.01)	(0.01)	(0.01)	(0.01)
α_1	0.856	0.580	-0.054	0.126
	(0.01)	(0.01)	(0.01)	(0.01)
ϕ	-	-	0.928	0.918
			(0.01)	(0.01)
ψ	0.079	0.0009	0.021	0.034
	(0.01)	(0.01)	(0.01)	(0.01)
LM[2]	0.395	0.746	0.511	1.103
	(0.98)	(0.945)	(0.97)	(0.89)

Note:
[1] For description of coefficients, please refer the equations 1 to 5, respectively in section 3.
[2] Represents Lagrange Multiplier statistics to test for the presence of additional ARCH effect in the residuals from AR (1) - GARCH (1, 1) and AR (1) - EGARCH (1, 1) models.

Table 4 reports the estimated results of AR (1)-GARCH (1, 1) as well as the same for AR (1)-EGARCH (1, 1) model in case of BSE 100 Index and exchange rates. The first panel shows the spillover explained through the use of GARCH (1,1) model both in case of stock market to foreign exchange market and vice versa. The second panel shows the volatility spillovers through the use of EGARCH (1, 1) model in the case of stock as well as foreign exchange markets correspondingly. From the Table 4, we conclude that all the coefficients of GARCH equation for BSE 100 Index obey the restrictions inherent in the model in terms of their sign and magnitude.

The results in Table 4 show that the volatility spillover parameter is significant for both the markets as well as for both the models. This result leads us to conclude that there also exist bidirectional volatility spillovers between stock market and foreign exchange market. From LM test, the results show non-existence of the same among the residuals after estimating GARCH and EGARCH models to validate the estimation.

In Table 5, we present the estimation results of AR (1)-GARCH (1, 1) as well as AR (1)-EGARCH (1, 1) models in case of S&P CNX Nifty index.

Table 4

Volatility spillover: BSE 100 Index

Coefficients[1]	**AR(1) – GARCH (1,1)**		**AR(1) - EGARCH (1,1)**	
	BSE 100 → Exchange rate	**Exchange rate→ BSE 100**	**BSE 100 → Exchange rate**	**Exchange rate → BSE 100**
c	-0.0002 (0.78)	0.051 (0.11)	0.002 (0.02)	0.034 (0.30)
τ	-0.087 (0.01)	0.173 (0.01)	-0.170 (0.01)	0.187 (0.01)
ω_0	0.00001 (0.57)	0.069 (0.01)	-0.400 (0.01)	-0.153 (0.01)
β_1	0.761 (0.01)	0.108 (0.01)	0.404 (0.01)	0.249 (0.01)
α_1	0.580 (0.01)	0.868 (0.01)	0.119 (0.01)	-0.034 (0.01)
ϕ	-	-	0.951 (0.01)	0.954 (0.01)
ψ	0.001 (0.01)	0.046 (0.01)	-0.141 (0.01)	0.126 (0.01)
LM[2]	0.775 (0.94)	4.048 (0.85)	0.278 (0.99)	0.227 (0.69)

[1] For description of coefficients, please refer the equations 1 to 5, respectively in section 3.
[2] Represents Lagrange Multiplier statistics to test for the presence of additional ARCH effect in the residuals from AR (1) - GARCH (1, 1) and AR (1) - EGARCH (1, 1) models.

Table 5
Volatility spillover: S&P CNX Nifty Index

Coefficients[1]	AR(1) – GARCH (1,1)		AR(1) - EGARCH (1,1)	
	Nifty→ Exchange rate	**Exchange rate → Nifty**	**Nifty→ Exchange rate**	**Exchange rate → Nifty**
c	0.012 (0.21)	0.075 (0.05)	0.001 (0.36)	0.036 (0.36)
τ	-0.109 (0.01)	0.093 (0.01)	-0.174 (0.01)	0.092 (0.01)
ω_0	0.039 (0.01)	0.115 (0.01)	-0.269 (0.01)	-0.085 (0.01)
β_1	0.140 (0.01)	0.094 (0.01)	0.218 (0.01)	0.213 (0.01)
α_1	0.542 (0.01)	0.868 (0.01)	0.082 (0.01)	-0.080 (0.01)
ϕ	-	-	0.965 (0.01)	0.917 (0.01)
ψ	-0.0008 (0.01)	-0.020 (0.84)	-0.104 (0.01)	0.065 (0.36)
LM[2]	0.379 (0.97)	3.62 (0.45)	6.934 (0.13)	3.053 (0.54)

[1] For description of coefficients, please refer the equations 1 to 5, respectively in section 3.
[2] Represents Lagrange Multiplier statistics to test for the presence of additional ARCH effect in the residuals from AR (1) - GARCH (1, 1) and AR (1) - EGARCH (1, 1) models.

