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INTERDEPENDENCE OF INTERNATIONAL FINANCIAL MARKETS: THE CASE OF INDIA AND U.S.

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Interdependence of International Financial Markets: The Case of India and U.S.

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ABSTRACT

This paper examines the nexus between domestic and foreign financial markets viz. Indian and U.S. money markets, equity markets and the common market for currency. We estimate volatility, spillovers-both in returns and in volatility, and cross-correlations in a multivariate framework for the financial markets. We utilize weekly data from June, 2000 to September, 2011 to model the interactions among the markets using a VAR(1)–MGARCH[2](1,1) BEKK framework. We formulate an alternative VAR(1)–MGARCH(1,1) EWMA model to examine the robustness of the findings. We also include policy rates viz. effective federal funds rate and reverse repo rate as well as an indicator for the prevalent global investment climate (Federal Reserve of St. Louis' financial stress index) in the analysis.

Domestic spillovers in returns exist from the Indian stock market to the currency market. International spillovers from returns on U.S. stock market to returns on Indian stock market are evident. Further, we find that the economy's policy rate significantly impacts the money market rate. The results also indicate that changes in financial stress index influence U.S. money market rates and returns on both the stock markets.

The study reveals that volatility in all the markets surges post the global financial crisis of 2008-09. Spillovers in volatility across the markets are found to be present due to both innovations effects as well as volatility persistence. In particular, findings for the lagged volatility persistence effects suggest existence of significant bi-directional spillovers across the two stock markets and the currency market. Further, we observe the conditional correlations across assets to be time-varying.

Keywords: Globalization, Volatility, Spillovers across financial markets, BEKK model

JEL Classification: C32, E44, G15

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[2] VAR stands for vector autoregressive, MGARCH stands for multivariate GARCH, BEKK model stands for Baba, Engle, Kraft and Kroner model and EWMA stands for Exponentially Weighted Moving Average model.

1. INTRODUCTION

Global integration of financial markets allows participants to move funds from markets in one country to another. International investors assess the potential portfolio rate of return and the associated risk in financial markets across countries, and finally invest in markets that provide the desired rate of return in accordance with their risk preference. Financial globalization, therefore, entails unification of markets internationally and a convergence of risk-adjusted rates of return on assets with identical maturity period across countries. In the post-1990s phase, there has been an increasing investment preference towards Less Developed Countries (LDCs) and emerging market economies (EMEs) which was aided by financial sector reforms taken up by these countries during the period. The deepening and broadening of financial markets has changed the contours of international investment in financial markets and led to increasingly inter-related movement of capital across borders or increasing integration of financial markets across the world.

India has undergone major institutional and structural changes during the 1990s. Growing integration between various market segments in India has been reflected in the "depth of the market and higher correlation among interest rates"[3]. Indian financial markets have attracted vast capital inflows in the post liberalization phase. Capital flows across borders play a pivotal role in the determination of the exchange rate, which is a key macroeconomic variable for open economies like India. Following the sub-prime crisis in 2008-09, the Rs. vs. USD exchange rate has depreciated considerably, witnessed huge year-on-year changes and has been extremely volatile. From the perspective of the Indian economy, major global events that have taken place post the Liberalization Privatization and Globalization (LPG) phase (of the 1990s) include the East Asian Crisis of 1997-98, opening up of derivative segments for Indian financial markets, and the global financial meltdown of 2008-09 along followed by the subsequent Euro-debt crisis in 2009-10. With the increasing fears of a financial market crisis, as witnessed in 2008-09 as well as 2009-10, global shocks have mounted great pressure on Indian financial markets especially the stock market. The inter-relationship between markets is reinforced by spillovers across different international asset prices. It is important from the perspective of international macro-finance to study the relationship among markets since benefits from diversification are based on the assumption that assets do not, in fact, co-move. Consequently, the issue is important both from the perspective of macroeconomics as well as finance since it involves aspects related to macroeconomic stability and portfolio diversification. The objective of this paper, therefore, is to analyze the relationship and extent of spillovers between stock market, money market and

[3] RBI Report on Currency and Finance (2008), pp. 300

foreign exchange market in India with those of international financial markets represented by the U.S.

According to the theoretical framework by Pavlova and Rigobon (2007), domestic stock market, domestic money market, currency market, foreign stock market and foreign money market are governed by the same set of factors. Further, the existing empirical literature on analysis of interdependence of financial markets has focused on the domestic transmission across various asset classes or international interdependence across the same asset market. There is a scarcity of literature that combines both these aspects under the same framework. The present study is an attempt in this direction. Further, a few studies such as Hakim and McAleer (2009, 2010) have looked at both return and volatility spillovers using variants of MGARCH DCC and CCC specifications. The techniques that have been utilized in the existing literature include GMM estimation, VAR and SVAR-ITH models, cointegration, panel data methods, VAR-MGARCH variants like CCC, DCC and BEKK. The VAR–MGARCH methodology is employed in this paper since it appropriately captures the mean and volatility interdependence as well as the volatility clustering characteristic of financial time series. We use the MGARCH BEKK specification which allows us to capture the direction of impact of shocks and previous volatility spillovers separately. Further, our estimation strategy involves simultaneous estimation of spillovers within domestic, within foreign, and across domestic and foreign financial markets. This is unlike most of the existing studies which focused on bivariate interactions across the markets. We also include key determinants of the markets in our analysis. We believe that we add to the existing literature since there is scant evidence on financial market interdependence for emerging market economies.

We explicitly accounted for the presence of structural breaks, which is characteristic of financial and macroeconomic time series, and henceforth utilized the Lee and Strazicich (2003) test for the stationarity of the variables. We tested for the adequacy of the multivariate ARCH effects and found these to be present in the VAR residuals of the model encompassing the endogenous variables. We then went on to test whether the MGARCH CCC framework is appropriate for the problem at hand using Tse (2000)'s test for constant conditional correlation and found evidence of time-varying conditional correlation among the markets.

The VAR(1)-MGARCH(1,1) BEKK model was formulated and we obtained evidence of existence of spillovers in mean across the markets along with the impact of crucial variables like policy rates and the global investment climate on the endogenous variables. Spillovers in volatility across markets were found to be present due to both innovations effects as well as volatility persistence. We found that volatility in all the markets surged post the recent global financial crisis. Further, the conditional correlations displayed a distinct pattern in the post-global financial crisis phase. The alternative VAR(1)-MGARCH(1,1) EWMA specification enabled us to test for the robustness of the conclusions obtained from the MGARCH BEKK specification and we found evidence regarding some of the results to be corroborated. The estimated volatility and conditional correlations from the alternative specification are similar to those from the MGARCH BEKK except that they are smoother.

The rest of the paper is organized as follows: Section 2 succinctly reviews the existing empirical literature on inter-linkages among financial markets. The theoretical model is presented in the third section. The methodology has been expounded in the fourth section. We present the empirical model and data in section 5. While the next section, i.e. section 6, would deal with the results and inferences of our study. The last section spells out the conclusions.

2. LINKAGES BETWEEN FINANCIAL MARKETS

The vast empirical literature on interdependence of financial markets has primarily focused on-inter-linkages among domestic assets, interdependence of a single asset across borders, international inter-linkages across two assets and finally international interdependence across more than two asset classes. In view of the plethora of studies in the first three categories, we shall not discuss them here for the sake of brevity. Empirical research in the fourth category has been scanty and the present study falls under this bracket.

Amongst papers that investigated only spillovers in returns across various international financial markets are Giovanini and Jorion (1987), and Swanson (2003). Giovanini and Jorion (1987) find that an increase in the interest rate causes an increase in the volatility of foreign exchange returns and stock market returns in the context of the U.S. Further, returns in both the markets are negatively correlated with the nominal rate of interest.

Some of the studies that examine only volatility spillovers, in a multiple asset framework across countries, are McNelis (1993), Bodart and Reding (1999), and Kuper and Lestano (2007). The paper by McNelis (1993) reveals that Australian stock market returns are highly correlated with U.K. stock market returns and volatility among the two markets is closely linked. Bodart and Reding (1999) find significant inter-linkages between bond market and foreign exchange market of European Monetary System (EMS) countries but did not find similar evidence for the stock markets. They conclude that uncertainty associated with the domestic monetary policy affects bond prices, while macroeconomic uncertainty impacts stock prices. Kuper and Lestano (2007) observe financial markets of Thailand and Indonesia to be interdependent but the interdependence is lower during the Asian crisis of the 1990s.

Papers that study spillovers in returns as well as volatility across countries and across assets include Weber (2007), Hakim and McAleer (2009, 2010), and Giannellis and Papadopoulos (2011). Weber (2007) finds that the short-term money markets of a group of Asia Pacific countries are dominated by the U.S. Hakim and McAleer (2009) show that the conditional correlations between bond markets and that between stock markets are relatively constant across developed and emerging markets, while those across emerging markets are dynamic. They also find the conditional correlations between stock and bond markets across developed and emerging markets to be more dynamic as compared with those among the emerging markets. Hakim and McAleer (2010) discover existence of international mean and volatility spillovers across stock, bond and money markets for a sample of countries namely Australia, Japan, New Zealand, Singapore and U.S. Giannellis and Papadopoulos (2011) obtain evidence of the existence of significant volatility spillovers across the exchange market, and the real, monetary and financial sectors of a group of European countries.

Cumby *et al.* (1994), and Flavin and Wickens (2006) utilize asset market linkages to study the issue of optimal portfolio allocation (of investment funds). Furthermore Choi *et al.* (1992), Pavlova and Rigobon (2007) and Ehrmann *et al.* (2011) explore inter-linkages between financial markets in the context of shocks. Ehrmann *et al.* (2011) find that asset prices react strongest to other domestic asset price shocks. Moreover, there are substantial international spillovers, both within and across asset classes for the U.S. and the Euro Area. Studies like Bailey (1989), Fair (2001), Kim *et al.* (2002), Hausman and Wongswan (2006) and Andersen *et al.* (2007) analyze news effects. Bailey (1989) finds that U.S. policy announcements significantly impact Canadian financial markets. Further, equity markets respond to news in a different way depending on the stage of the business cycle. Andersen *et al.* (2007) using data for U.S., German and British financial markets, conclude that U.S. macroeconomic shocks and the business cycle regime drive cross country and domestic asset market returns.

2.1 Estimation Methodology

The sophistication of econometric methodology utilized to study the interdependence of markets has grown over the years. Giovanini and Jorion (1987) used GMM (Generalized Method of Moments) methodology in their study. The paper by McNelis (1993) utilized Kalman Filters and VAR (Vector Autoregression) techniques. Swanson (2003) employed cointegration, while Hausman and Wongswan (2006) have used panel data methods. Andersen *et al.* (2007) used a two-stage estimation technique to discern the news effects. Most of the papers analyzing the issue of return and volatility spillovers across markets resorted to MGARCH formulations. Cumby (1994), Bodart and Reding (1999), Engle (2002), Flavin and Wickens (2006), Kuper and Lestano (2007), Hakim and McAleer (2009, 2010) and, Giannellis and Papadopoulos (2011) have applied MGARCH methodology. Ehrmann *et al.* (2011) utilized a VAR framework for the exercise and imposed important theoretical considerations as restrictions to solve the SVAR (Structural VAR) system. They along with Weber (2007) use the identification through heteroscedasticity (ITH) methodology proposed by Rigobon (2003). The present study employs VAR–MGARCH methodology since it appropriately captures the mean and volatility interdependence as well as the volatility clustering characteristic of financial time series. We use the MGARCH BEKK specification since it allows us to capture the direction of impact of shocks (or innovations or news effects) and previous volatility spillovers (or volatility persistence) separately.

3. THEORETICAL MODEL

There exists a huge body of literature which explores theoretical underpinnings of the relationship between financial markets but very few papers focus on the inter-linkages between them in an international macro-finance context[4]. Pavlova and Rigobon (2007) examine the implications of introduction of demand shocks and goods trade in a standard international asset pricing model. They develop a two-country, two-good model in which the stock prices, bond prices, and exchange rates are governed by the same set of factors and show that these markets are inter-related. They prove that aspects related to international economics or trades have a strong influence on the behavior of asset prices. Other theoretical studies which focus on the inter-linkages between the financial markets include Fama (1981), Geske and Roll (1983), Ma and Kao (1990), Uppal (1993), Zapatero (1995), and Hau and Rey (2006).

