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US financial conditions index and its empirical impact on information transmissions across US-BRIC equity markets

Amanjot Singh*, Manjit Singh

University School of Applied Management, Punjabi University, Patiala, Punjab 147002, India

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Abstract

Both price discovery and volatility spillovers act as information transmission mechanisms across foreign boundaries. In this regard, the present study attempts to extend the findings reported by Singh and Kaur[46] by considering pairwise volatility spillover effects among the US-BRIC equity markets and capturing the impact of overall US financial market conditions on pairwise volatility spillover effects across the years 2004–2014 by employing diverse econometric models. The results report bi-directional volatility spillover effects between the US-BRIC equity markets and significant impact of the US financial conditions on ex-ante probabilities for the existence of positive volatility spillovers from the US to Brazilian, Russian and Chinese equity markets only. With an improvement in the US financial condition, probability for the same reduces in the context of Brazilian and Russian equity markets, whereas, in case of the Chinese equity market, probability reduces but at a slower pace. The results bear strong implications for portfolio managers and policy makers and first of its kind.

Keywords: BRIC; Financial condition; Information transmissions; US; Volatility spillovers

1. Introduction

Both price discovery (first moment) and volatility spillovers (second moment) act as information transmission mechanisms, whereby information emanating from one equity market has an impact on other equity markets across the foreign boundaries; as studied by Booth et al.,[11] Tse,[54] Gagnon and Karolyi,[23] Rittler,[40] Sehgal et al.,[44] and Singh and Kaur.[46] In this era of globalization and increasing global diversified funds, it is always advisable to capture cross market dynamic interactions among the undertaken equity markets. In the event of cross market effects, portfolio diversification benefits are undermined in the wake of excessive co-movement and spillover effects among the said equity markets.[33] Moreover, it is well documented that international financial markets are not perfectly decoupled from each other. Seemingly, voluminous literature has tried to capture return-volatility spillover effects among the international financial markets, for instance, Cappiello et al.,[12] Dooley and Hutchison,[19] Kenourgios et al.,[27]

* Corresponding author. 303-C Rajguru Nagar, Ludhiana, Punjab 141012, India.
E-mail address: amanjot_42@yahoo.com (A. Singh).
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Kenourgios and Padhi,[26] Zhou et al.,[57] Suardi,[50] Bianconi et al,[8] Ahmad et al,[1] Mohammadi and Tan,[34] Singh and Singh,[48] and Jebran and Iqbal,[24] etc. Most of the studies have tried to capture these dynamic interactions, especially during a crisis period, like the US subprime crisis. To quote, the US dollar has effectively become the global reserve currency for emerging markets underpinning implied dependence of the latter markets on the direction of global capital flows and US monetary policy actions.[45]

Generally, these spillover effects are analyzed against the backdrop of ever increasing trade as well as financial linkages among the international economies, i.e. fundamental linkages.[36] But apart from these fundamental linkages, there are several other factors ranging from portfolio based to the irrationality of the market participants accounting for the said spillover effects. Consequently, there are some studies that have further tried to gather the impact of some macroeconomic announcements, news or variables on respective stock market returns and volatility. For instance, Sun and Zhang,[51] Jiang et al.,[25] Rahman and Sidek,[38] Kim et al.,[28] and Belgacem et al.[6] are some of the studies accounting for the impact of macroeconomic variables on stock market returns, volatility and even on spillover effects. Most of the studies have considered individual macroeconomic variables like implied volatility indices (VIX), inflation indices, unemployment variables, etc. However, the ultimate root of these studies is based on the interactions between respective stock markets and macroeconomic activities; inspired from seminal Arbitrage Pricing Theory (APT) proposed by Ross.[42] Consequently, the said studies are the core crux of Efficient Market Hypotheses (EMH), whereby it is assumed that a stock market discounts all the relevant information contents as and when floated in the market.

The emerging markets witness higher level of volatility and spillover effects compared to the emerged markets owing to greater degree of information asymmetry and riskiness attached to the former markets; as studied in Worthington and Higgs,[56] Lhost,[31] and Celik.[13] The market participants prefer switching to other safer asset classes, like the Japanese Yen, German bunds, etc. during a crisis or stressful episode thereby augmenting spillover effects among the undertaken markets.[22] Likewise, Singh and Kaur[46] reported that overall volatility spillover effects increase in the event of adverse market scenarios among the US-BRIC equity markets through the creation of a total volatility spillover index. During the Lehman Brothers' episode, volatility spillover index witnessed explosive roots indicating magnified spillover effects across the said markets. The acronym ‘BRIC’[1] stands for Brazil, Russia, India and China; a geopolitical and economic collection of most promising and opportunities instilled emerging markets. In this regard, the present study attempts to extend the findings reported by Singh and Kaur[46] by considering pairwise volatility spillover effects among the US-BRIC equity markets instead of total volatility spillover effects in the form of an index. Additionally, the present study attempts to capture the impact of overall US financial market conditions (macroeconomic event) on pairwise volatility spillover effects between the US-BRIC equity markets across the years 2004–2014. *A priori* one would expect a significant impact of the US financial market conditions on volatility spillover effects across the US-BRIC equity markets. A possible explanation for this could be the dominant stance of the US economy amidst growing financial interdependence among the international economies.

There are numerous studies that have tried to account for return-volatility spillover effects among the US and BRIC equity markets. Bhar and Nikolova,[7] Bianconi et al.,[8] Bekiros,[5] Evgenii and Elena,[21] Syriopoulos et al.[53] and Singh and Kaur[47] are some of the studies accounting for return-volatility spillover effects among the latter equity markets. But the present study is the first of its kind, capturing the impact of overall US financial market conditions on information transmissions, i.e. volatility spillover effects across the US-BRIC equity markets. In order to capture conditional/time-varying variances and spillover effects, the study employs autoregressive-moving average (1,1) exponential generalized autoregressive conditional heteroskedastic model in ‘mean’ [ARMA (1,1) EGARCH-M (1,1)] and Diebold and Yilmaz's[18] generalized spillover index under Vector Autoregression (VAR) framework. Lastly, binary logistic regression model is employed in order to generate ex-ante probabilities for the existence of international information transmissions. For this, the US financial conditions index and Chicago Board Options Exchange's implied volatility index (CBOE-VIX) are taken as explanatory variables. The results report bi-directional volatility spillover effects among the US-BRIC equity markets and significant impact of the US financial conditions index in explaining volatility spillover effects thereon. With an improvement in the US financial condition, probability for the existence of positive spillovers from the US to Brazilian and Russian equity markets reduces. However, in case of the Chinese equity market, probability for the same reduces at a considerably lower pace.

[1] We are not considering the South African equity market owing to its recent joining to the club. Our study dates back to 2004 to 2014.

The findings are critically important for market participants and policy makers. Short term investors or active investors are usually interested in accounting for short run spikes in asset prices in the wake of enjoying arbitrage opportunities. So, the reported findings may help them in comprehending probable flow of volatility spillovers or information transmissions across the US-BRIC equity markets. Furthermore, these findings are also helpful to the policy makers in their attempt to analyze the financial contagion impact across international economies. In layman terms, volatility can be denoted as uncertainty in asset prices or risks attached to asset prices having an impact on the overall investment environment, portfolio risk, asset allocation decisions and portfolio returns. Normally, an increase in volatility is followed by a decrease in market participants' rate and investments thereon. So, it is quite pertinent to capture cross market volatility spillovers and that too, considering some macroeconomic events, like the US overall financial conditions. Moreover, empirical models capturing correlation or spillovers in the second moment (volatility) of the stock markets are found to be more efficient comparing to the first moment (returns).[53] Our study adds to the existing literature by empirically quantifying the respective responses of pairwise volatility spillover effects toward the US financial market conditions. A case of one emerged market (the US) and most promising emerging market bloc (BRIC) is considered in analyzing the said impact. The rest of the article is organized as follows: Section (2) reports empirical framework, Section (3) highlights empirical findings and discussion, and lastly Section (4) concludes the paper.