Table 6
Volatility spillover: S&P CNX 500 Index

Coefficients[1]	AR(1) – GARCH (1,1)		AR(1) - EGARCH (1,1)	
	S&P → Exchange rate	**Exchange rate → S&P**	**S&P → Exchange rate**	**Exchange rate → S&P**
C	-0.000005 (0.99)	0.0931 (0.02)	0.00003 (0.98)	0.0759 (0.06)
τ	-0.1912 (0.01)	0.1407 (0.01)	-0.2017 (0.01)	0.1600 (0.01)
ω_0	0.0002 (0.01)	0.1433 (0.01)	-0.3414 (0.01)	-0.1313 (0.01)
β_1	0.459 (0.01)	0.1333 (0.01)	0.2651 (0.01)	0.2835 (0.01)
α_1	0.6011 (0.01)	0.8208 (0.01)	0.0921 (0.01)	-0.0553 (0.01)
ϕ	-	-	0.9562 (0.01)	0.9079 (0.01)
ψ	0.0010 (0.01)	0.1184 (0.48)	-0.1358 (0.01)	0.1305 (0.10)
LM[2]	1.785 (0.77)	2.388 (0.66)	3.067 (0.54)	2.552 (0.63)

[1] For description of coefficients, please refer the equations 1 to 5, respectively in section 3.
[2] Represents Lagrange Multiplier statistics to test for the presence of additional ARCH effect in the residuals from AR (1) - GARCH (1, 1) and AR (1) - EGARCH (1, 1) models.

In the panel, one of the results shows that all the coefficients of GARCH equation for S&P CNX Nifty Index obey the restrictions inherent in the model in terms of their signs as well as magnitude. In the case of GARCH (1, 1) model, the volatility spillover parameter (ψ) is significant for S&P CNX Nifty to the exchange rate, whereas it is not significant in case of the exchange rate to S&P CNX Nifty. Therefore, there exists a unidirectional volatility spillover from the stock market to the foreign exchange market. In the second panel, where we estimate the AR (1)-EGARCH (1, 1) model in the context of S&P CNX Nifty and the exchange rate, we find that the coefficient of volatility spillover parameter (ψ) is significant for S&P CNX Nifty to the exchange rate, but the same is insignificant in case of the exchange rate to S&P CNX Nifty. Therefore, there exists a unidirectional volatility spillover from the stock market to the foreign exchange market. The estimation of the model is also validated by checking for autocorrelation as well as ARCH effect in the residuals and squared residuals, which shows non-existence of the same among the residuals after estimating GARCH and EGARCH models from LM test.

In case of S&P CNX 500, the results presented in Table 6 show that all the coefficients of GARCH equation obey the restrictions inherent in the model in terms of their signs as well as magnitude. The first panel shows the spillover explained through GARCH models, where the coefficient of volatility spillover parameter is significant from S&P 500 to the exchange rates, but the same is insignificant in case of the exchange rate to S&P 500. Thus, there exists a unidirectional volatility, which spills over from the stock market to the foreign exchange market. However, this result contradicts the second panel results, where we estimate the volatility spillover through EGARCH model. From, the results, we can conclude that there exists a bidirectional volatility spillover for both the markets. Checking for autocorrelation as well as ARCH effect in the residuals and squared residuals also validates the estimation of the models. The results show non-existence of the same among the residuals after estimating GARCH and EGARCH models.

The second approach that we adopt to test for volatility spillover is through cointegration analysis. The results of the same are presented in Tables 7 to 12. Here we first extract the volatility series from each of the models as well as for each market. Then we explore cointegration relationship, if any, between volatility series from the stock market and the foreign exchange market. To examine the cointegration relationship we use Johansen Maximum Likelihood (1988) procedure. The results of cointegration relationship between the volatility series of Sensex and Exchange rate through GARCH and EGARCH model are presented in Tables 7 and 8, respectively.