A survey of the theoretical linkages (along with standard theories like Uncovered Interest Parity (UIP), International Capital Asset Pricing Model (ICAPM), International Arbitrage Pricing Theory (IAPT) and so on) and in view of these financial markets being governed by the same set of factors viz. supply and demand shocks (Pavlova and Rigobon, 2007), we can express the theoretical model for the markets as follows

Domestic Markets: Money and Stock Markets:

$$i = g(i^*, s^*, s, e, shocks, x_1)$$
$$s = j(i, i^*, s^*, e, shocks, x_2)$$

Foreign Markets: Money and Stock Markets:

$$i^* = f(i, s^*, s, e, shocks, x_3)$$
$$s^* = h(i^*, i, s, e, shocks, x_4)$$

Common Market for Currency:

$$e = k(i^*, i, s^*, s, shocks, x_5)$$

where

i^*-money market rates in the foreign economy

i- money market rates in the domestic economy

s-stock market prices in the domestic economy

s^*-stock market prices in the foreign economy

e-exchange rate between the domestic and foreign currency

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[4] See Pavlova and Rigobon (2010) for details on the international-macro finance theoretical literature

x_i-other exogenous determinants
Therefore, domestic money and stock markets, foreign money and stock markets along with currency markets all affect each other and we model them simultaneously.

Expected Signs

An appraisal of the theoretical literature yields the following expected signs among the variables included in the model-

Table 1a: Expected Signs

	i^*	i	s^*	s	e
i^*	+/-				
i	+/-	+/-			
s^*	+/-	+	+/-		
s	+/-	+/-	+/-	+/-	
e	+/-	+/-	-	+/-	+/-

The expected signs are ambiguous since the relationship between the markets is contingent on whether these are being subject to demand or supply shocks within the framework of Pavlova and Rigobon (2007).

4. METHODOLOGY

The methodology adopted to accomplish the stated objective of this paper is expounded in this section.

4.1 Unit Root Tests

The first step of the econometric methodology is to test if the time series is nonstationary (or difference stationary) or it contains a unit root which is usually the case for asset prices. Various tests have been proposed in the literature to test for the presence of a unit root in the time series. In this paper, we employ the Dickey-Fuller generalized least squares (DF-GLS) test proposed by Elliot *et al.* (1996) which has improved power against the standard augmented Dickey-Fuller (1979, 1981) ADF test. Further, we also utilize the KPSS test proposed by Kwiatkowski *et al.* (1992), and the Lee and Strazicich (2003) minimum LM test for a unit root with a structural break. The null hypothesis of the DF-GLS test is that the series contains a unit root. On the other hand, the KPSS unit root test assumes that the time series is trend stationary under the null hypothesis as opposed to the null of nonstationarity assumed in the ADF or DF-GLS test. It is noteworthy that the KPSS test was put forward to complement the Dickey-Fuller ADF Tests.

4.1.1 Unit Root Tests with Structural Break

Using simulations, Perron (1989, 1990) makes the fundamental point about reduced power of the ADF test when the true data generating process includes a structural change in the trend function. Further, Byrne and Perman (2007) note that despite improved power of the DF-GLS test, it is still susceptible to breaks in the original series. Moreover, Perron (1989) has been criticized for assuming the break date to be exogenous and the choice of the date is, henceforth, considered to be an outcome of data mining by some authors. Subsequent studies like Zivot and Andrews (1992) attempt to identify the break dates endogenously. Endogeneity of the break points has led to a burgeoning literature on the testing for structural breaks and simultaneous estimation of the break points from the data. Another direction in which the research has expanded is testing for multiple breaks. In particular, Lumsdaine and Papell (1997) extend the Zivot and Andrews (1992) methodology to the case with two endogenous breaks. According to Lee and Strazicich (2003), however, the literature on determination of break dates endogenously has ignored that the null hypothesis of a unit root with structural breaks does not necessarily imply an alternative hypothesis of stationarity but rather a unit root without structural breaks. Financial and macroeconomic time series have been empirically observed to have various structural breaks and therefore, we use the Lee and Strazicich (2003) unit root test.

4.1.2 Lee and Strazicich (2003)

Lee and Strazicich propose a two-break minimum LM unit root test with breaks in the level and trend under the null hypothesis which, according to them, conclusively implies trend stationarity under the alternative hypothesis and is based on Schmidt and Phillips (1992) and Amsler and Lee (1995). They have also conducted a simulation study and provided evidence of improved power properties in comparison to Lumsdaine and Papell (1997).
The initial regression equation estimated is as follows

$$y_t = \zeta' Z_t + e_t, t = 1, \dots, T \text{ and } e_t = \beta e_{t-1} + \epsilon_t, \epsilon_t \sim Niid(0, \sigma^2)$$

where Z_t is the vector of exogenous variables depending on the specification i.e. two shifts in level, and two changes in level and trend are considered and T is the total sample.
Break points are estimated from the data and found to be where the LM statistic is minimized. The regression specification is as follows

$$\Delta y_t = \zeta' \Delta Z_t + \phi \tilde{S}_{t-1} + \eta_t, \eta_t \sim iid(0, \sigma_\eta^2)$$
$$\tilde{S}_t = y_t - \widetilde{\psi_x} - Z_t \tilde{\zeta}$$

where $\tilde{\zeta}$ are the coefficients of the regression of Δy_t on ΔZ_t and $\widetilde{\psi_x}$ is given as $y_1 - Z_1 \tilde{\zeta}$ with y_1 and Z_1 as the first observations of y_t and Z_t respectively.
$\tilde{\varphi} = T\tilde{\phi}$ and $\tilde{\tau}$ is the t-statistic testing the null hypothesis of $\phi = 0$.
The Lee and Strazicich (2003) test determines the breakpoints (TB_j) by conducting a grid search as under

$LM_{\varphi} = \underset{\lambda}{Inf}\ \tilde{\varphi}(\lambda)$ and $LM_{\tau} = \underset{\lambda}{Inf}\ \tilde{\tau}(\lambda)$, λ is the vector denoting the location of the breaks.

4.2 Vector Autoregressive Model (VAR)

In the second step, a VAR (Vector autoregressive) model is formulated by selecting the appropriate lag length on the basis of standard lag length selection criteria (AIC, SBC, HQ and F-test) and lag exclusion tests. A time series $\{y_{1t}\}$ may be serially dependent on its past values as well as possibly dependent on different time series like y_{2t}, y_{3t} and so on. This necessitates extension of the univariate analysis to a multivariate framework since such a cross-dependence may be crucial for analyzing and predicting y_{1t}. A time series y_t can be represented as a VAR (Vector autoregressive) model of order 1 in the following way

$$y_t = \phi_0 + A' y_{t-1} + \varepsilon_t$$

where ϕ_0 is a K-dimensional vector and K is the number of variables.
A is a KxK matrix of parameters and $\{\varepsilon_t\}$ is a sequence of serially uncorrelated random vectors with mean zero and unconditional covariance matrix Σ_t which must be positive definite.

4.3 Multivariate ARCH Test

In view of the immense computational burden of estimating MGARCH models it is necessary to ascertain the adequacy of the specification and in the third step, test for MARCH (Multivariate ARCH) effects is conducted on the residuals of the VAR model selected in the above step.
Lütkepohl (2005) presents a test to ascertain if multivariate ARCH effects exist in the residuals of a VAR. The following auxiliary model is considered[5]

$$vech(\varepsilon_t \varepsilon_t') = \beta_0 + C_1 vech(\varepsilon_{t-1}\varepsilon_{t-1}') + \cdots + C_q vech\left(\varepsilon_{t-q}\varepsilon_{t-q}'\right) + error_t$$

where, β_0 is K(K+1) dimensional vector of constants and C_j's are $(\frac{1}{2}K(K+1) \times \frac{1}{2}K(K+1))$ coefficient matrices such that (j=1,…q).
$H_0: C_1 = \cdots = C_q = 0$ i.e. there are no ARCH effects in the VAR residuals
$H_1: C_1 \neq 0\ or\ \ldots or C_q \neq 0$
The LM statistic (obtained from the estimated residuals of the VAR under the assumption of ε_t satisfying standard conditions) is given by-

$$LM_{ARCH}(q) = \frac{1}{2}TK(K+1) - Ttr\left(\hat{\Sigma}_{vech}\hat{\Sigma}_0^{-1}\right) \sim asymptotically \chi^2_{qK^2(K+1)^2/4}$$

[5] Vech (.) means the procedure that converts a matrix into a vector and denotes the half vectorization operator that stacks the elements lower triangular portion of a quadratic (KxK) matrix from the main diagonal downwards in a $\frac{1}{2}K(K+1)$ dimensional vector.

where, $\hat{\Sigma}_{vech}$-residuals covariance matrix estimator based on the auxiliary regression and $\hat{\Sigma}_0$-residuals covariance matrix estimator based on the auxiliary regression with q=0.

4.4.1 Univariate ARCH/GARCH models

Financial data have, in general, been characterized by periods of sporadic disturbances and high volatility. Further, such episodes are clustered and therefore, errors would be serially correlated. The seminal paper by Engle (1982) extends the AR framework for modeling the mean equation to the volatility equation such that the conditional variance is modeled as an AR (autoregressive) process using squares of the estimated errors an ARCH(q)[6]. The conditional variance of a zero mean and serially uncorrelated process ε_t can be represented by an ARCH(q) process as

$$y_t = E(y_t|\mathcal{F}_{t-1}) + \varepsilon_t;\ \varepsilon_t = v_t\sqrt{h_t}$$

$$h_t = Var(\varepsilon_t|\mathcal{F}_{t-1}) = E(\varepsilon_t^2|\mathcal{F}_{t-1}) = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \cdots + \gamma_q\varepsilon_{t-q}^2$$

where, $\mathcal{F}_{t-1} = \{\varepsilon_{t-1}, \varepsilon_{t-2}, ...\}$ is the set of past information on the error or $\varepsilon_t|\mathcal{F}_{t-1} \sim (0, h_t)$ and v_t is white noise or the standardized residuals. Bollerslev (1986) suggests an extension analogous to ARMA (Autoregressive Moving Average) models which improved parsimony. This model is called GARCH(p,q)[7], wherein the conditional variance follows an MA process as well and is specified as

$$h_t = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \cdots + \gamma_p\varepsilon_{t-p}^2 + \varrho_1 h_{t-1} + \cdots + \varrho_q h_{t-q}$$

4.4.2 Heteroscedasticity: Multivariate GARCH (MGARCH)

At a time, the economic variables (or financial markets) may be inter-linked and an increase in the volatility of one market may impact the volatility of the other markets. These scenarios warrant the use of multivariate GARCH models to study the co-movement and spillovers among these asset markets. Despite being intuitively straightforward, generalization of univariate GARCH models to multivariate specifications "involves very large parameter spaces and thus will prove to be analytically and computationally quite demanding" Herwatz (2004, pp. 212). Generalization requires estimation of large number of parameters (curse of dimensionality), estimation problem increasingly becomes complicated leading to convergence issues, needs to ensure that the conditional variances are positive and the implied correlation coefficients lie between -1 and +1. The univariate GARCH model was extended to a multivariate framework by

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[6] ARCH(q) stands for Autoregressive conditional heteroscedastic process of order q

[7] GARCH(p,q) stands for Generalized autoregressive conditional heteroscedasticity with order p and q

Bollerslev *et al.* in 1988. This model came to be known as Vech-GARCH. It is the most generalized specification but was marred by too many parameters to be estimated.

4.4.3 BEKK

The BEKK variant propounded by Baba, Engle, Kraft and Kroner (1989), and Engle and Kroner (1995) considers a quadratic form which is relatively parsimonious and is as follows

$$\mathrm{H}_t = F'F + B_i{}'\varepsilon_{t-i}\varepsilon_{t-i}{}'B_i + G_j{}'\mathrm{H}_{t-j}G_j$$

F-symmetric (KxK) parameter matrix and B_i and G_j-unrestricted (KxK) parameter matrices

A bivariate MGARCH(1,1) BEKK setup has 11 parameters while a corresponding Vech model has 21. Further, in the BEKK process, the variance-covariance matrices are guaranteed to be positive definite under reasonably weak conditions. This specification, allows for cross-equation dynamics among the series. Parameters enter the model via quadratic form and variances are all positive. $h_{11,t}$ depends on squared residuals, cross products of the residuals and the conditional variances and covariances of all variables in the system and the model allows for shocks to the variances of one of the variables to "spillover to the others." Engle and Kroner (1995) discuss the properties of MGARCH BEKK models, particularly, uniqueness, stability and stationarity.