2. Empirical framework

The whole empirical framework part is divided into three sections. Section (2.1) reports methodology employed to capture conditional variances in the respective US-BRIC equity markets; Section (2.2) reports Diebold and Yilmaz's[18] framework accounting for volatility spillover effects among the US-BRIC equity markets; lastly Section (2.3) highlights binary logistic regression model in order to capture the impact of the US financial conditions index on probable volatility spillover effects.

2.1. Univariate ARMA (1,1) EGARCH-M (1,1) model

In order to model conditional variances, daily closing local values of the respective benchmark equity indices [S&P 500 (US), IBOVESPA (Brazil), RTS (Russia), NIFTY (India) and Shanghai composite index SSE (China)] are taken ranging from 01/01/2004 to 30/11/2014; covering pre-crisis, crisis and post global financial crisis period events. The source of data is Bloomberg and Yahoo financial databases as per availability of data on a continuous basis. Common trading days are taken into consideration and daily continuously compounding gross index logged returns are used in the analysis; $R_t = \text{Ln}\ (P_t/P_{t-1})\ {*}100$, where R_t is daily gross index return, Ln is the logarithmic term, P_t is current day's closing price and P_{t-1} is previous day's closing price. To model conditional variances, ARMA (1,1) EGARCH-M (1,1) model is employed taking ARMA (1,1) as the ‘mean’ equation. GARCH based models are found to be quite efficient in capturing time-varying aspect of variances. The plain vanilla GARCH (1,1) model was proposed by Bollerslev[10] wherein current conditional variance is a function of recent market shock and past conditional variance. As an extension, EGARCH model also considers the asymmetric response of conditional variance towards negative market shocks, i.e. leverage effects studied by Nelson.[35] Our version of univariate ARMA (1,1) EGARCH-M (1,1) model also captures volatility feedback hypothesis, i.e. impact of conditional variance on ex-ante conditional returns.

Mean equation:

$$\boldsymbol{R_t = c + pR_{t-1} + qe_{t-1} + \gamma h_t + \varepsilon_t} \tag{1}$$

where R_t is the respective index returns (US-BRIC), c is the constant term, p and q are respective coefficients of the Autoregressive (AR) and Moving average (MA) terms capturing the impact of one day lagged conditional return and one day lagged market shock on current conditional return respectively. ε_t is the error term assumed to be identically and independently distributed, i.e. *N(0,1)*. The respective lag lengths are determined on the basis of Autocorrelation Functions (ACF), Partial Autocorrelation Functions (PACF) and significance level of Ljung Box test statistics of the stock market returns. γ captures volatility feedback hypothesis and h_t is the conditional variance. It may be noted that for the application of GARCH based models, autoregressive conditional heteroskedastic (ARCH) effects are bound to be in existence in the residuals derived from the ‘mean’ equation (Eq. (1)). The derived residuals are further appended into variance equations in order to capture time-varying variances.

Variance equation:

$$\boldsymbol{logh_t} = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1\left(\frac{|\boldsymbol{\varepsilon}_{t-1}|}{\boldsymbol{h}_{t-1}} - \sqrt{\frac{2}{\boldsymbol{\pi}}}\right) + \boldsymbol{\delta}\frac{\boldsymbol{\varepsilon}_{t-1}}{\boldsymbol{h}_{t-1}} + \boldsymbol{\beta}_1\boldsymbol{h}_{t-1} + \boldsymbol{e}_t \tag{2}$$

where α_0 is the long run variance and δ is the asymmetric coefficient. The leverage effect will be there when $\delta < 0$ and found to be significant. α_1 captures the impact of a recent market shock, whereas β_1 captures the impact of past variance on current conditional variance. For stationary purposes, the value of β_1 is expected to be less than one. For non-negativity constraints, all the coefficients are expected to be greater than one, except the asymmetric coefficient. The standardized residuals derived from the variance equation (Eq. (2)) are required to be white noise and homoskedastic for the overall adequacy of the model. The results relating to best fit distribution are reported confirming the robustness across different distributions.

2.2. Volatility spillover effects under Diebold and Yilmaz's[18] framework

The univariate conditional variances are further used in generating pairwise volatility spillover effects following Diebold and Yilmaz's[18] framework. Diebold and Yilmaz[18] came out with a spillover index to compute total contribution of the shocks on an asset arising from the contribution of all other markets using forecast error variance decompositions under the VAR framework.[46] The model has widely been used to account for spillover effects, for instance, Kumar,[30] Cronin,[17] and Liow,[32] etc. The generalized forecast error variance decompositions under the VAR framework of Koop et al.[29] and Pesaran and Shin,[37] [KPPS here after] shows the percentage of variance to variable i that is out of the result of innovations to variable j. The generalized version makes the whole process order invariant.

Consider a N-dimensional vector, X_t, depicting conditional variances of five assets modeled by a covariance stationary VAR model in generalized form. A covariance stationary VAR (p) model with N variables can be specified as, $X_t = \sum_{i=1}^{p}\Phi_i X_{t-i} + \varepsilon_t$, where ε_t is a vector of independent and identically distributed market innovations and X_t is a vector of N endogenous variables. For each of the US-BRIC equity markets, the VAR equations are modeled given by latter equation. The moving average representation is $X_t = \sum_{i=0}^{\infty}\mathrm{A}_i\varepsilon_{t-i}$, where the N × N coefficient matrices A_i follow the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 being an N × N identity matrix and $A_i = 0$ for $i < 0$. The variance decompositions register explanatory power of one variable in explaining forecast error variations of another. Consequently, the model proposes two types of variance shares, i.e., own variance shares as well as cross variance shares. Under KPPS, for H-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(H)$, for $H=1,2 \ldots$, we have

$$\boldsymbol{\theta}_{ij}^{g}(\boldsymbol{H}) = \frac{\boldsymbol{\sigma}_{ii}^{-1}\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\boldsymbol{A}_h\sum\boldsymbol{e}_j\right)^2}{\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\boldsymbol{A}_h\sum\boldsymbol{A}_h'\boldsymbol{e}_i\right)^2} \tag{3}$$

where σ_{ii} is the ith element on the principle diagonal of Σ (variance matrix for the error vector) and e_i is the selection vector with one as ith element and zeros otherwise. Normalization of each entry of the variance decomposition matrix is done by the row sum since each row of θ_{ij}^{g} is not equal to one:

$$\boldsymbol{\theta}_{ij}^{\sim g}(\boldsymbol{H}) = \frac{\boldsymbol{\theta}_{ij}^{g}(\boldsymbol{H})}{\sum_{j=1}^{N}\boldsymbol{\theta}_{ij}^{g}(\boldsymbol{H})} \tag{4}$$

Accordingly, it may be noted that, by construction, $\sum_{j=1}^{N}\theta_{ij}^{\sim g}(H) = 1$ and $\sum_{i,j=1}^{N}\theta_{ij}^{\sim g}(H) = N$. In this way, the index measures the contribution of volatility spillovers across five different asset classes to the total forecast error variance in the form of an index. It is pertinent to mention that the model also measures directional volatility spillover effects. Subsequently, the results generated out of spillover effects largely summarize overall transmission effects regardless of a specific source or destination of the same. In order to overcome this problem, Diebold and Yilmaz's[18] framework also incorporates net pairwise spillover effects between the underlying markets. The only difference lies in the fact that pairs are considered for the purpose of analysis and the rest of the discussion is similar. As we are interested in gathering spillover effects among the US-BRIC equity markets, so, four different pairs are created for the purpose of capturing time-varying spillover effects between them [US-Brazil, US-Russia, US−India and US-China].