Table 7 summarizes the cointegration result of the volatility series of return of Sensex and the exchange rate. The test of trace statistics shows that the null hypothesis of variables are not cointegrated ($r = 0$) against the alternative hypothesis of one or more cointegrating vectors ($r > 0$). Since 359.03 exceed the 5% critical value of λ_{trace} statistic (in the first panel of Table 7), we reject the null hypothesis of no cointegrating vectors and accept the alternative of one or more cointegrating vectors. Next, we use the λ_{trace} (1) statistic to test the null hypothesis of $r \leq 1$ against the alternative of two cointegrating vectors. Since the λ_{trace} (1) statistic of 64.43 is greater than the 5% critical value of 15.41, we conclude that there are two cointegrating vectors.

Table 7
Cointegration analysis: GARCH aariance (sensitive index and exchange rate)

Null Hypothesis	Alternative Hypothesis	04.01.1993 to 31.12.2003	Critical Values	
λ Trace Tests	**λ Trace Tests**	**λ Trace Values**	**5%**	**1%**
r = 0	r > 0	359.0308	15.41	20.04
r ≤ 1	r > 1	64.43148	3.76	6.65
r ≤ 2	r > 2	-		
λ Max Tests	**λ Max Tests**	**λ Max Values**	**5%**	**1%**
r = 0	r = 1	294.5993	14.07	18.63
r = 1	r = 2	64.43148	3.76	6.65
r = 2	r = 3	-	-	-

Note: r refers to number of cointegrating vectors.

Table 8
Cointegration analysis: EGARCH variance (sensitive index and exchange rate)

Null Hypothesis	Alternative Hypothesis	04.01.1993 to 31.12.2003	Critical Values	
λ Trace Tests	**λ Trace Tests**	**λ Trace Values**	**5%**	**1%**
R = 0	R > 0	384.2155	15.41	20.04
R ≤ 1	R > 1	68.74763	3.76	6.65
R ≤ 2	R > 2	-		
λ Max Tests	**λ Max Tests**	**λ Max Values**	**5%**	**1%**
r = 0	r = 1	315.4679	14.07	18.63
r = 1	r = 2	68.74763	3.76	6.65
r = 2	r = 3	-	-	-

Note: r refers to number of cointegrating vectors.

Table 9
Cointegration analysis: GARCH variance (BSE 100 Index and exchange rate)

Null Hypothesis	Alternative Hypothesis	04.01.1993 to 31.12.2003	Critical Values	
λ Trace Tests	**λ Trace Tests**	**λ Trace Values**	**5%**	**1%**
R = 0	R > 0	343.3943	15.41	20.04
R ≤ 1	R > 1	54.99429	3.76	6.65
R ≤ 2	R > 2	-		
λ Max Tests	**λ Max Tests**	**λ Max Values**	**5%**	**1%**
r = 0	r = 1	288.4000	14.07	18.63
r = 1	r = 2	54.99429	3.76	6.65
r = 2	r = 3	-	-	-

Note: r refers to number of cointegrating vectors.

Table 10
Cointegration analysis: EGARCH variance (BSE 100 Index and exchange rate)

Null Hypothesis	Alternative Hypothesis	04.01.1993 to 31.12.2003	Critical Values	
λ Trace Tests	**λ Trace Tests**	**λ Trace Values**	**5%**	**1%**
R = 0	R > 0	372.2418	15.41	20.04
R ≤ 1	R > 1	65.92051	3.76	6.65
R ≤ 2	R > 2	-		
λ Max Tests	λ Max **Tests**	**λ Max Values**	**5%**	**1%**
R = 0	R = 1	306.3213	14.07	18.63
R = 1	R = 2	65.92051	3.76	6.65
R = 2	R = 3	-	-	-

Note: r refers to number of cointegrating vectors.

If we use the λ_{max} statistic, the null hypothesis of no cointegrating vectors (r =0) against the specific alternative r = 1 is already rejected. The calculated value λ_{max} (0, 1) = 294.60 exceed the 5% and 1% critical values. Hence, the null hypothesis is rejected. To test r = 1 against the alternative hypothesis of r = 2, the calculated value of λ_{max} (1, 2) is 64.43 which exceeds the critical values at the 5% and 1% significance levels are 3.76% and 6.65%, respectively. Therefore, there are two cointegrating vectors.

We also find two cointegrating vectors between the volatility series of the return of Sensex and the exchange rates through EGARCH model as shown in Table 8, which implies that there exists a long run relationship between the volatility of return series of Sensex and the India rupee/U.S. dollar exchange rates and both the markets move in tandem with each other.