A bivariate MGARCH(1,1) BEKK model is specified as under

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} f_{11} & 0 \\ f_{21} & f_{22} \end{bmatrix} \begin{bmatrix} f_{11} & 0 \\ f_{21} & f_{22} \end{bmatrix}' + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}'$$

Interpretation of BEKK Coefficients

In order to understand the impact of the signs of shocks, we write the above in terms of equations

$$h_{11,t} = f_{11} + \left(b_{11}^2\varepsilon_{1,t-1}^2 + 2b_{11}b_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{21}^2\varepsilon_{2,t-1}^2\right) + (g_{11}^2h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2h_{22,t-1})$$

$$h_{12,t} = h_{21,t} = f_{12} + \left[b_{11}b_{12}\varepsilon_{1,t-1}^2 + (b_{21}b_{12} + b_{11}b_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{21}b_{22}\varepsilon_{2,t-1}^2\right] + [g_{11}g_{21}h_{11,t-1} + (g_{12}g_{21} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1}]$$

$$h_{22,t} = f_{22} + \left(b_{12}^2\varepsilon_{1,t-1}^2 + 2b_{12}b_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{22}^2\varepsilon_{2,t-1}^2\right) + (g_{12}^2h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2h_{22,t-1})$$

Rewriting,

$$b_{11}^2\varepsilon_{1,t-1}^2 + 2b_{11}b_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{21}^2\varepsilon_{2,t-1}^2 \; as \; [b_{11}\varepsilon_{1,t-1} + b_{21}\varepsilon_{2,t-1}]^2$$

And

$$g_{12}^2\varepsilon_{1,t-1}^2 + 2g_{12}g_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + g_{22}^2\varepsilon_{2,t-1}^2 \; as \; [g_{12}\varepsilon_{1,t-1} + g_{22}\varepsilon_{2,t-1}]^2$$

Therefore, b_{11} and b_{22} represent the impact of an own market shock on the future uncertainty of the time series y_{1t} and y_{2t} respectively. While b_{21} can be interpreted as the effect of a shock on

y_{2t} on the future uncertainty of y_{1t} and vice versa for b_{12}. If the signs of $b_{11}\ and\ b_{21}$ are different (same) then shocks with opposite (same) signs in the two series will lead to an increase in the future uncertainty of y_{1t} and shocks with same (opposite) signs will lead to a decrease in the future uncertainty of y_{1t}. Further, g_{12}can be interpreted as the effect of last period's variance in y_{1t} on the current period volatility of y_{2t}. Therefore, the interpretation is similar except that the volatility would always increase[8].

4.4.4 Constant Conditional Correlation Model (CCC) and Dynamic Conditional Correlation Model (DCC)

The second wave of MGARCH models enabled the study of correlation dynamics and not the covariances and includes the MGARCH CCC specification. Bollerslev (1990) suggests keeping the conditional correlations to be constant using a GARCH form for estimating each of the conditional variances. Therefore, the conditional covariances could be derived by using the correlation matrix along with the corresponding conditional standard deviations.

$$H_t = M_t R_t M_t = (\rho_{ij}\sqrt{h_{ii,t} h_{jj,t}})$$

where $M_t = diag(h_{11,t}^{1/2} \dots h_{KK,t}^{1/2})$ is a matrix which is diagonal and contains the time-varying standard deviations on the diagonal. If R_t=R i.e. the conditional correlation coefficient is assumed to be constant overtime or time invariant. $h_{ii,t}$ may be defined as a univariate GARCH model and $R = \rho_{ij}$ is a symmetric and positive definite matrix with $\rho_{ii} = 1, \forall i$ and denotes the constant conditional correlations. However, the assumption of constant conditional correlation may not be appropriate in many economic applications and requires pretesting. Engle (2002) and, Tse and Tsui (2002) generalize the CCC model by proposing the DCC (Dynamic conditional correlation) model such that correlations are time-varying. The DCC model is estimated using a two-step procedure and two additional parameters drive the dynamics of all the correlations. However, Enders (2004, pp. 179) points out that "the estimates are not as efficient as those from one-step procedures such as BEKK (*sic*) and diagonal vech models."

4.4.5 Exponentially Weighted Moving Average Model (EWMA)

One possible method to model univariate conditional heteroscedasticity in a multivariate framework is to use exponential smoothing to assign higher weight to recent shocks and thereby generate a time-varying covariance matrix (Riskmetrics, 1996).

$$h_{ij,t} = (1 - \vartheta)\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \vartheta h_{ij,t-1}$$

The decay factor ϑ is estimated from the data. The model is easy to apply, work with and simple from the perspective of estimation although it imposes similar dynamics on all the series.

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[8] See Wang (2009) for details

4.5 Test for Constant Conditional Correlation

Tse (2000) develops an LM statistic to test for the hypothesis of constant conditional correlation among the variables. He extends the MGARCH CCC model to time-varying correlation specification and then constrains the parameters so as to obtain the CCC specification. The test requires only estimates of the CCC model under the null hypothesis.

$$\rho_{ijt} = \rho_{ij} + \delta_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1}$$
$$h_{ijt} = \rho_{ijt} h_{ii,t}^{-1/2} h_{jj,t}^{-1/2}$$

where δ_{ij} are additional parameters for $1 \leq i < j \leq K$.

Considering Bollerslev (1990)'s CCC model, the hypothesis of Constant Correlation would be-

$H_0\colon \delta_{ij} = 0\ for\ 1 \leq i < j \leq K\ i.e. \frac{K(K-1)}{2}$ independent restrictions.

The (Kx1) score vector is defined as-

$s = \frac{\partial L_T(\theta)}{\partial \theta} = \sum_{t=1}^{T} \frac{\partial L_T(\theta)}{\partial \theta}$, $L_T(\theta)$ is the conditional log likelihood

The (KxK) information matrix is given by

$$V = E\left[-\frac{\partial^2 L_T(\theta)}{\partial \theta \partial \theta'}\right]$$

The LM statistic under the H_0 is $\hat{s}'(\hat{V})^{-1}\hat{s}$, the hats denote evaluation at $\hat{\theta}$ the MLE of the parameters (under the H_0).

Tse proposes replacement of V by the sum of cross-products of the first derivatives of L_T and we will get the test statistic, $LMC = \hat{s}'(\hat{S}'\hat{S})^{-1}\hat{s} \sim asymptotically \chi^2_{(K(K-1)/2}$

where, S=(TxK) matrix the rows of which are the partial derivatives of the log-likelihood function with respect to the vector of parameters $\frac{\partial L_T(\theta)}{\partial \theta'}$. $\hat{S}$ is defined as S evaluated at $\hat{\theta}$.

After testing for whether the second moments display constant conditional correlation (CCC) multivariate GARCH, the final model with the VAR and MGARCH is formulated, analyzed and the multivariate Ljung-Box statistic for the standardized residuals is examined.

5. EMPIRICAL MODEL AND DATA

In view of the estimation methodology described in the previous section, the theoretical model presented in section 3 is formulated as the empirical model which will be estimated and tested. This section contains all the aspects in this regard.

5.1 Empirical Model

We represent the first and second moments of returns in the Indian stock market, U.S. stock market, market for foreign exchange and changes in Indian and U.S. interest rates (money market Treasury bill rates) by a five-dimensional VAR(1)-MGARCH(1,1) BEKK process.

Its general specification has the following form

$$y_t = \alpha + A' y_{t-1} + X_t + \varepsilon_t$$

where $y_t = \begin{pmatrix} i^{US} \\ i^{IND} \\ e \\ s^{US} \\ s^{IND} \end{pmatrix}$ is a 5x1 vector of changes in U.S. Treasury Bill rates, changes in Indian Treasury bill rates , returns on the exchange rate, returns on the U.S. stock market and returns on the Indian stock market. Therefore, the endogenous variables from the theoretical model viz. i*, i, e, s* and s will be represented by i^{US}, i^{IND}, e, s^{US} and s^{IND} hereafter.

y_{t-1} is the corresponding vector of lagged returns

X_t is a vector of exogenous variables which includes dummies for structural breaks and exogenous variables.

The residual vector ε_t of the 5 variables is normally distributed $\varepsilon_t | \mathcal{F}_{t-1} \sim (0, H_t)$, given v_t a white-noise error process and $\varepsilon_t = v_t H_t^{-1/2}$ with its conditional variance covariance matrix given by

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} & h_{14,t} & h_{15,t} \\ h_{21,t} & h_{22,t} & h_{23,t} & h_{24,t} & h_{25,t} \\ h_{31,t} & h_{32,t} & h_{33,t} & h_{34,t} & h_{35,t} \\ h_{41,t} & h_{42,t} & h_{43,t} & h_{44,t} & h_{45,t} \\ h_{51,t} & h_{52,t} & h_{53,t} & h_{54,t} & h_{55,t} \end{pmatrix}$$

The multivariate GARCH (1,1)-BEKK representation proposed by Engle and Kroner (1995) takes the following form

$$H_t = F'F + B'\varepsilon_{t-1}\varepsilon_{t-1}'B + G'H_{t-1}G + D'I_t I_t' D$$

$$I_t = \begin{cases} 1 \; if \; t \in September, 2008 \; onwards \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases}$$

This models the dynamic process of the conditional variance covariance matrix as a linear function of its own past values as well as own and cross products of past innovations, allowing for own-market and cross-market influences in the conditional variances. The parameters are given by F, which is restricted to be upper triangular and the three matrices B, G and D[9].

The alternative specification for the conditional variance matrix is the MGARCH(1,1) EWMA, specification which also incorporates the cross-market influences, is formulated as under

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[9] Engle and Kroner (1995) have considered exogenous regressors in their original formulation and deem all the proofs would be the same in the presence of exogenous regressors in the variance-covariance equations.

$$H_t = (1-\vartheta)\varepsilon_{t-1}\varepsilon_{t-1}' + \vartheta H_{t-1}$$

ϑ is the decay factor, which will be estimated from the data.

5.2 Data

In order to fulfill the objective of this paper, secondary data at weekly frequency from various sources have been collected and used. The sample under study is from June, 2000 to September, 2011. Table 2 indicates the sources of data used in the analysis. We have utilized the time series data for the stock, money and currency markets in U.S. and India viz. S&P 500 Index, U.S. 3-months Treasury bills rate, exchange rate[10] (Rs. vs. USD), Indian 91-days Treasury bills rate and S&P CNX Nifty 50 Index. Plots of the variables in the returns form are given in Figures 1 A-E.

In accordance with the theoretical analysis of financial markets and the existing empirical literature, the series for exchange rate (Rs. vs. USD), S&P 500 and Nifty 50 are modelled as the logarithmic first differences, while those for the Indian and U.S. Treasury bill rates are defined as first differences. Moreover, we include dummies for structural breaks in the series which we obtain from Lee and Strazicich (2003) unit root test as it enables us to determine the break points endogenously from the data. The three dummies, namely DTBU, DTBI and DEX, are defined as per Lee and Strazicich (2003) test results for the mean equations of i^{US}, i^{IND} and e respectively. The dummies DSP and DNIFTY have been outlined according to Economic cycle Research Institute (ECRI) downturn cycles during the sub-prime crisis for U.S. and India respectively, and are included in the mean equations for s^{US} and s^{IND}. We have also defined a dummy (i.e. DGFC) to capture the impact of the recent financial crisis on the variance equations. Further, other exogenous variables have also been included in the analysis. In particular, mean equations for the money markets include policy rates namely change in Effective Federal Funds rate (DEFFR) and change in Reverse Repo rate (DRR). The prevalent global investment climate captured by change in the Federal Reserve of St. Louis' Financial Stress Index[11] (DFS), is allowed to influence the equations for i^{US}, s^{US} and s^{IND}. Expected signs for these exogenous variables are given in Table 1b.

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[10] Exchange rate is defined as the rupees per one dollar value and therefore, a rise in the exchange rate signifies a depreciation of the Indian rupee (and an appreciation of the USD).

[11] The Federal Reserve of St. Louis' Financial Stress Index is constructed using the first principal component of 18 weekly series comprising interest rates, yield spreads and other indicators related to global financial markets. It therefore, captures financial stress in U.S. money market and the stock markets appropriately.

Table 1b: Expected Signs

	i^{US}	i^{IND}	s^{US}	s^{IND}	e
DEFFR	+				
DFS	-		-	-	
DRR		+			

6. RESULTS

This section outlines and discusses the results and findings of the analysis undertaken to study the inter-linkages amongst the financial markets.

Table 3 presents the descriptive statistics of the variables in returns form which clearly indicate the presence of univariate ARCH effects in all the endogenous variables. In the first step, we check for the non-stationarity of the variables used in the analysis. In particular, the endogenous variables have been specified in returns form (log first differences for stock and currency markets and first differences for Treasury bill rates) and therefore, we conduct the unit root tests for the variables in this form only. However, the exogenous variables viz. Financial Stress Index, Effective Federal Funds rate and Reverse repo rate have been tested in levels[12] and in first-differences thereafter. Towards this end, we employ the KPSS test, the DF-GLS test and the Lee-Strazicich (2003) unit root tests. The Results of these tests are given in Tables 4-6. If a majority of 2 out of 3 unit root tests imply a nonstationary series then the series is treated as I(1). The tests by majority rule indicate that all the endogenous variables are stationary. The exogenous variables were tested for nonstationarity in levels and they were found to contain a unit root process. Further testing of differences of the exogenous variables corroborates that all these variables are integrated of order one. Reverse repo rate was found to be stationary in levels according to the DF-GLS test but the other two tests indicated otherwise and we therefore, concluded that it is I(1) in levels. Subsequently, the exogenous variables were differenced and utilized for the analysis.