$$S_{ij}^{g}(H) = \left[\frac{\theta_{ij}^{\sim g}(H)}{\sum_{k=1}^{N} \theta_{ik}^{\sim g}(H)} - \frac{\theta_{ji}^{\sim g}(H)}{\sum_{k=1}^{N} \theta_{jk}^{\sim g}(H)} \right] \times 100 \tag{5}$$

where i denotes the US equity market and j denotes the respective BRIC equity markets in pairwise analyses. The first component $\frac{\theta_{ij}^{\sim g}(H)}{\sum_{k=1}^{N} \theta_{ik}^{\sim g}(H)}$ on the right hand side captures gross volatility transmission effects from market *i to j*, i.e. from the US market to respective BRIC equity markets and second component $\frac{\theta_{ji}^{\sim g}(H)}{\sum_{k=1}^{N} \theta_{jk}^{\sim g}(H)}$ ascertains gross volatility transmission effects from market *j to i*, i.e. from the respective BRIC equity markets to US market under pairwise analyses. The net pairwise spillovers are computed by deducting gross receiving effects from gross transmitting effects. If the resulting value is positive, then there are spillover effects running from the US market to respective BRIC markets, whereas if the resultant value is negative, then there are spillover effects from the respective BRIC markets to US market. In order to incorporate time-varying aspect in pairwise volatility spillovers, rolling window estimation (200 days) is done across the period 2004 to 2014 with 10 days ahead variances. The rolling window of 200 days is quite reasonable considering average trading days in a year.

2.3. Binary logistic regression model

Lastly, we employ binary logistic regression model in order to capture the impact of the US financial conditions on volatility spillover effects among the US-BRIC equity markets. As mentioned earlier that macroeconomic events also have an impact on domestic market returns and volatility, so, impact of overall US financial conditions on volatility spillover effects is also of interest to the market makers. For the said purpose, we employ Bloomberg's financial conditions index (FCI) capturing overall financial condition of the US economy. It is an equally weighted standardized index tracking money market, bond market and equity market indicators.[41] The index comprises ten different variables and its values revolve around average (mean) value times the standard deviation. Apart from Bloomberg's FCI, there are various other indices that account for overall US financial market conditions, for instance, IMF US FCI, Chicago Fed National Financial Conditions Index (NFCI) and Citi FCI. But all of these indices report financial conditions on either weekly or monthly basis. On the other hand, Bloomberg's FCI reports US financial conditions on a daily basis, which means that the index is quite sensitive and responsive in tracking movements in the US financial market. However, in order to ensure reliability and sensitivity free information contents, we use monthly closing values of Bloomberg FCI and net pairwise volatility spillover indices. The CBOE-VIX's monthly closing index values are also factored into the regression equation as a control variable.

The benefit of using logistic regression technique is that we can ascertain the said interactions between volatility spillovers and US financial conditions in probability terms. Under logistic regression model, a dependent variable is a binomial probability distribution as it has only two values either 0 or 1 and is a non-linear function of independent variables. The value 1 denotes existence of a condition (P), whereas the value 0 denotes absence of a condition $(1 - P)$. Since, net pairwise spillover indices are expressed in positive or/and negative terms respectively, we consider the value 1 as existence of positive spillover effects from the US to respective BRIC equity markets and the value 0 as negative spillover effects. Considering the US economy, the results are quite expected to be in favor of positive volatility spillover effects from the US to other BRIC equity markets. However, the present study attempts to capture the same in quantitative terms and as a response to the overall US financial conditions. The logistic regression equation is expressed as follows; as in Chauhan[14] and Singh and Singh[49]:

$$\log\left(\frac{P_i}{1 - P_i}\right) = a_0 + \beta_1 FCI_t + \beta_2 FCI_{t-1} + \beta_3 US_{VIX,t} + \varepsilon_t \tag{6}$$

where a_0 is the constant term and β_1 is the slope coefficient of the US financial conditions index spotlighting 'contemporaneous' impact, i.e. same month impact and β_2 is the coefficient capturing 'dynamic' one month lagged impact of the US financial conditions index owing to time differences. Moreover, CBOE-VIX US implied volatility index values are included in the regression equation as a control variable (β_3). Technically, (P_i), probability for the existence of a condition is regarded as $\left(P_i = \frac{e^z}{1+e^z}\right)$ and $(1 - P_i)$, probability for the absence of a condition is regarded as $\left(\frac{1}{1+e^z}\right)$. Where, e^z is the exponential function of the logistic regression equation, so, $log\left(\frac{P_i}{1-P_i}\right)$ is the odd ratio. Considering the complexity in comprehending the said relationship, exponential beta values are computed denoting rate of change in odd ratio relating to per unit change in the respective independent variables. If the exponential beta is greater than 1, then the independent variable is observed to be having a positive significant impact on the existence of a condition, otherwise values lesser than 1 denote negative impact on the existence of a condition. The Wald test statistic captures the impact of an independent variable on the dependent one. The whole model is estimated using the Maximum Likelihood Estimation (MLE) method. The rest of the analysis has been done taking the US financial conditions indices (contemporaneous and dynamic) and the US implied volatility index values as explanatory and binomial probability distribution (volatility spillover effects) as dependent variables. Lastly, to capture the impact of the US financial conditions on the existence of positive or negative spillovers in a graphical format, the ex-ante probabilities are computed $\left(P_i = \frac{e^z}{1+e^z}\right)$ out of the regression model results.

3. Empirical findings and discussion

Fig. 1 is the graphical presentation of the respective US-BRIC equity markets' benchmark equity index returns and prices. The shaded portion relates to the US financial crisis period. As per the Business Cycle Dating Committee of the National Bureau of Economic Research (2010), the recovery from the US crisis started from June 2009. Seemingly, the sub-prime crisis lasted for around two years on an average; further inspired from Bekaert et al.[4] So, the period from July 2007 to June 2009 is regarded as the US financial crisis period. It is quite apparent from the movement of the indices that BRIC equity markets witnessed a substantial fall and increased volatility during the financial crisis period. Interestingly, both the US and Indian equity markets have surpassed their previous highest levels ever since the financial crisis. As mentioned earlier, for the application of GARCH based models, ARCH effects or volatility clustering phenomenon is required to be in existence. The said phenomenon is clearly visible as small changes are followed by smaller ones and large changes are followed by larger ones.

Table 1 reports descriptive statistics of the respective index returns across the years 2004–2014. On an average, Indian equity market witness highest level of returns coupled with a lesser level of standard deviation. The lowest average returns are observed in case of the Russian equity market along with the highest level of volatility relative to others. The next best returns are observed for the Brazilian, US and Chinese equity markets. However, the skewness values are negative with respect to each of the countries. This means that there is greater probability of negative returns in comparison to the positive returns in all of the markets. Furthermore, Kurtosis values report fat-tailed distribution of the index returns with respect to all the equity markets. The existence of fat-tailed and skewed distributions further supports the application of GARCH based models. Jarque–Bera test results confirm non-normal distribution of index returns with respect to all the equity markets. This spotlights the existence of abnormal returns in the markets. The total number of observations are 2334.

Moving ahead, financial time series data are required to be 'mean' reverting i.e. stationary for the application of different statistical models. Consequently, we employ Augmented Dickey Fuller (ADF), Philips–Perron and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests in order to ensure stationary distribution of the respective equity index returns. The ADF and Philips–Perron tests support the rejection of null hypothesis relating to non-stationary distribution at 5 percent significance level. On a similar note, KPSS test supports the acceptance of null hypothesis relating to stationary time series. Barring the Indian equity market, all other equity markets are found to be inefficient in the context of the impact of past conditional returns on current ones (significant autocorrelation coefficients at 5 percent significance level). Even the 36th order lagged values are observed to be having a significant impact on the current index returns.