Tables 9 and 10 report the result of cointegrating relationship of the volatility series of return of BSE 100 Index and the exchange rates through GARCH and EGARCH models, respectively. λ_{max} statistics shows the presence of two cointegrating vectors as the null hypothesis r = 1 is rejected. The result is exactly same in case of cointegrating relationship between the volatility series of return of BSE 100 Index and the exchange rate through EGARCH model for which the results are reported in Table 10. Hence, there exists a long run relationship exist between the BSE 100 Index and the Indian rupee/U.S. dollar exchange rates.

In Tables 11 and 12 we report the result of cointegrating relationship between the volatility series of return of NSE Nifty Index and the exchange rates both through GARCH and EGARCH models, respectively.

λ_{max} statistics shows that there are two cointegrating vectors as the null hypothesis r = 1 is rejected, which implies a long run relationship between S&P CNX Nifty index and Exchange rates.

Table 11
Cointegration analysis: GARCH variance (Nifty Index and exchange rate)

Null Hypothesis	Alternative Hypothesis	04.01.1993 to 31.12.2003	Critical Values	
λ Trace Tests	**λ Trace Tests**	**λ Trace Values**	**5%**	**1%**
R = 0	R > 0	188.1428	15.41	20.04
R ≤ 1	R > 1	52.25685	3.76	6.65
R ≤ 2	R > 2	-		
λ Max Tests	**λ Max Tests**	**λ Max Values**	**5%**	**1%**
R = 0	R = 1	135.8860	14.07	18.63
R = 1	R = 2	52.25685	3.76	6.65
R = 2	R = 3	-	-	-

Note: r refers to number of cointegrating vectors.

Table 12
Cointegration analysis: EGARCH variance (Nifty Index and exchange rate)

Null Hypothesis	Alternative Hypothesis	04.01.1993 to 31.12.2003	Critical Values	
λ Trace Tests	**λ Trace Tests**	**λ Trace Values**	**5%**	**1%**
R = 0	R > 0	121.8705	15.41	20.04
R ≤ 1	R > 1	49.53945	3.76	6.65
R ≤ 2	R > 2	-		
λ Max Tests	**λ Max Tests**	**λ Max Values**	**5%**	**1%**
R = 0	R = 1	72.33107	14.07	18.63
R = 1	R = 2	49.53945	3.76	6.65
R = 2	R = 3	-	-	-

Note: r refers to number of cointegrating vectors.

Finally, in Tables 13 and 14, we report the result of cointegrating relationship of the volatility series of NSE S&P 500 Index and the exchange rates both through GARCH and EGARCH models, respectively. λ_{max} statistics shows two cointegrating vectors and a long run relationship between NSE S&P 500 and the exchange rates. Both markets also move in tandem.[6]

VI. SUMMARY AND CONCLUSIONS

This paper explores the issue of volatility spillovers between the Indian stock and foreign exchange markets. The objective of the paper is to determine if volatility surprises in one market influence the volatility of returns in the other market. We use ARCH school of models such as GARCH (1, 1) and EGARCH (1, 1) for modeling of spillovers between stock returns and exchange rate returns. We find that the volatility in both the markets is highly persistent and predictable on the basis of past innovations. The impact of these innovations is asymmetric.

We also find evidence of bidirectional volatility spillover between the stock market and foreign exchange market except the stock indices such as S&P CNX NIFTY and S&P CNX 500. The findings of the study also suggest that both the markets move in tandem with each other and there is a long run relationship between these two markets.

In general, the results of significant bidirectional volatility spillover suggest that there is an information flow (transmission) between these two markets and both these markets are integrated with each other. These results suggest that investors can predict the behavior of one market by using the information of the other. The long run relationship between these markets also suggests that at least there is a unidirectional causality between two variables in either way. Accordingly, financial managers can obtain more insights in the management of their portfolio affected by these two variables (stock price and exchange rate). This should be particularly important to domestic as well as international investors for hedging and diversifying their portfolio.

ENDNOTES

1. The BSE Sensex or Bombay Stock Exchange Sensitive Index is a value-weighted index composed of 30 stocks with the base April 1979 = 100.
2. BSE-100 is a broader based index of 100 stocks.
3. S&P CNX Nifty is a well diversified 50 stock index accounting for 25 sectors of the economy.
4. The S&P CNX 500 is India’s first broad-based benchmark of the Indian capital market for comparing portfolio returns vis-à-vis market returns. The S&P CNX 500 represents about 92.66% of total market capitalization and about 86.44% of the total turnover on the NSE.
5. In other words, by squaring the lagged error in the conditional volatility equation, the sign is lost.
6. Table 13 and Table 14 have not been included in the paper due to space constraints. Tables are available upon request from authors.

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