The VAR model with lag 1 is specified after testing for the appropriate lag length using standard lag selection (AIC, SBC, HQ, F-test) and lag exclusion tests[13]. Next, we tested for the presence of multivariate ARCH effects in the residuals of the VAR (1) model. Results indicated presence of multivariate ARCH effects in the residuals (p-value=0.00) as the null hypothesis of no

[12] Results for the level stationarity tests, lag selection and exclusion tests, Test for MARCH and Test for CCC are available with the authors on request.

[13] We find that the lag selection criterion selected lags between 0 and 2 for the VAR model. We subsequently conducted lag exclusion tests for 2 vs. 1 and 1 vs. 0 lags and found lag 1 to be the appropriate lag (p-value=0.23).

multivariate ARCH effects was rejected. Since we find presence of multivariate ARCH effects, the fifth step entails testing for the presence of constant conditional correlation (by specifying a VAR(1)-MGARCH(1,1) CCC model) by employing the test proposed by Tse (2000). The null hypothesis of constant conditional correlation is found to be rejected at 10% level of significance in the data and therefore, we do not consider MGARCH CCC specification for the analysis. This also signifies the existence of time-varying conditional correlation among the series. Sixth, the VAR(1)-MGARCH(1,1) BEKK and the alternative VAR(1)-MGARCH(1,1) EWMA models are specified, estimated and their diagnostics examined.

We have presented estimates of two VAR-MGARCH models which were formulated to capture the dynamics of the series along with other key variables. These are: Model I-VAR(1)-MGARCH(1,1) BEKK and Model II-VAR(1)-MGARCH (1,1) EWMA. It is important to note that the second model is restrictive and the results of this model are meant to serve as a robustness check for the findings of model I as we would like to study the same in the context of alternative assumptions on the MGARCH structure.

Results of VAR(1) with BEKK and EWMA multivariate GARCH specifications are given in Tables 7 and 12 respectively. The volatility plots are given in Figures 2 A-E and the correlation plots are furnished in Figures 3A-J. The diagnostic statistic viz. multivariate Q-statistic for the standardized residuals of models I and II are presented in tables 8 and 13, and indicate the absence of serial correlation in the residuals. Further, we note that the BEKK MGARCH model produced white noise squared standardized residuals.

6.1 Model I: VAR(1)-MGARCH(1,1) BEKK

Mean Spillovers

Estimates of VAR(1)-MGARCH(1,1) BEKK for the mean equations are presented in Table 7. With respect to the spillovers in mean across Indian and U.S. financial markets, we find significant spillovers in mean from returns on Nifty 50 to returns on the exchange rate (Rs. vs. USD) and from returns on S&P 500 to returns on Nifty 50. Further, it is found that the signs and directions are plausible and in conformity with the expected signs presented in section 3. Returns on S&P 500 are positively causal for returns on Nifty 50. Also, an increase in returns on Nifty 50 causes the returns on exchange rate to fall or the exchange rate appreciates in response to the inflow of funds to cash in on the higher return on the Nifty 50. Spillovers in mean from returns on S&P 500 to returns on Nifty 50 and from returns on Nifty 50 to the returns on the exchange rate are also found to be Granger causal (Table 9). We have also controlled for change in financial stress index or the global investment climate in the mean equations for U.S. money market rates and the stock markets. Results indicate that an increase in the financial stress index causes returns on S&P 500 and Nifty 50 to fall. Further, it causes interest rates in the U.S.

Treasury bills market to fall. Moreover, we have incorporated the impact of policy rates on changes in the interest rates in India and U.S. Change in the Effective Federal Funds rate as well as change in the Reverse repo rate have significant and positive impact on changes in interest rates in the two countries. We intend to study the robustness of these results using Model II.

Shock Interdependence

US Money Market-We find that the coefficient b_{21}[14] is significant at 1% level of significance (although the magnitude is small) implying significant impact of the shocks from the Indian Treasury bills market to the U.S. Treasury bills market. However, b_{31}, b_{41} and b_{51} are insignificant and so there do not exist any shock spillovers from other markets. Since both b_{11} and b_{21} have the same sign, we conclude that only when the shocks in the two markets are in the same direction, there is a resultant increase in the volatility of the U.S. Treasury bills market. This is probably because shocks in the same direction indicate a synchronous movement in global money markets and are likely to be significant. However, the magnitude of the effect is found to be negligible.

Indian Money Market-We find that the coefficients b_{12}, b_{32} and b_{52} are insignificant. However, b_{42} and b_{22} are positive and significant at 1% level. The Indian Treasury bills market is affected positively by the past shocks in S&P 500. Therefore, it indicates that shocks in both the markets in the same direction will lead to an increase in the volatility of Indian Treasury bills market. Moreover, b_{42}>b_{22} and so, cross-news sensitivity effects offset the own-news sensitivity effect and could be attributed to the central place accorded to U.S. stock market news by the investors.

Exchange Rate Market- All the cross-market innovation effects are insignificant and therefore, the exchange market seems to respond to only its own-past innovations. It is possible that since the market encompasses trade and financial transactions and is subject to shocks from the real economy, the impact of shocks is internalized within the market.

U.S. Stock Market -It is found that all the markets except the Indian Treasury bills market exert significant cross-news effects on the S&P 500. So, b_{14} is found to be positive and significant at 1% level, b_{24} is insignificant, b_{34} is negative and significant at 1% level and b_{54} is negative and significant at 10% level. The own-news effects of the S&P 500 i.e. b_{44} are significant and positive. Interestingly, innovations in the same direction in the U.S. Treasury bills market increase volatility while those in the opposite direction in the exchange market and Nifty 50 lead to increase in volatility of S&P 500. So, we find that own-country financial market innovations

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[14] b_{ij} measures the degree of lagged and cross innovation from market i to market j.

in the same direction lead to an increase volatility and other country shocks in the opposite direction cause a rise in volatility of S&P 500.

Indian Stock Market-Nifty 50 is found to be the most sensitive to cross-news effects from all the other markets in addition to its own innovation effect. The coefficients indicate that similar to the case of S&P 500, own country financial market shocks in the same direction and other country financial market shocks in the opposite direction lead to a spurt in volatility of Nifty 50. It is found that b_{15} is positive and significant at 1% level, b_{25} is negative and significant at 5%level, b_{35} is negative and significant at 1% level, b_{45} is positive and significant at 5%level and b_{55} is negative and significant at 1% level.

There exists significant asymmetry in the reactions of financial markets to cross-market past news effects. Only S&P 500 and Nifty 50 share bi-directional cross-innovation interdependence. However, $b_{45}>b_{54}$ indicates that news effects from S&P 500 have a higher impact on Nifty 50 than those from Nifty 50 to S&P 500. The degree of own-news sensitivity or ARCH effect, given by b_{ii} is significant for all the markets at 1% level.

Volatility Interdependence

US Money Market -g_{21}[15] (which denotes the impact of past volatility in the Indian Treasury bills market) is found to be significant at 1% level but its magnitude relative to the own volatility effect of the U.S. Treasury bills market i.e. g_{11} is negligible. Further, we find evidence of cross-volatility spillovers from the exchange market to the U.S. Treasury bills market and the coefficient is significant at 1% level. The coefficient for g_{41} is significant at 5% level i.e. S&P 500 also exerts significant cross-volatility effects. Finally, g_{51} the coefficient measuring the cross-volatility from Nifty 50 is also significant at 10% level. Although we find spillovers from the Indian markets to be significant, the magnitude is very small.

Indian Money Market –The only cross-market volatility effect which is significant is g_{42} i.e. the S&P 500 volatility influences volatility of the Indian Treasury bills market. However, the own-volatility effect g_{22} is higher and therefore own-market volatility effects are more important.

Exchange Rate Market-We find that g_{33} is insignificant and so the own-market past volatility effect or GARCH effect is absent. Also, money market cross-volatilities do not seem to impact the exchange rate. It is only affected by the stock market volatilites since both g_{43} and g_{53} are significant at 10% and 1% level respectively. This indicates that the movement of funds

[15] g_{ij} signifies the persistence of conditional volatility between market i and market j.

originating and destined for equity market investment and the volatility thereof, significantly impact volatility of the exchange rate.

U.S. Stock Market –S&P 500 is significantly impacted by the volatility effects from all the markets, captured by the coefficients g_{14}, g_{24}, g_{34} and g_{54} at 1% level. It is interesting to note however that $g_{41}>g_{14}$, $g_{42}>g_{24}$ and $g_{45}>g_{54}$ i.e. the impact of S&P 500 volatility is higher on the volatility of the other markets except the exchange rate market wherein $g_{34}>g_{53}$. This can be attributed to the exchange rate being a key macroeconomic aggregate.

Indian Stock Market-Apart from the U.S. Treasury bills market, the rest of the coefficients i.e. g_{25}, g_{35} and g_{45} are all significant at 1% level. In fact, we find that $g_{35}>g_{53}$ and $g_{45}>g_{54}$ i.e. the volatility spillovers from exchange rate market and S&P 500 are larger than the spillovers from Nifty 50 to these markets. Clearly, the volatility of S&P 500 and exchange rate have a significant bearing on the volatility of Nifty 50.

We also, find that the cross-volatility effects are smaller than own previous period volatility effect for all the markets (except the cross-volatility effect of the currency market is slightly larger than the own volatility effect for the Nifty 50). However, this effect (i.e. GARCH effect) is absent for the currency market.

Further, we tested for impact of the recent global financial crisis on the conditional covariance matrix of asset returns and found the statistic for no impact to be rejected at 1% level of significance (Table 10).

6.2 Model II: VAR(1)-MGARCH(1,1) EWMA

Evidence regarding significant and positive spillovers from returns on S&P 500 to returns on Nifty 50 is corroborated from this model and these are found to be Granger-causal (Table 11). We also find significant impact of change in Financial Stress Index on changes is U.S. Treasury bill rates, returns on S&P 500 and returns on Nifty 50. Further, policy rates continue to influence the Treasury bill rates in both U.S. and India significantly and positively. However, the conclusion regarding negative spillovers from returns on Nifty 50 to the returns on the exchange rate does not seem to hold.

6.3 Volatility Plots

The volatility plots estimated from VAR(1)-MGARCH(1,1) BEKK and VAR(1)-MGARCH(1,1) EWMA have been shown in Figures 2A-E. It may be observed that the volatility in all the markets surged during the recent financial crisis. Also, it is interesting to note that the volatility in the money markets and the stock markets was rising even before the Lehman Brothers' bankruptcy in September, 2008. In particular, these markets seem to have been more volatile after the housing bubble burst of 2007 in the U.S. However, these markets have possibly recovered from the high uncertainty prevalent during the crisis. On the other hand, the volatility of the currency market has continued to remain high.

6.4 Correlation Plots

Conditional correlation plots amongst the markets estimated from Models I and II are presented in Figures 3A-J. We find the plots generated by the MGARCH EWMA specification are smoother than those generated by the MGARCH BEKK specification. Further, we find the conditional correlation in all the markets to be time-varying. Moreover, the time-varying correlation between assets has bearing on the allocation of assets in a portfolio and risk management especially from the perspective of diversification.

No clear pattern is discernible for the conditional correlations in Figures 3A, 3E, 3F and 3G. The conditional correlation between U.S. Treasury bill rates and the exchange market (Figure 3B) is positive in the post-crisis phase especially since the beginning of 2009. This is possibly due to the mild rise in U.S. Treasury bill rates being accompanied by the depreciating Rupee. The conditional correlation between U.S. Treasury bill rates and returns on Nifty 50 were positive during the worst phase of the crisis since both interest rates and stock returns were falling (Figure 3D). Further, the conditional correlation between U.S. Treasury bill rates and returns on the stock markets (Figures 3C and 3D) has been negative since 2009. This may be attributed to a flight to safety phenomenon since the recovery phase has been marred by high uncertainty in the financial markets. This has generated huge demand for the U.S. Treasury bills and kept their yield rates subdued while the stock market returns have been volatile. The conditional correlation between the exchange rate and the stock markets (Figures 3H and 3I) has been negative in the post-crisis period. This is possibly due to the role played by FIIs (Foreign Institutional Investors) in this period wherein whenever the stock market returns fell, huge FII outflow triggered depreciation of the Rupee simultaneously. Since the stock markets themselves have been very closely inter-related in the aftermath of the crisis, a similar conditional correlation pattern is observed in Figure 3H as well. Finally, in Figure 3J, the conditional correlations among the stock markets fell from mid-2007 till mid-2008 possibly due to the U.S. stock market reacting more swiftly to the housing bubble burst. The Indian stock market followed suit but with a lag initially and so the correlations spiked during the Lehman Brothers' bankruptcy and then fell down for a brief period. However, in the recovery phase the two stock markets have been more closely linked than any other period post-2000.