3.1. Univariate conditional variances

After confirming the overall descriptive properties and stationary distribution of daily index returns, univariate conditional variances are generated through the application of ARMA (1,1) EGARCH-M (1,1) model. It may be noted

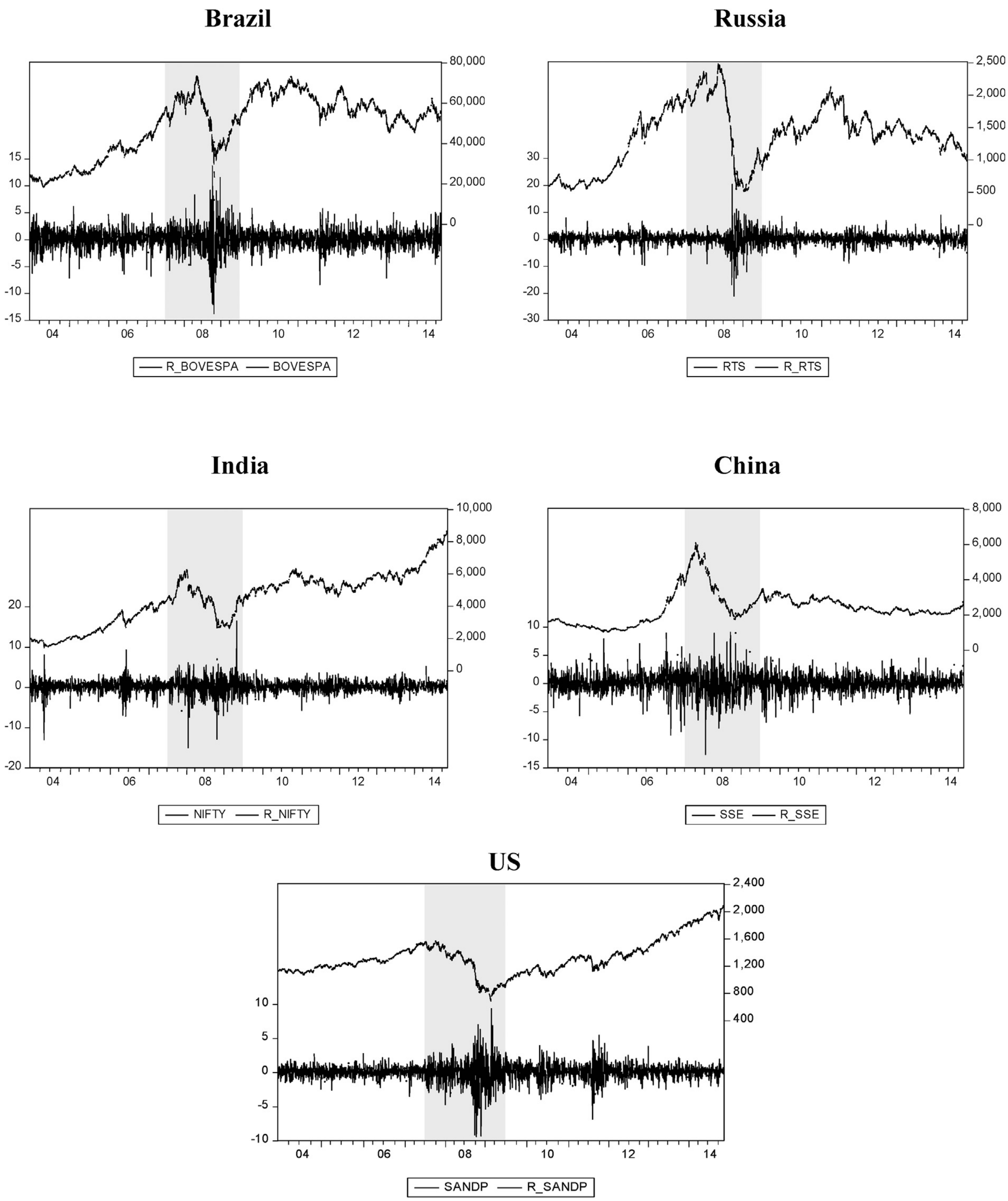

Fig. 1. Graphical presentation of indices at price level and returns.
Source: Computed by the authors.

Table 1
Index returns: descriptive statistics.

	Brazil	Russia	India	China	US
Mean	0.036159	0.021775	0.063411	0.023001	0.026181
Sigma	1.959227	2.335913	1.715757	1.750481	1.263634
Skewness	−0.116098	−0.529874	−0.582679	−0.213119	−0.534525
Kurtosis	9.627516	14.48651	13.78256	7.571819	11.71885
Jarque−Bera	4276.849	12940.36	11438.71	2050.342	7503.920
Probability	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
Observations	2334	2334	2334	2334	2334
ADF test	−37.126[b]	−42.501[b]	−48.209[b]	−47.713[b]	−53.989[b]
Philips−Perron	−50.837[b]	−42.403[b]	−48.213[b]	−47.744[b]	−54.008[b]
KPSS	0.1884[c]	0.2784[c]	0.0627[c]	0.1683[c]	0.2137[c]
Ljung−Box (1)	3.9622[d]	36.770[d]	0.0054	0.2935	28.952[d]
Ljung−Box (12)	30.355[d]	53.254[d]	12.856	25.703[d]	57.343[d]
Ljung−Box (36)	88.641[d]	114.43[d]	47.806	63.249[d]	148.43[d]

[a] Reject null hypothesis of normal distribution at 5% significance level.
[b] Reject null hypothesis of non-stationary time series at 5% significance level.
[c] Accept null hypothesis of stationary time series with critical value 0.4630 at 5% significance level.
[d] Reject null hypothesis of independent distribution of the index returns at 5% significance level.
Source: Computed by the authors.

that the residuals derived from respective ARMA (1,1) equations support the existence of ARCH effects in the residuals with respect to all the markets. The existence of the same empirically confirms the application of EGARCH models.

Table 2 reports ARMA (1,1) EGARCH-M (1,1) model results. There is existence of volatility feedback hypothesis, i.e. positive risk-return relationship in case of the Chinese equity market. The ex-ante relationship is observed to be positive, whereby an increased level of volatility commands increased level of returns. The results are consistent with the findings of Chen.[15] Only the Chinese market returns are significantly influenced by one day lagged conditional returns and one day lagged market shocks at 5 percent significance level. The market shocks are found to be having a reducing impact on the current conditional returns, whereas the impact of one day lagged returns is increasing in nature. The magnitude of the impact is almost similar, meaning that the lagged impacts

Table 2
ARMA (1,1) EGARCH-M (1,1) model results.[46]

Coefficients	China	Russia	India	Brazil	US
$\boldsymbol{\gamma}$	0.0344[b]	−0.0109	0.0166	0.0248	0.0219
$\boldsymbol{c}$	0.4349	0.1561[a]	0.0854[a]	−0.0120	0.0490[a]
$\boldsymbol{p}$	0.9987[a]	−0.3646	−0.2834	0.5555	0.3607
$\boldsymbol{q}$	−0.9884[a]	0.4157[b]	0.3299	−0.5702	−0.4114
$\boldsymbol{\alpha}_0$	−0.0622[a]	−0.1050[a]	−0.1189[a]	−0.0768[a]	−0.0991[a]
$\boldsymbol{\alpha}_1$	0.0973[a]	0.1847[a]	0.1822[a]	0.1398[a]	0.1199[a]
$\boldsymbol{\delta}$	−0.0112	−0.0615[a]	−0.1106[a]	−0.0941[a]	−0.1416[a]
$\boldsymbol{\beta}_1$	0.9920[a]	0.9737[a]	0.9681[a]	0.9702[a]	0.9783[a]
Distribution	GED Stationary	GED Stationary	Student-t Stationary	Student-t Stationary	GED Stationary
Sign bias test	0.1099	0.0600	−0.1066	−0.0559	0.1323
Nega. size bias test	0.0911	0.0014	0.0010	0.0793	0.1457
Posi. size bias test	−0.0848	−0.0641	−0.1349	−0.2621[a]	−0.1818
Joint LM test	3.1194	1.9074	1.1023	8.4378[c]	10.2690[c]

[a] Reject null hypothesis of no significant relationship at 5% significance level.
[b] Reject null hypothesis of no significant relationship at 10% significance level.
[c] Reject null hypothesis of no sign and size bias at 5% significance level; Joint test of Sign and Size bias, $\varepsilon_t^2 = a_0 + a_1 S_{t-1}^- + a_2 S_{t-1}^- \varepsilon_{t-1} + a_3 S_{t-1}^+ \varepsilon_{t-1} + u_t$, wherein coefficient a_1 is sign bias, a_2 is negative size bias and a_3 is positive size bias.
Source: Computed by the authors.

counter-balance each other. Other markets are observed to be efficient in the context of insignificant impact of past returns on current conditional returns. One of the main properties of EGARCH model is that the model captures both size (α_1) as well as sign (δ) effects. Barring the Chinese equity market, both size as well as sign effects are present with respect to all the other equity markets. Size effects denote that the size of a recent market shock commands an increased level of volatility, whereas sign effects denote that positive and negative shocks have an asymmetric impact on current conditional variance, meaning that negative shocks drive greater magnitude of volatility comparing to the positive shocks. In other words, falling equity returns increase conditional volatility on account of increasing financial risks.[9,16]

All the beta values are less than one, thereby confirming overall stationarity of the model parameters and greater magnitude impact of past conditional variances on current ones. This means that the market investors take a considerable number of days to come out of the impact of past conditional volatility. The recent market shocks do not drive conditional volatility in a much greater magnitude. Fig. 2 reports news impact curves with respect to each of the equity markets. On x-axis, we have market shocks (z) and on y-axis conditional variances are plotted. The market shocks are standardized residuals derived from the respective ARMA (1,1) EGARCH-M (1,1) models. The conditional variances are modeled through the following equation:

$$\boldsymbol{var_t} = \boldsymbol{a}_0 + \boldsymbol{\beta}_1 * \boldsymbol{log}(\boldsymbol{med}) + \boldsymbol{a}_1 * \boldsymbol{abs}(\boldsymbol{z_t}) + \boldsymbol{\delta} * \boldsymbol{z_t} \tag{7}$$

where, med is median scalar value of the conditional variances generated from respective EGARCH models.[43] As the asymmetric coefficient is not statistically different from zero in case of the Chinese equity market, the news impact curve demonstrates symmetric response of the conditional variances toward market shocks irrespective of an asymmetric response towards negative market shocks. It is quite apparent from the graphs that the conditional variances respond asymmetrically toward negative market shocks in the context of other US-BRIC equity markets. We further employ sign and size bias test proposed by Engle and Ng[20] owing to existence of asymmetric responses. Most of the parameters indicate fitness of the models with non-existence of size and sign biases after the application of EGARCH models for all of the US-BRIC equity markets. Moreover, the standardized residuals derived from GARCH equations confirm overall adequacy of the models in the context of non-existence of serial autocorrelation and heteroskedastic error terms. Lastly, Fig. 3 reports conditional variances across the years 2004–2014. All the markets witnessed an increased level of volatility during the US financial crisis period. Interestingly, magnitude of volatility is quite high in case of the Brazilian and Russian equity markets, whereas in case of the Chinese equity market, volatility spikes are found to be lesser as compared to rest of the markets. A possible explanation for this higher level of volatility in the Russian and Brazilian markets could be their greater reliance on export led commodity markets. The commodities are generally expressed in US dollar terms.

3.2. Net pairwise volatility spillover effects

After discussing about univariate conditional variances, we analyze the daily net pairwise volatility spillover effects in this subsection. The univariate conditional variances are used for the purpose of capturing volatility spillover effects among the US-BRIC equity markets under Diebold and Yilmaz's[18] VAR framework. It may be noted that 15 days' lagged values are incorporated in the VAR framework because under the VAR framework dependent variable is a function of its own lagged values as well as lagged values of other variables; evidenced from Schwarz Information Criterion (SIC) values. The benefit of generating net pairwise spillover effects is that we can clearly relate the extent of spillovers from one economy to another. One economy may be a net transmitter of volatility on an overall basis, while another can be a net receiver of volatility. The rolling window aspect of these net volatility spillover effects further captures time-varying information transmissions among the said markets. Fig. 4 is the graphical presentation of net pairwise volatility spillover effects among the US-BRIC equity markets.

All the markets are found to be both transmitter as well as receiver of volatility spillover effects. During the financial crisis period, the US equity market was net transmitter of volatility to the Brazilian, Russian and Indian equity markets. However, in case of the Chinese equity market, the US equity market is observed to be both transmitter as well as receiver of volatility spillover effects from the Chinese equity market during that period. The magnitude of spillover effects is almost equal. These findings are consistent with Zhou et al,[57] wherein the authors have also argued a positive spillover impact of the Chinese equity market on other markets since 2005.

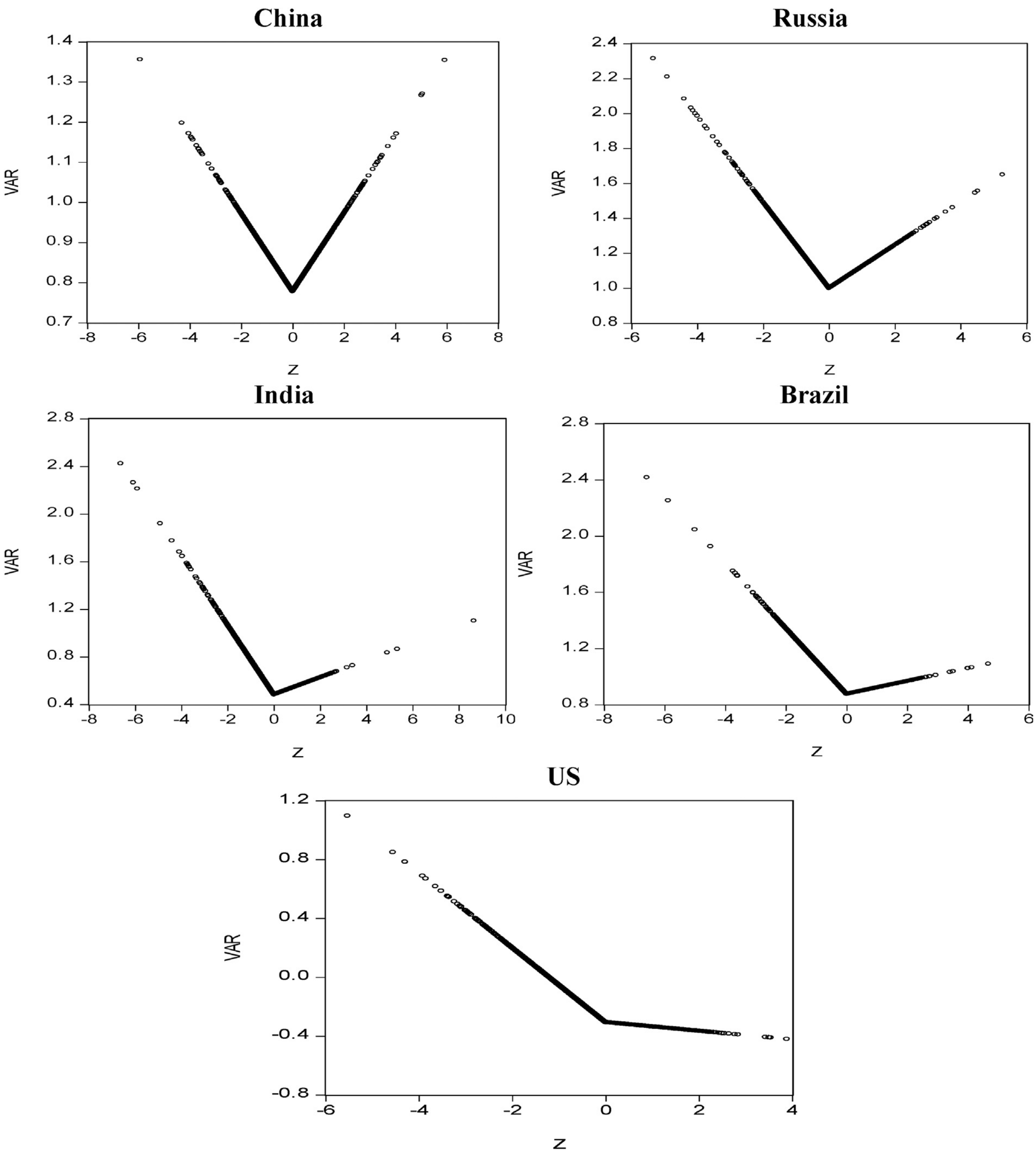

Fig. 2. News impact curves.
Source: Computed by the authors.