6.5 Inferences

Implications of the analysis elicited from the results of the paper are discussed in this section.

We have found a negative and significant impact of returns on Nifty 50 on the exchange rate returns. This is a possible outcome of the foreign portfolio inflows which seek the higher returns on Nifty 50. The, thus, resultant capital inflow may cause the exchange rate to appreciate and returns on the same to fall. Considering the magnitude of FII (Foreign Institutional Investment) inflows to India, this is not a surprising result. However, we do not find this relationship to be robust to change in the MGARCH specification.

We also find that there exist significant and positive spillovers from returns on S&P 500 to the returns on Nifty 50 which are robust to change in the MGARCH specification. This is because U.S. stock markets are leaders and most emerging, developing and developed stock markets are followers. Similar evidence has been found by Swanson (2003) and Ehrmann *et al.* (2011).

Further, the change in Financial Stress Index has significant negative impact on changes in U.S. Treasury bills rate, returns on S&P 500 as well returns on Nifty 50. The Financial Stress Index is an indicator of the global investment climate and captures global risk attitude, financial conditions and in particular the strain exerted on financial markets by global developments. This indicates that deterioration of the investment climate leads to a fall in the demand for risky financial assets and therefore, their returns also dwindle. However, worsening of the investment climate causes higher demand for less risky assets like U.S. Treasury bills. This causes the Treasury bill prices to rise and their corresponding yield rates to fall.

Finally, we find both the policy rates in U.S. as well as in India viz. change in Effective Federal Funds rate and Reverse Repo rate exert positive and significant impact on the respective changes in Treasury bill rates. Bodart and Reding (1999) find that monetary policy significantly affects the bond markets and macroeconomic uncertainties affect the stock market. Therefore, there exists a critical role for policy, and money market rates are to a great extent policy determined.

Significant evidence is found in support of the hypothesis that breakout of the recent financial meltdown has impacted the conditional covariance matrix of the asset returns. The post crisis uncertainty stirred the markets and the volatility of asset returns soared. The beginning of the crisis was marked by the declaration of bankruptcy by Lehman Brothers in September, 2008. The subsequent phase has, in fact, been marred by huge uncertainty for the investors in view of the impending Euro-debt crisis in 2009 and rekindling of fears again many times.

We find evidence of substantial spillovers in volatility across the financial markets and similar results have been found by Hakim and McAleer (2010) and Giannellis and Papadopoulos (2011).

Ehrmann *et al.* (2011) suggested that asset prices react strongest to the shocks originating within the economy. We find that the volatility in both the stock markets rises in response to domestic shocks in the same direction. The results confirm the supremacy of US stock markets as a driver of global financial markets as the innovation or news effects originating therein significantly impact the currency, Indian money market and Indian stock market. Furthermore, relationship of the currency market with the two stock markets is marked by existence of significant bi-directional volatility spillovers. Significant volatility spillovers across stock markets were also found by McNelis (1993).

7. CONCLUSIONS

This paper examines the nexus between domestic and foreign financial markets viz. Indian and U.S. money markets, equity markets and the common market for currency. We estimate volatility, spillovers-both in returns and volatility, and cross-correlations in a multivariate framework for the financial markets. Weekly data from June, 2000 to September, 2011 are utilized to model the interactions among the markets using a VAR(1)–MGARCH(1,1) BEKK framework. We also formulate an alternative VAR(1)–MGARCH(1,1) EWMA model to examine the robustness of the findings.

Domestic spillovers in returns exist from the Indian stock market to the currency market and cause the latter to appreciate in response to higher returns on the Indian stock market. Positive international spillovers from returns on U.S. stock market to returns on Indian stock market are evident. However, in the alternative specifications, only the inference regarding spillovers from U.S. stock market returns to Indian stock market returns is corroborated. Further, we find that change in the economy's policy rate exerts a positive impact on the change in money market rates in the respective countries and the same is validated in the alternative specification. We also find that changes in financial stress index influence changes in U.S. money market rates and returns on both the stock markets negatively. This indicates that investors substitute stock market assets for money market assets as the global investment climate deteriorates.

We find that volatility in all the markets surged post the recent global financial crisis. Amongst the volatility spillovers, all the markets display sensitivity towards own innovations and previous period volatilities except the currency market which only displays ARCH effects. There exist significant cross market news effects originating from the U.S. money market to the U.S. stock and the Indian stock market, and significant cross-volatility effects to the U.S. stock market. Similarly, innovations in Indian money market are found to impact the Indian stock market. Cross volatility effects from the Indian money market to all the other markets (except the currency market) are significant but are negligible in magnitude. Shocks originating in the U.S. stock market significantly impacted the currency market, Indian money market and Indian stock market. Cross-market volatility effects from S&P 500 to the other four markets are significant. The currency market is impervious to shocks from all other markets but impacts both the stock markets and the U.S. money market. In addition, significant cross volatility effects are also found from the Indian stock market to three of the other markets (barring the Indian money market). Findings for the lagged volatility persistence effects suggest existence of significant bi-directional spillovers across the two stock markets and the currency market. Shocks in the same direction across all markets within a country tend to increase the volatility of the stock markets. Further, the conditional correlations across assets are found to be time-varying. The paper finds evidence of the two stock markets and the currency market being closely inter-linked and presence of spillovers both in returns and volatility persistence across these markets.

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TABLES

Table 2: Sources of Data

Variable Name	Source
S&P CNX Nifty Index	NSE website: www.nseindia.org
S&P 500 Index	Federal Reserve of St. Louis; http://research.stlouisfed.org
Exchange rate (Rs v/s USD)	Federal Reserve of St. Louis; http://research.stlouisfed.org
Indian Treasury Bill Rates (91-days)	RBI website: www.rbi.org.in
U.S. Treasury bills (3 months)	Federal Reserve of St. Louis; http://research.stlouisfed.org
Effective Federal Funds Rate	Federal Reserve of St. Louis; http://research.stlouisfed.org
Reverse Repo Rate	RBI website: www.rbi.org.in
Financial Stress Index	Federal Reserve of St. Louis; http://research.stlouisfed.org

Table 3: Descriptive Statistics of returns

	i^{US}	i^{IND}	**e**	s^{US}	s^{IND}
Mean	-0.0094	-0.0008	0.0002	-0.0004	0.0022
Variance	0.0114	0.0487	0.0001	0.0005	0.0010
Standard Deviation	0.1066	0.2208	0.0072	0.0217	0.0317
Maximum	0.59	2.0193	0.0323	0.0831	0.1637
Minimum	-0.98	-1.5017	-0.04331	-0.1528	-0.1481
ARCH LM Test (lag=1)	24.831***	4.290**	23.020***	32.324***	7.452***

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively.

Table 4: Unit Root Test Results- DF-GLS and KPSS Tests (Constant and Trend)

DF-GLS Test: H_0 is that there exists a unit root or nonstationarity
KPSS Level Stationarity Test: H_0 is stationarity or absence of a unit root

VARIABLE	DF-GLS STATISTIC	DF-GLS: INFERENCE	KPSS STATISTIC	KPSS: INFERENCE
i^{US}	-3.618861***	I (0)	0.305480***	I (1)
i^{IND}	-13.60198***	I (0)	0.066917	I (0)
e	-17.91507***	I (0)	0.080078	I (0)
s^{US}	-9.806870***	I (0)	0.104613	I (0)
s^{IND}	-10.00936***	I (0)	0.069352	I (0)
DEFFR	-4.322631***	I (0)	0.365566***	I (1)
DRR	-9.181844***	I (0)	0.049926	I (0)
DFS	-6.655273***	I (0)	0.058941	I (0)
		Critical Values		
10%	-2.570000		0.119000	
5%	-2.890000		0.146000	
1%	-3.480000		0.216000	

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively.

Table 5: Lee-Strazicich Unit Root Test for Structural Change

VARIABLE	TREND BREAK MODEL	CRASH MODEL	INFERENCE
i^{US}	-22.3697***	-19.0686***	I (0)
i^{IND}	-22.9458***	-23.2171***	I (0)
e	-19.9376***	-18.2421***	I (0)
s^{US}	-21.5943***	-20.0118***	I (0)
s^{IND}	-20.4555***	-16.1441***	I (0)
DEFFR	-29.4736***	-29.0150***	I (0)
DRR	-17.7335***	-17.6317***	I (0)
DFS	-18.9430***	-16.6645***	I (0)
	Critical values		
CRASH MODEL	1%	5%	10%
LM_{τ}	-4.545	-3.842	-3.504
TREND BREAK MODEL		λ_2	
λ_1	0.4	0.6	0.8
0.2	-6.16, -5.59, -5.27	-6.41, -5.74, -5.32	-6.33, -5.71, -5.33
0.4	-	-6.45, -5.67, -5.31	-6.42, -5.65, -5.32
0.6	-	-	-6.32, -5.73, -5.32

Note: Critical values are at the 1%, 5% and 10% levels, respectively. λ_j denotes the location of breaks.

Table 6: Unit Root Test Results: Summary

VARIABLE	DFGLS	KPSS	LEE-STRAZICICH	CONCLUSION
i^{US}	I(0)	I (1)	I(0)	I(0)
i^{IND}	I(0)	I (0)	I(0)	I(0)
E	I(0)	I (0)	I(0)	I(0)
s^{US}	I(0)	I (0)	I(0)	I(0)
s^{IND}	I(0)	I (0)	I(0)	I(0)
DEFFR	I(0)	I (1)	I(0)	I(0)
DRR	I(0)	I (0)	I(0)	I(0)
DFS	I(0)	I (0)	I(0)	I(0)

Table 7: Estimation Results- VAR(1)-MGARCH(1,1) BEKK

Estimated coefficients for conditional mean return equations (Robust s.e.)										
	i^{US} (i=1)		**i^{IND} (i=2)**		**e (i=3)**		**s^{US} (i=4)**		**s^{IND} (i=5)**	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
Constant	0.00062	0.00146	0.01565**	0.00775	-0.00015	0.0002	0.00134**	0.00064	0.00271***	0.00099
DEFFR	0.06258***	0.02297								
DTBU	-0.08940**	0.04153								
DFS	-0.14437***	0.03003					-0.11580***	0.01001	-0.03170***	0.00763
DTBI			-0.08228***	0.01885						
DRR			0.28225***	0.05630						
DEX					0.00373 ***	0.00086				
DSP							0.00060	0.00090		
DNIFTY									-0.00662***	0.00215
ai1	0.27193***	0.05129	-0.02762	0.08724	0.00268	0.00213	-0.00560	0.00821	0.00200	0.01088
ai2	0.00545	0.01562	0.14595***	0.05032	-0.00111	0.00102	0.00167	0.00296	-0.00032	0.00410
ai3	0.19536	0.22444	-1.57196	1.03310	0.32032***	0.04942	0.03553	0.08676	-0.050558	0.15506
ai4	-0.10864	0.08302	0.10181	0.29939	-0.00715	0.00806	0.02185	0.03200	0.16928***	0.04931
ai5	-0.06536	0.05116	-0.30749	0.21521	-0.01110*	0.00674	0.00130	0.01666	0.18579***	0.03997

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively.

Table 7: Estimation Results- VAR(1)-MGARCH(1,1) BEKK [continued]

	Estimated coefficients for variance covariance equations									
	i^{US} **(j=1)**		i^{IND} **(j=2)**		**e (j=3)**		s^{US} **(j=4)**		s^{IND} **(j=5)**	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
f1j	0.00895 ***	0.00199								
f2j	0.01444	0.00929	-0.04251***	0.00871						
f3j	0.00066	0.00076	0.00056	0.00066	-0.00277***	0.00047				
f4j	-0.00045	0.00062	-0.00006	0.00052	0.00142***	0.00047	-0.00118***	0.00046		
f5j	-0.00089	0.00105	0.00351**	0.00140	0.00147	0.00117	0.00381***	0.00097	-0.00000	0.00075
b1j	0.46524***	0.05886	0.07881	0.10406	0.00550	0.00511	0.02557***	0.00813	0.03575***	0.01071
b2j	0.03026***	0.01074	0.35880***	0.05844	0.00120	0.00204	-0.00237	0.00193	-0.01054**	0.00489
b3j	0.33463	0.24507	-1.39189	2.05756	0.76682***	0.12214	-0.40885***	0.10130	-1.14258***	0.21502
b4j	-0.13948	0.11700	1.18756***	0.38343	0.01507	0.01324	0.26076***	0.03791	0.12116**	0.05723
b5j	0.07114	0.06623	-0.13973	0.17647	-0.00030	0.01574	-0.02686*	0.01468	-0.17035***	0.04135
g1j	0.90142***	0.01812	-0.03602	0.04064	-0.00296	0.00251	-0.01104***	0.00264	-0.00032	0.00268
g2j	-0.01015***	0.00348	0.90505***	0.02177	-0.00031	0.00101	0.00313***	0.00104	0.00907***	0.00222
g3j	-0.84411***	0.25084	1.47790	2.24807	-0.03737	0.16927	0.71785***	0.06610	1.02272***	0.29051
g4j	0.07338**	0.03252	-0.59909***	0.13502	0.02402*	0.01309	0.91155***	0.01018	-0.08216***	0.02440
g5j	-0.04250*	0.022393	-0.01220	0.14294	-0.04564***	0.00938	0.06353***	0.00658	1.01881***	0.01439

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively. We have also controlled for crisis in the conditional variance covariance equations. Note that fijs are symmetric. Standard errors are robust HAC corrected.

Table 8: Diagnostic Checking Multivariate Q-statistic (Lags selected is 6 by rule of thumb for LB Q-stat)

(a) Multivariate Q-Statistic for standardized residuals		**(b) Multivariate Q-Statistic for squares of standardized residuals**	
Test Statistic	153.36	**Test Statistic**	150.96
Degrees of Freedom	150	**Degrees of Freedom**	150
p-value	0.40870	**p-value**	0.46257

Table 9: Tests for causality in mean for VAR(1)-MGARCH(1,1) BEKK

Null Hypothesis	**t-statistic** (p-value)	**Conclusion**
No Causality from s^{US} to s^{IND}	3.43 (0.00)***	Reject H_0
No Causality from s^{IND} to e	-1.65 (0.09)*	Reject H_0

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively.

Table 10: Tests for DGFC

	Test for the impact of DGFC on the covariance matrix in MGARCH BEKK
Test Statistic (χ^2_{15})	373.89
p-value	0.000

Table 11: Tests for causality in mean for VAR(1)–MGARCH(1,1) EWMA

Null Hypothesis	**t-statistic** (p-value)	**Conclusion**
No Causality from s^{US} to s^{IND}	3.94 (0.00)***	Reject H_0

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively.

Table 12: Alternative Specification- VAR(1)–MGARCH(1,1) EWMA

Estimated coefficients for conditional mean return equations (Robust s.e.)										
	i^{US} **(i=1)**		i^{IND} **(i=2)**		**e (i=3)**		s^{US} **(i=4)**		s^{IND} **(i=5)**	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
Constant	0.00370	0.00229	0.02208**	0.00937	-0.00009	0.00014	0.00094	0.00065	0.00166***	0.00093
DEFFR	0.04261	0.02790								
DTBU	-0.07016***	0.02042								
DFS	-0.21878***	0.06645					-0.08896***	0.01317	-0.02830**	0.01319
DTBI			-0.08610***	0.02568						
DRR			0.23557***	0.05662						
DEX					0.00176	0.00134				
DSP							0.00138	0.0001		
DNIFTY									-0.00167	0.00401
ai1	0.23210***	0.05893	-0.00121	0.10056	-0.00014	0.00154	-0.01259	0.00802	-0.01089	0.01292
ai2	-0.00018	0.02314	0.14999***	0.04574	0.000364	0.00067	0.00182	0.00274	0.00739	0.00474
ai3	0.24486	0.31839	0.58760	1.16212	0.34786***	0.04756	0.10726	0.09763	-0.06353	0.14117
ai4	-0.15162	0.13046	-0.22952	0.30494	0.00100	0.00479	0.04814	0.04297	0.18211***	0.04923
ai5	-0.08359	0.12570	0.43478	0.31703	-0.00514	0.00581	-0.002330	0.02235	0.19539***	0.04954

Variance-Covariance Equation	
Estimated Coefficient (ϑ)	0.05578***
Standard Error	0.00387

Note: *,** and *** indicate significance at 10%, 5% and 1% respectively. We have also controlled for crisis in the conditional variance covariance equations. Standard errors are robust HAC corrected.

Table 13: Diagnostic Checking

	Multivariate Q-Statistic for standardized residuals
Test Statistic	168.20
Degrees of Freedom	150
p-value	0.14701

FIGURES

Figure 1A: Plot of weekly change in yield rate on U.S. Treasury bills

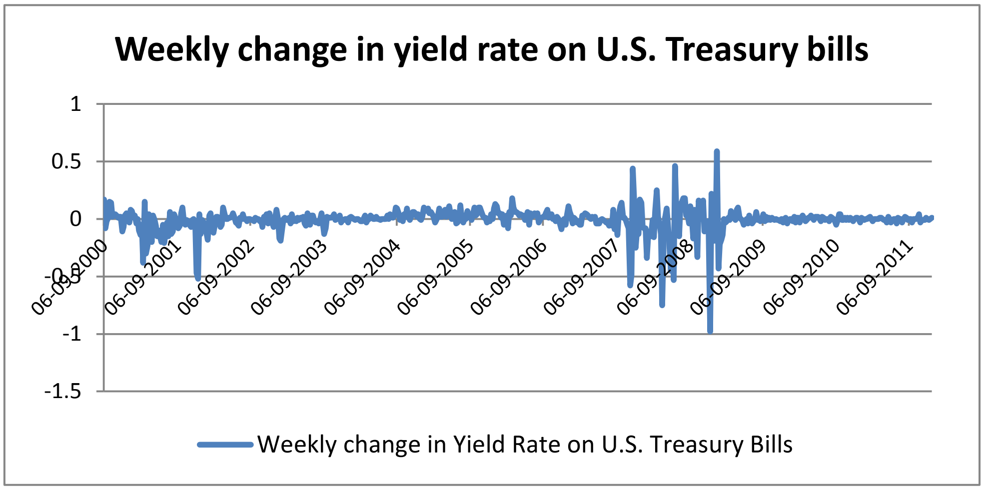


Figure 1B: Plot of weekly change in yield rate on Indian Treasury bills

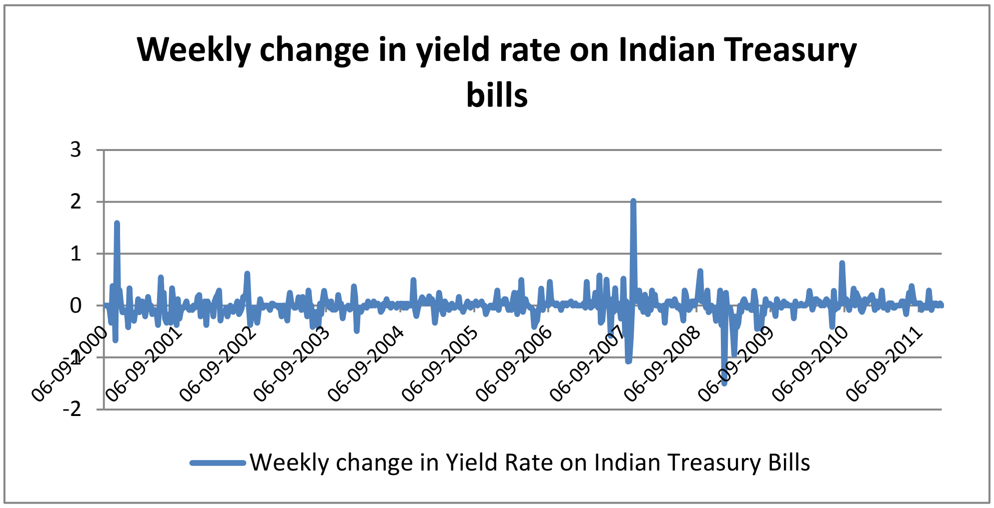


Figure 1C: Plot of weekly returns on Exchange rate (Rs. vs. USD)