Moreover, the degree of openness is also comparatively higher in case of India comparable to China, so, the former market is strongly influenced by volatility spillovers from the US equity market. Further, the US equity market is also found to be net transmitter of volatility during the Euro-zone sovereign debt crisis period (late 2011) to the Russian, Indian and Chinese equity markets in varying degrees. On the whole, magnitude of spillovers is quite lesser in case of the Chinese equity market amongst other BRIC equity markets. This may be due to somewhat closed economic system prevalent in the Chinese economy. Table 3 highlights descriptive statistics concerning net pairwise volatility spillover

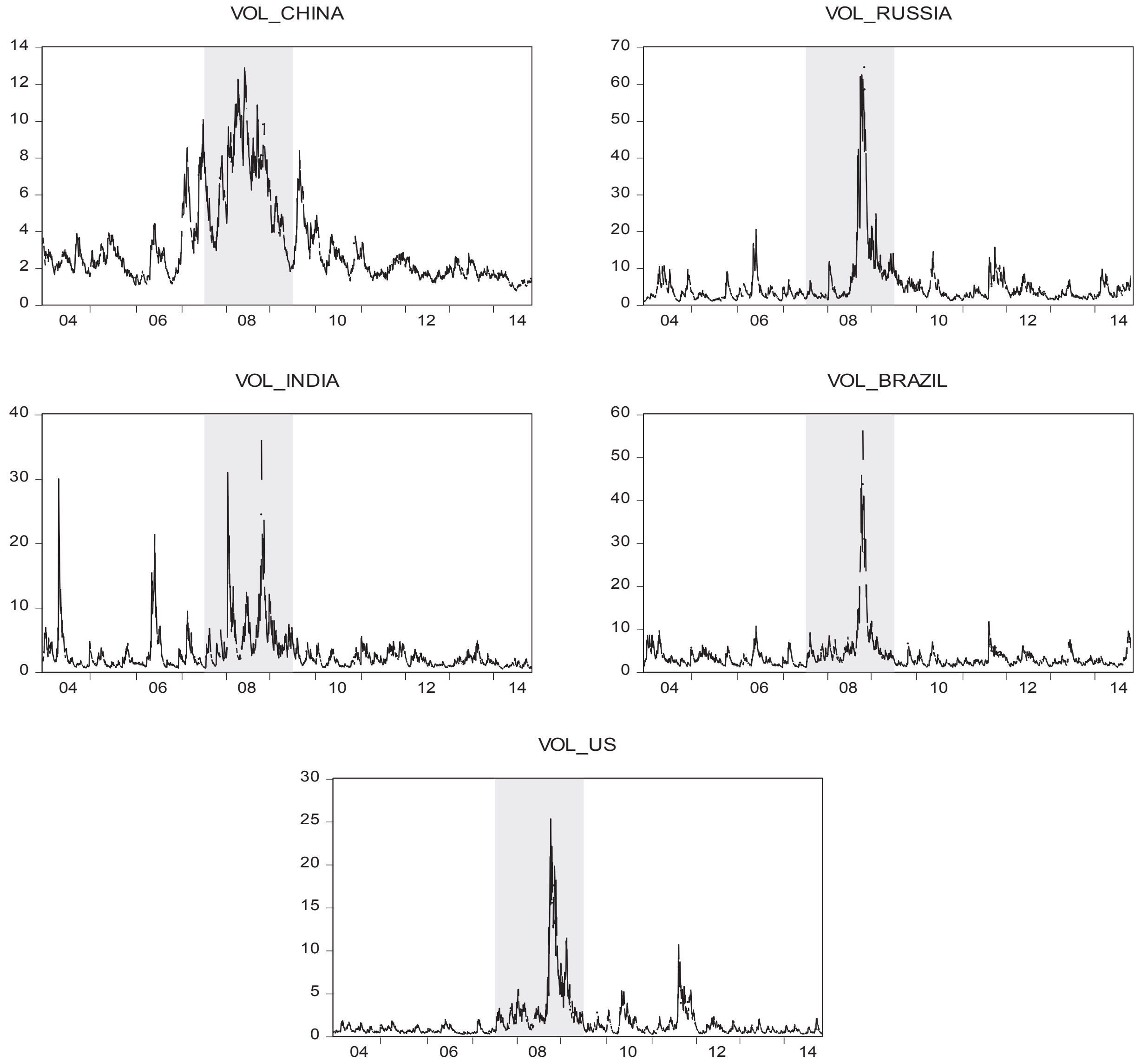

Fig. 3. Conditional variances.
Source: Computed by the authors.

effects. Considering the economically dominant stance of the US equity market, all the BRIC equity markets are found to be net receivers of volatility from the US equity market. This shows that on an average, there are dominant information transmissions from the US to BRIC equity markets. These findings raise concerns over decoupling hypothesis, whereby the emerging equity markets are expected to remain decoupled from the emerged ones owing to diverse economic and financial fundamentals.[19] Volatility spillover effects between the US-Brazilian and US-Indian equity markets are the most volatile as compared to others.

The distribution of all the net pairwise spillover indices is fat-tailed because the values of fourth moment are greater than 3. Moreover, skewness values are positive with respect to US-Brazil, US-Russia and US−India indicating that the probability of positive spillovers is higher compared to negative spillover effects. In other words, probability of information transmissions from the US to BRI equity markets is higher as compared to the other way around. But, on the other hand, skewness value is negative with respect to the Chinese equity market, whereby information transmissions are expected from the Chinese to US equity market. The results are consistent with the findings of Wang and Wang.[55]