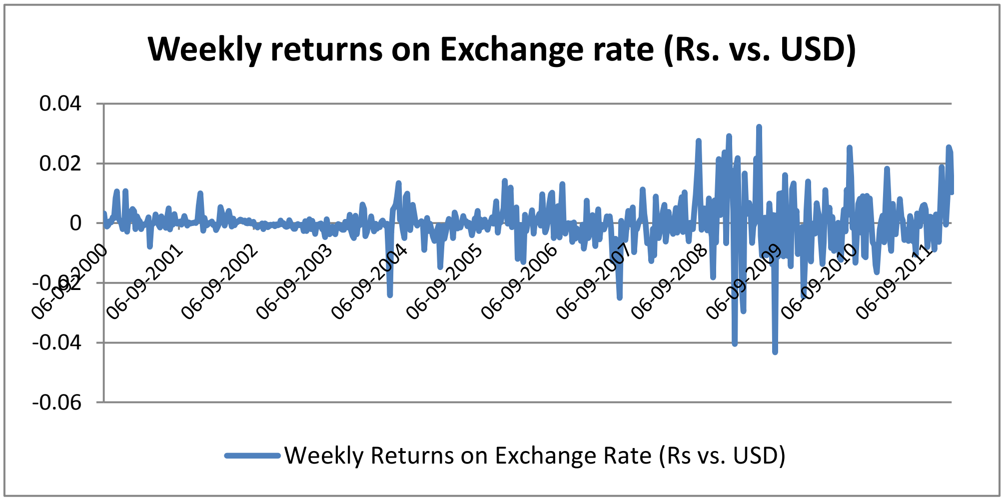


Figure 1D: Plot of weekly returns on S&P 500 Index

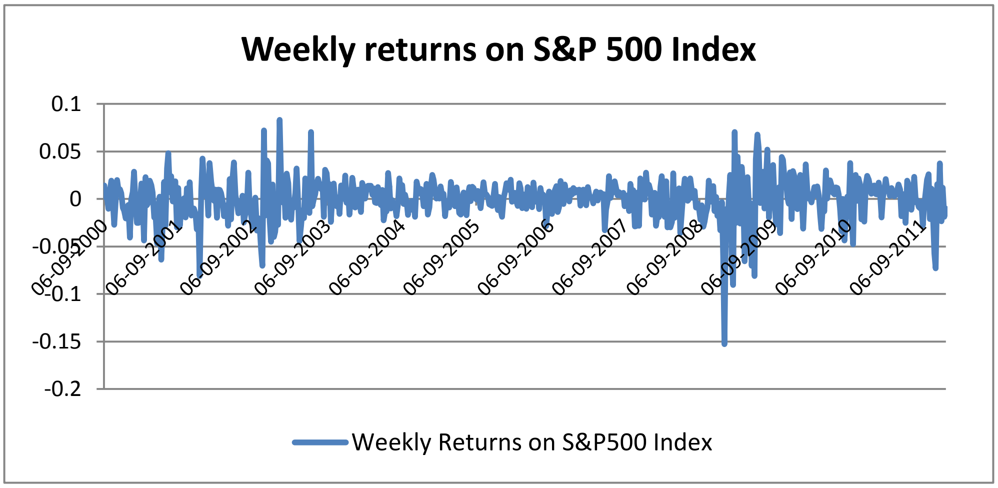


Figure 1E: Plot of weekly returns on S&P CNX Nifty 50 Index

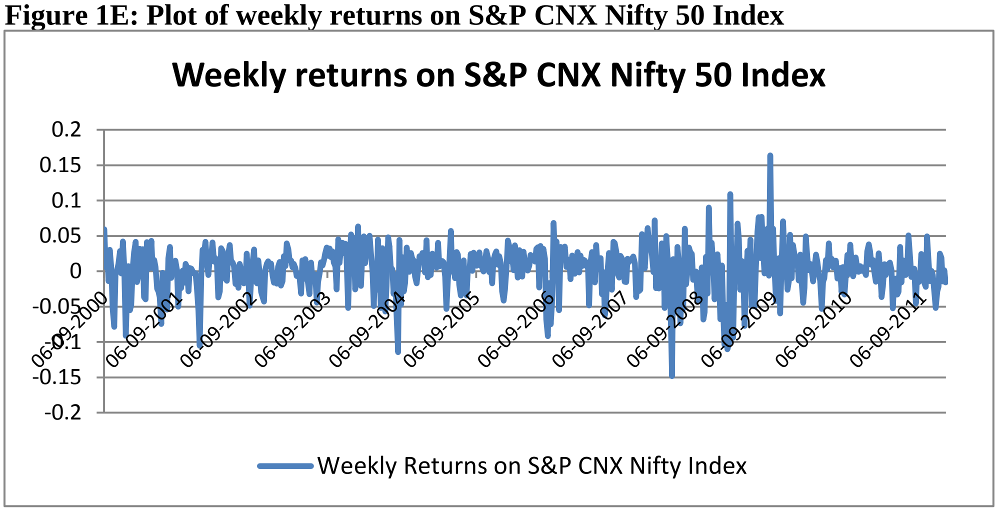
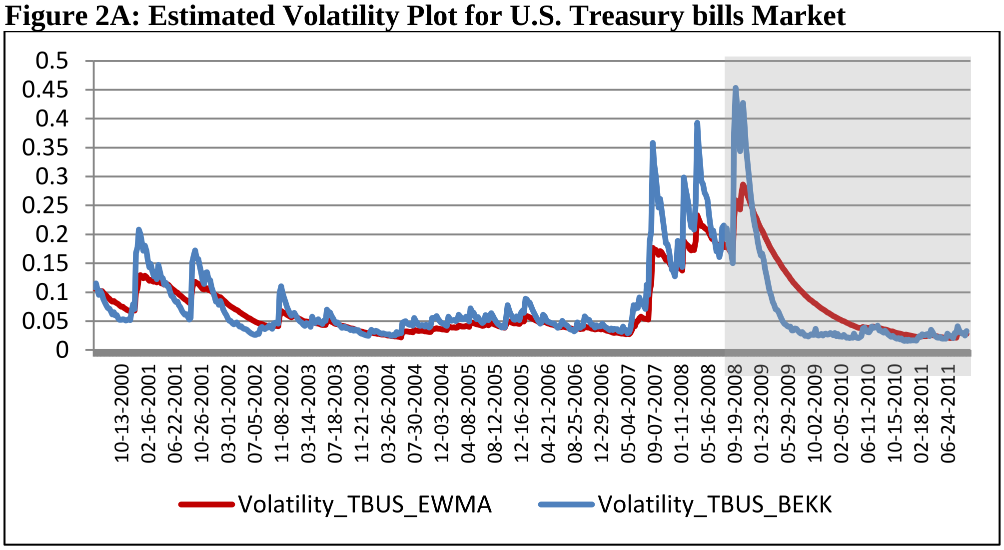
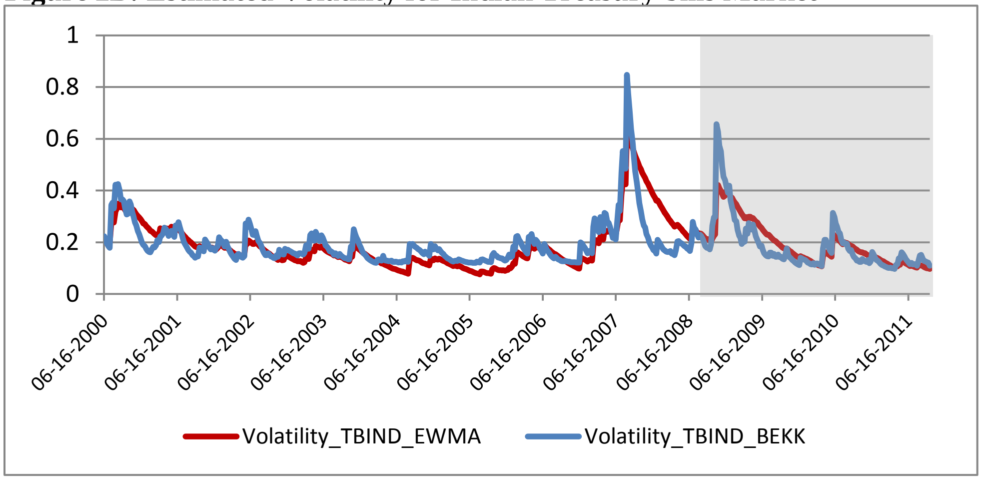


Figure 2A: Estimated Volatility Plot for U.S. Treasury bills Market



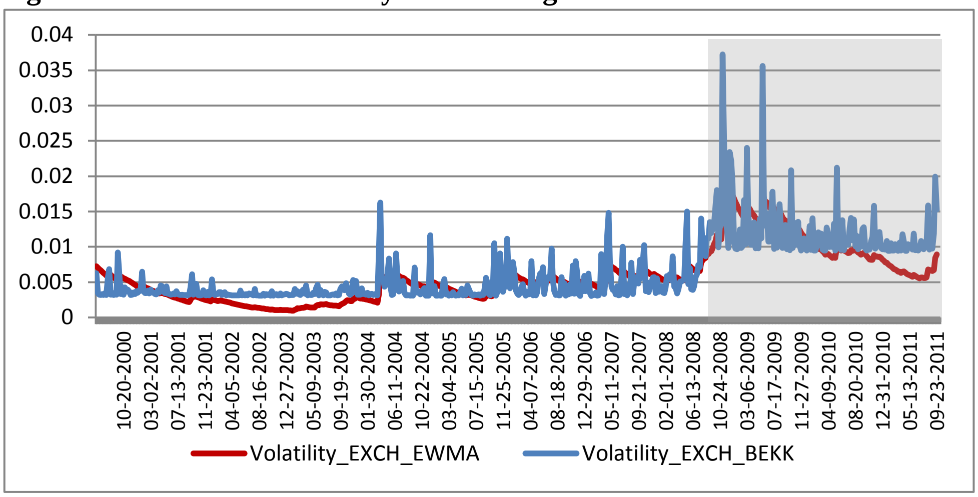
Note: Shaded areas represent the post-global financial crisis phase

Figure 2B: Estimated Volatility for Indian Treasury bills Market



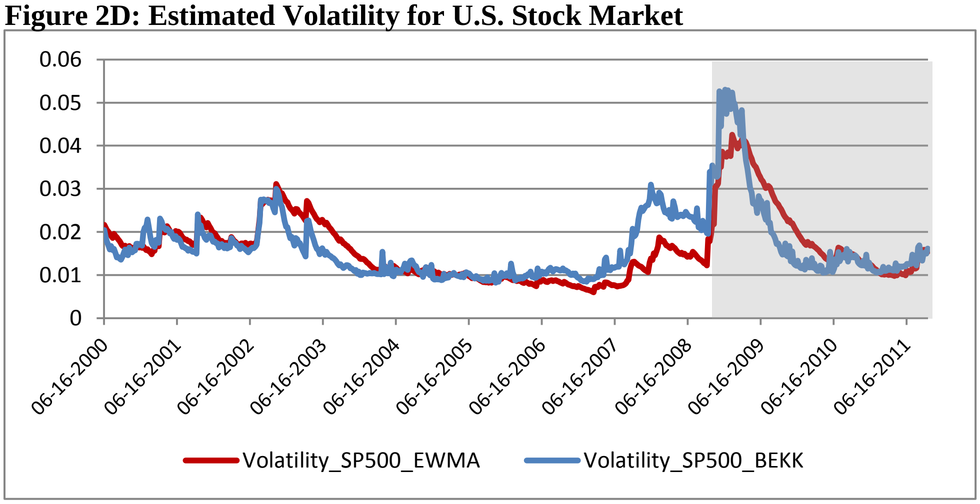
Note: Shaded areas represent the post-global financial crisis phase

Figure 2C: Estimated Volatility for Exchange Rate Market



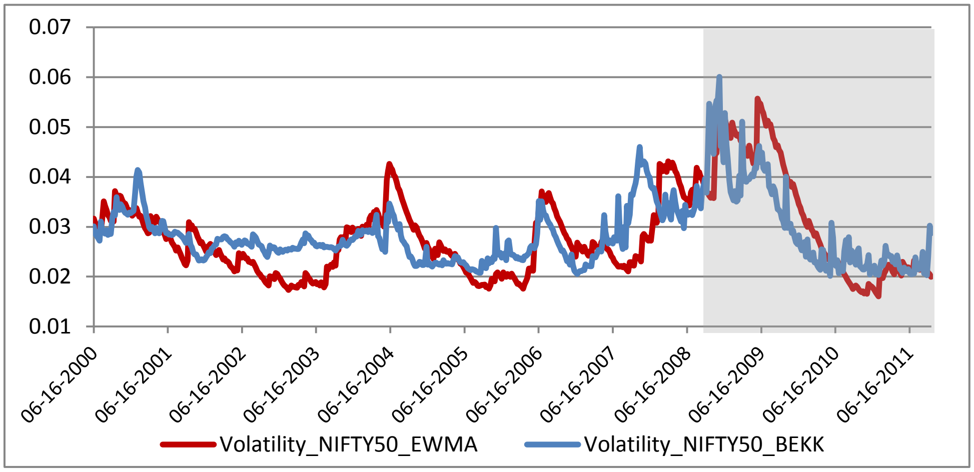
Note: Shaded areas represent the post-global financial crisis phase

Figure 2D: Estimated Volatility for U.S. Stock Market



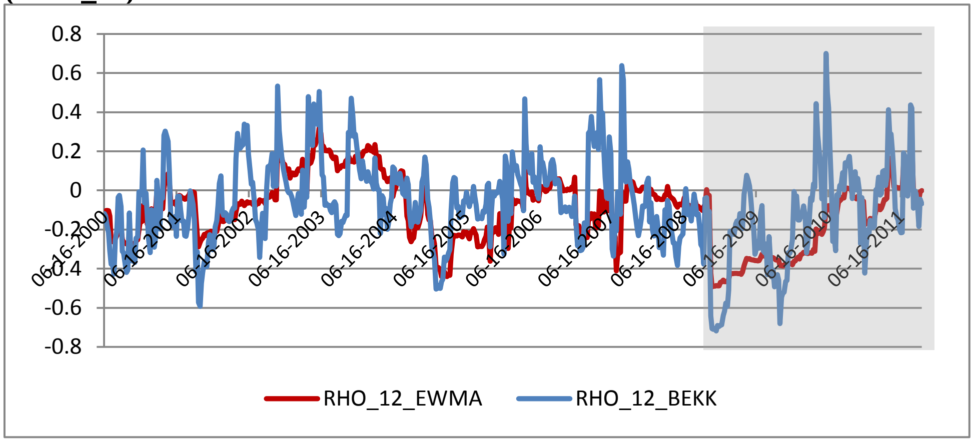
Note: Shaded areas represent the post-global financial crisis phase

Figure 2E: Estimated Volatility for Indian Stock Market



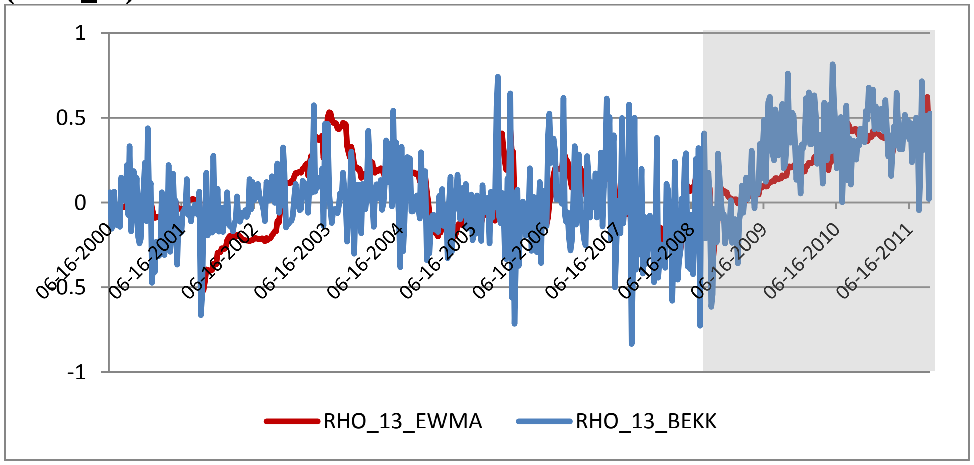
Note: Shaded areas represent the post-global financial crisis phase

Figure 3A: Conditional Correlation between U.S. Tbills Market and Indian Tbills market (RHO_12)



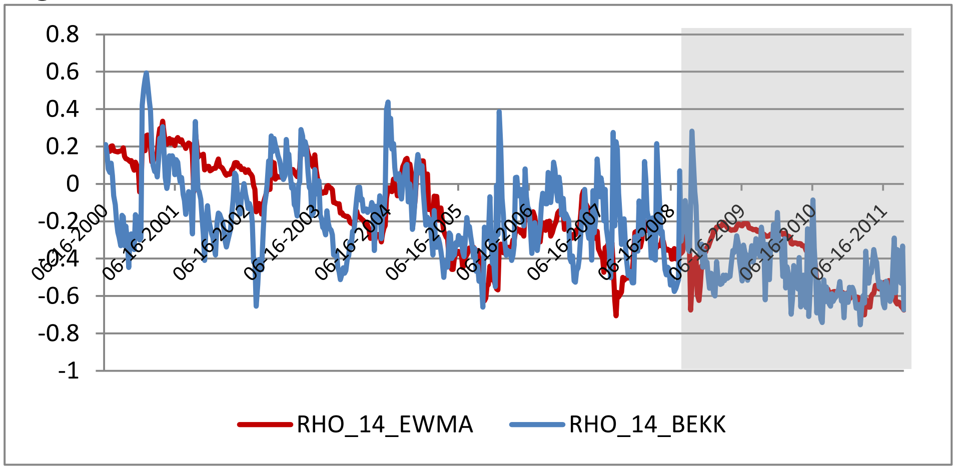
Note: Shaded areas represent the post-global financial crisis phase

Figure 3B: Conditional Correlation between U.S. Tbills Market and Exchange Rate market (RHO_13)



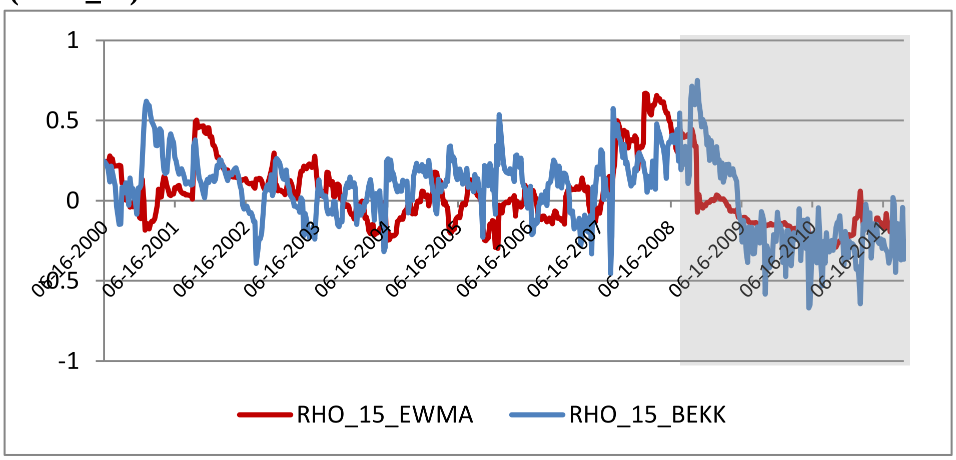
Note: Shaded areas represent the post-global financial crisis phase

Figure 3C: Conditional Correlation between U.S. Tbills Market and U.S. Stock market (RHO_14)



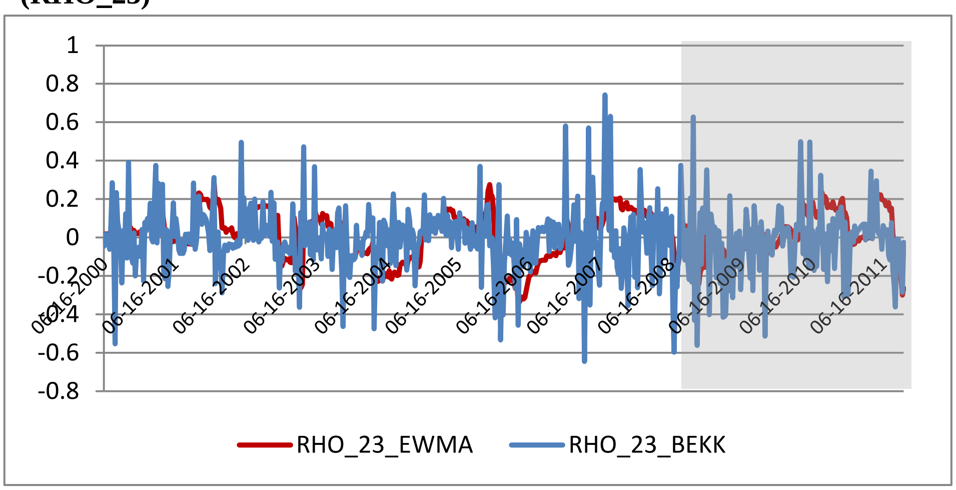
Note: Shaded areas represent the post-global financial crisis phase

Figure 3D: Conditional Correlation between U.S. Tbills Market and Indian Stock market (RHO_15)



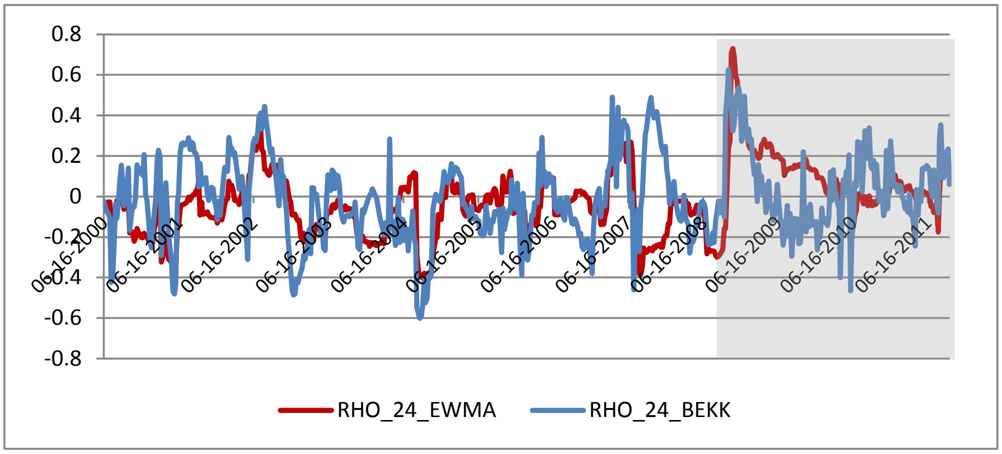
Note: Shaded areas represent the post-global financial crisis phase

Figure 3E: Conditional Correlation between Indian Tbills Market and Exchange rate market (RHO_23)



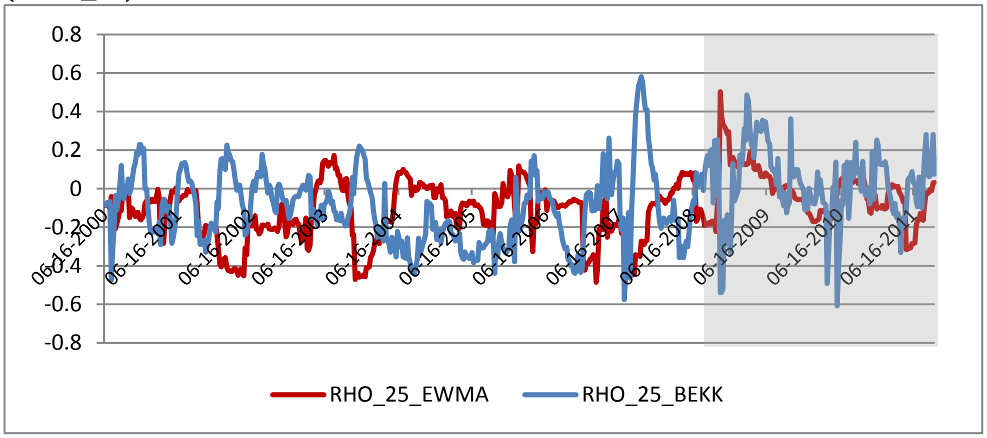
Note: Shaded areas represent the post-global financial crisis phase

Figure 3F: Conditional Correlation between Indian Tbills Market and U.S. Stock market (RHO_24)



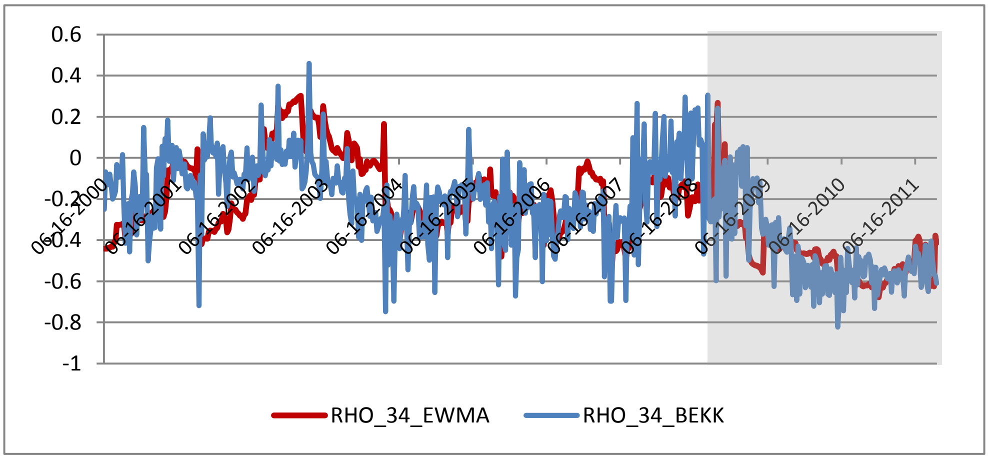
Note: Shaded areas represent the post-global financial crisis phase

Figure 3G: Conditional Correlation between Indian Tbills Market and Indian Stock market (RHO_25)



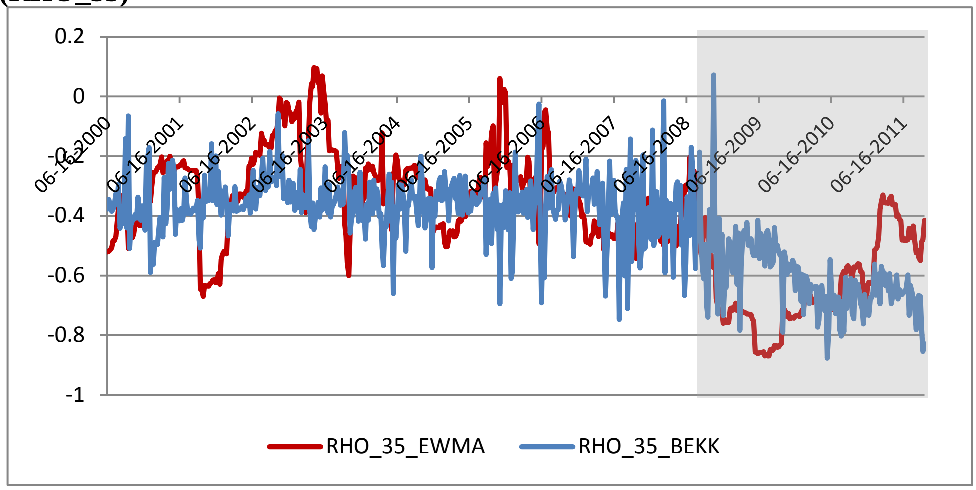
Note: Shaded areas represent the post-global financial crisis phase

Figure 3H: Conditional Correlation between Exchange Rate Market and U.S. Stock market (RHO_34)



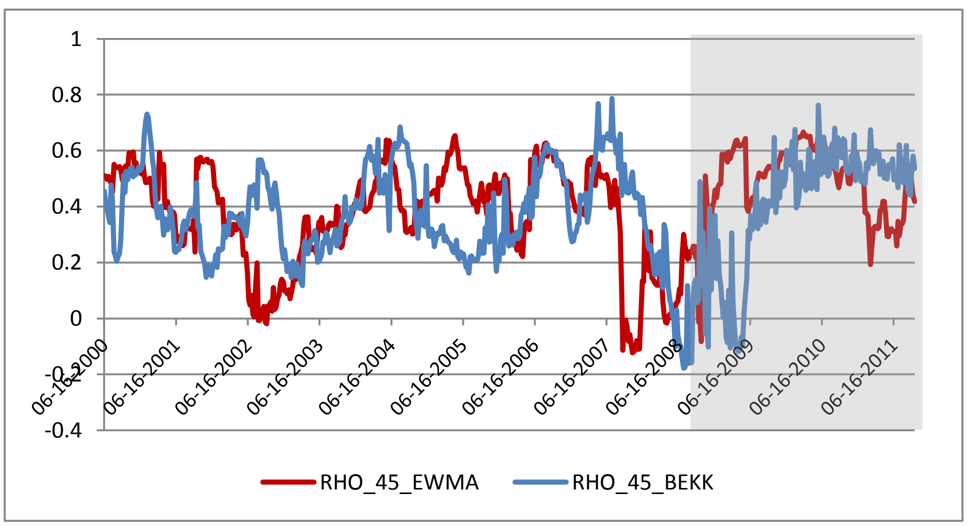
Note: Shaded areas represent the post-global financial crisis phase

Figure 3I: Conditional Correlation between Exchange Rate Market and Indian Stock market (RHO_35)



Note: Shaded areas represent the post-global financial crisis phase

Figure 3J: Conditional Correlation between U.S. Stock Market and Indian Stock market (RHO_45)



Note: Shaded areas represent the post-global financial crisis phase