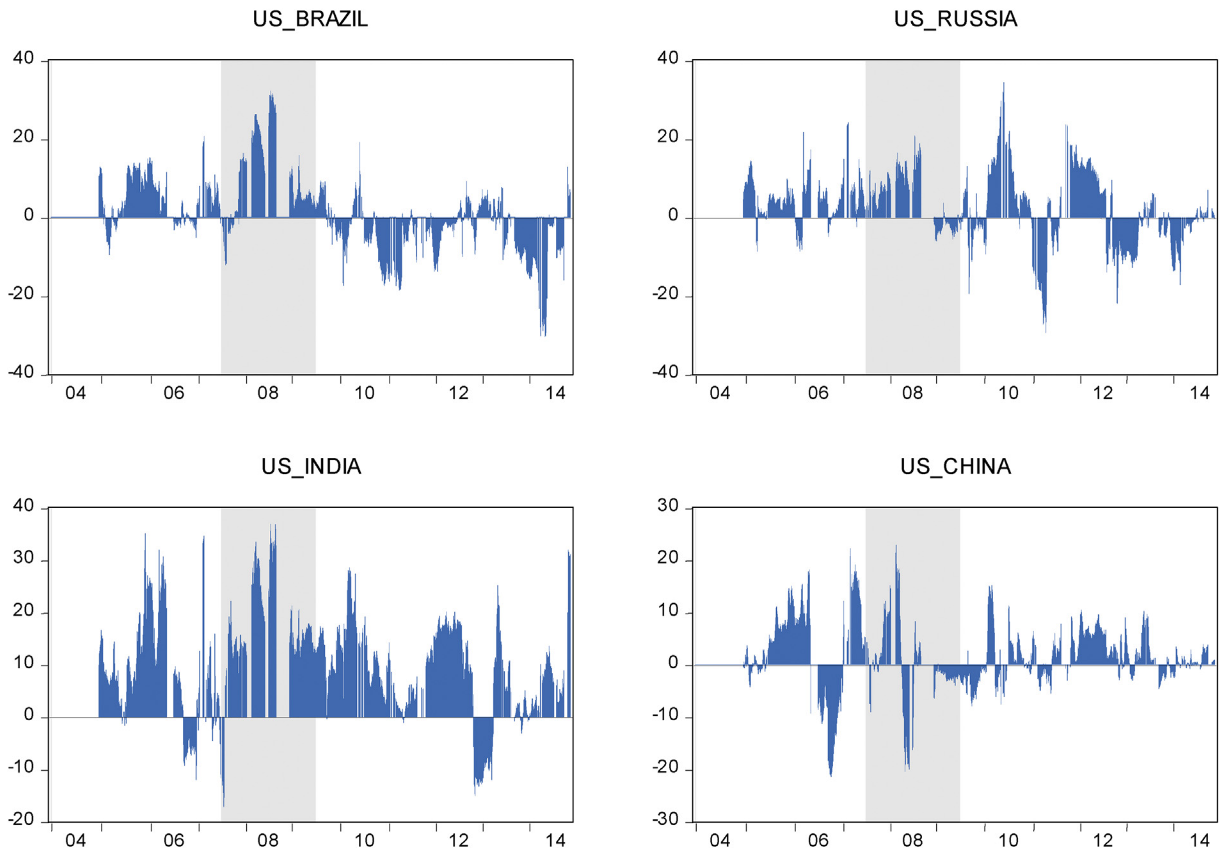

Fig. 4. Net pairwise volatility spillover effects.

Source: Computed by the Authors; figure explains time-varying net spillover effects between the US-BRIC equity markets as in Eq. (5); i denoting the US equity market is fixed, whereas, j denoting the respective BRIC equity markets pertains to four different pairs; values greater than zero highlight spillover effects from the US to other BRIC equity markets and values lesser than zero denote spillover effects from the respective BRIC equity markets to US equity market.

Table 3
Net pairwise volatility spillover effects: descriptive statistics.

	US_Brazil	US_Russian	US_India	US_China
Mean	0.441315	1.862024	7.675817	1.188508
Sigma	8.428995	7.657737	9.572564	5.852523
Skewness	0.357558	0.038741	0.478778	−0.141894
Kurtosis	5.564057	4.573726	3.018797	5.737573

Source: Computed by the authors.

The authors also reported volatility transmission effects from the Greater China markets to the US and Japan to an almost equal degree. Moreover, this also justifies the views of Rajwade,[39] who in his article titled “China's Global Economic Power”, highlighted the dominance stance of Yuan as the future reserve currency playing a significant rather dominant role in channelizing global financial system. In order to confirm the robustness of net pairwise spillover indices, we also constructed total spillover indices with 75 days rolling window and 10 and 2 days' ahead forecast horizons. Both the indices are found to be similar and robust with total spillover index constructed via 200 days rolling window and 10 days ahead forecast horizons. This confirms the overall robustness of the net spillover indices.[2]

[2] For brevity, results are not reported, but can be provided upon request.

3.3. US financial conditions index and its impact on volatility spillovers

Moving ahead, the study attempts to capture the response of these information transmissions toward the US overall financial conditions index (FCI) by employing binary logistic regression models. The said analyses would help in comprehending the impact of US overall financial conditions on volatility spillover effects among the US-BRIC equity markets. For this, monthly closing values of respective volatility spillover indices, US financial conditions index and CBOE's implied volatility index (VIX) are considered. The binary probability distributions are created considering the positive and negative spillover effects between the US and other BRIC equity markets. Fig. 5 is the graphical presentation of binary distribution with 1 being volatility spillover effects from the US to other BRIC equity markets and 0 being volatility spillover effects from the BRIC to US equity market. All the graphic elements report bi-directional spillover effects between the US and other BRIC equity markets during the sample period.

On a similar note, the Indian equity market witness greatest information transmissions from the US equity market, whereas on the other hand, the Chinese equity market witness somewhat lower information transmissions from the US equity market. Further, Fig. 6 reports FCI and VIX movements across the years 2004—2014. During the financial crisis period, US FCI fell to its lowest level depicting significant deterioration in the US financial market conditions. Correspondingly, volatility index (VIX) also increased to its highest level indicating substantial uncertainty in the US equity market at that time. Our hypothesis is that these varying movements in US FCI and VIX may have an impact on volatility spillover effects among the US-BRIC equity markets. The findings may support market participants and policy makers in analyzing probable spillover effects in the event of improving or deteriorating US financial conditions.

Tables 4—7 along with their sub-parts report logistic regression model results with respect to all the BRIC equity markets. In case of US-Brazil spillover effects, the R-square value ranges from 12 to 15 percent (Table 4(a)); quite reasonable considering the impact of other economic and financial variables as well. Table 4(b) reports classification

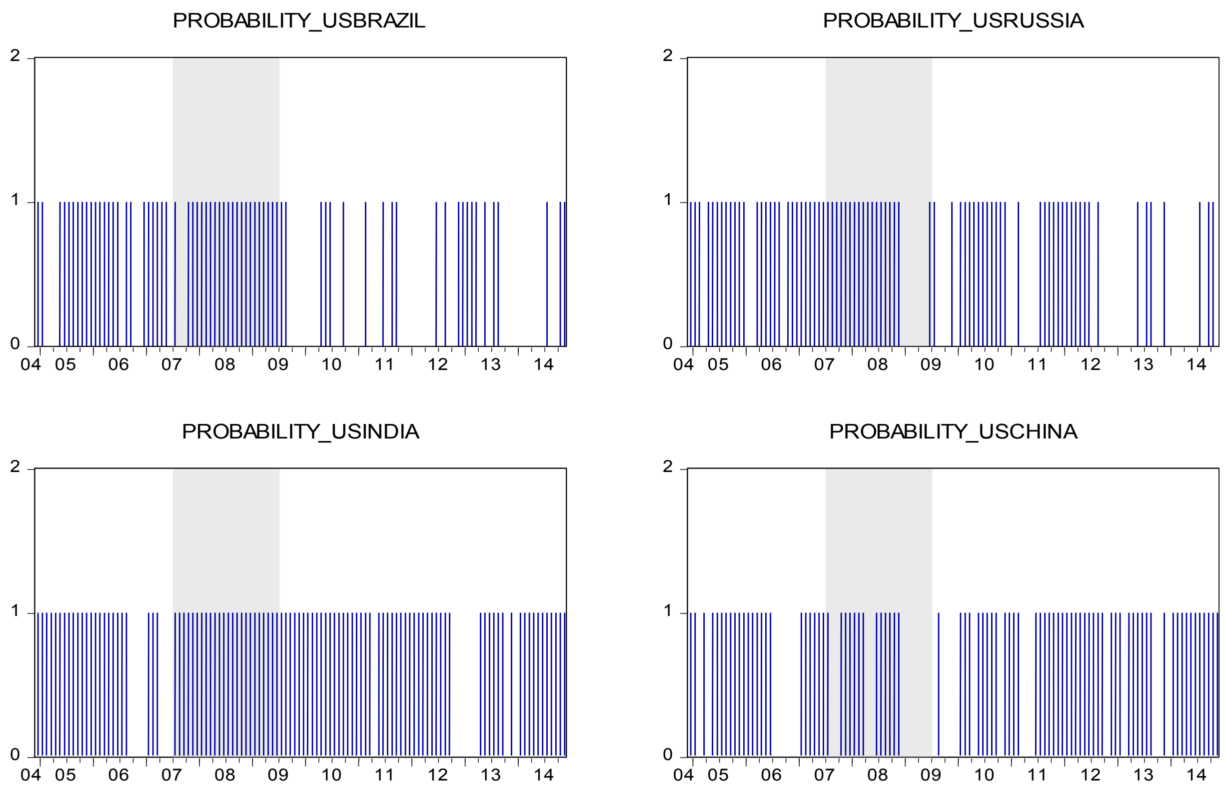

Fig. 5. Binary distribution with codes (1 and 0).
Source: Computed by the authors.

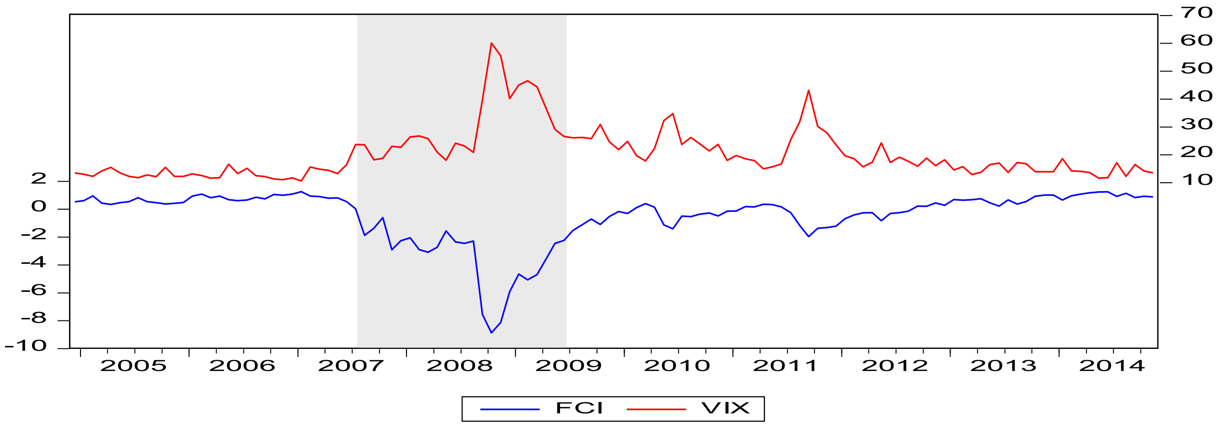

Fig. 6. US FCI and CBOE-VIX.
Source: Computed by the authors.

Table 4
Logistic regression results (US–Brazil).

(a) Model summary

Step	−2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	147.988[a]	0.115	0.154

(b) Classification table[b]

	Observed		Predicted		
			probability_usbrazil		Percentage correct
			0	1	
Step 1	probability_usbrazil	0	29	22	56.9
		1	23	45	66.2
	Overall percentage				62.2

(c) Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[c]	FCI	−1.394	0.711	3.841	1	0.050**	0.248
	Lagged_fci	0.397	0.491	0.655	1	0.418	1.488
	vix	−0.120	0.060	3.945	1	0.047*	0.887
	Constant	2.334	1.125	4.302	1	0.038*	10.315

[a] Estimation terminated at iteration number 5 because parameter estimates changed by less than 0.001.
[b] The cut value is 0.500.
[c] Variable(s) entered on step 1: FCI, lagged_fci, vix.
Source: Computed by the authors; Tables explain impact of the US financial conditions on information transmissions across the US-Brazilian equity markets; * Reject null hypothesis of no significant relation at 5% significance level; ** Reject null hypothesis of no significant relation at 10% significance level.

results indicating percentage of correct predictions done by the model employed. Around 62 percent of the predictions are correct, which are sufficiently greater than the cutoff value of 50 percent. For instance, both the expected and actual values report information transmissions from the US to Brazilian market around 45 times. Finally, Table 4(c) shows overall regression model results, whereby both the FCI (contemporaneous) and VIX indicators are found to be significant at 10 and 5 percent significance levels respectively. However, dynamic, i.e. one month lagged impact of FCI is not statistically different from zero. The coefficients are negative with exponential beta values less than 1, indicating reducing impact of both FCI and VIX on probability for positive volatility spillovers from the US to Brazilian equity market. With an improvement in the US overall financial market conditions, probability of volatility spillover effects from the US to Brazilian market reduces.

Table 5
Logistic regression results (US−Russia).

(a) Model summary

Step	−2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	141.616[a]	0.093	0.129

(b) Classification table[b]

	Observed		Predicted		
			probability_usrussia		Percentage Correct
			0	1	
Step 1	probability_usrussia	0	8	33	19.5
		1	5	73	93.6
	Overall percentage				68.1

(c) Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[c]	FCI	−2.215	0.823	7.243	1	0.007*	0.109
	lagged_fci	1.452	0.557	6.794	1	0.009*	4.271
	vix	−0.118	0.064	3.434	1	0.064**	0.889
	Constant	2.831	1.198	5.584	1	0.018*	16.970

[a] Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001.
[b] The cut value is 0.500.
[c] Variable(s) entered on step 1: FCI, lagged_fci, vix.
Source: Computed by the authors; Tables explain impact of the US financial conditions on information transmissions across the US-Russian equity markets; * Reject null hypothesis of no significant relation at 5% significance level; ** Reject null hypothesis of no significant relation at 10% significance level.

Table 6
Logistic regression results (US−India).

(a) Model summary

Step	−2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	76.819[a]	0.134	0.246

(b) Classification table[b]

	Observed		Predicted		
			probability_usindia		Percentage correct
			0	1	
Step 1	probability_usindia	0	0	16	0.0
		1	0	103	100.0
	Overall percentage				86.6

(c) Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[c]	FCI	−1.249	1.666	0.562	1	0.454	0.287
	lagged_fci	0.001	1.195	0.000	1	0.999	1.001
	vix	0.072	0.151	0.231	1	0.631	1.075
	Constant	1.051	2.699	0.152	1	0.697	2.860

[a] Estimation terminated at iteration number 8 because parameter estimates changed by less than 0.001.
[b] The cut value is 0.500.
[c] Variable(s) entered on step 1: FCI, lagged_fci, vix.
Source: Computed by the authors; Tables explain impact of the US financial conditions on information transmissions across the US-Indian equity markets; * Reject null hypothesis of no significant relation at 5% significance level; ** Reject null hypothesis of no significant relation at 10% significance level.

Table 7
Logistic regression results (US−China).

(a) Model summary

Step	−2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	131.977[a]	0.084	0.120

(b) Classification table[b]

	Observed		Predicted		
			probability_uschina		Percentage correct
			0	1	
Step 1	probability_uschina	0	6	28	17.6
		1	2	83	97.6
	Overall percentage				74.8

(c) Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp(B)
–Step 1[c]	FCI	−1.058	0.620	2.909	1	0.088**	0.347
	lagged_fci	1.130	0.476	5.636	1	0.018*	3.095
	vix	−0.017	0.059	0.087	1	0.769	0.983
	Constant	1.402	1.080	1.685	1	0.194	4.063

[a] Estimation terminated at iteration number 5 because parameter estimates changed by less than 0.001.
[b] The cut value is 0.500.
[c] Variable(s) entered on step 1: FCI, lagged_fci, vix.

Source: Computed by the authors; Tables explain impact of the US financial conditions on information transmissions across the US-Chinese equity markets; * Reject null hypothesis of no significant relation at 5% significance level; ** Reject null hypothesis of no significant relation at 10% significance level.

Similarly, in case of US−Russia spillover effects, the R-square value ranges from 9 to 13 (Table 5(a)) percent with a percentage of correct predictions of around 68 percent (Table 5(b)). All the parameters are found to be significant at 5 and 10 percent significance levels (Table 5(c)). Interestingly, one month lagged impact of FCI is increasing in nature, whereas on the other hand, the contemporaneous impact of the same is decreasing in nature. However, magnitude of contemporaneous impact is higher as compared to the dynamic impact. With an increase in the US FCI, probability of volatility spillover effects from the US to Russian equity market reduces. Contrary to this, one month lagged financial conditions increase probability of volatility spillovers from the US equity market. Interestingly, for both the US-Brazil and US-Russia markets, probability of positive spillovers decreases with corresponding increase in implied volatility in the US equity market.

In other words, with an increase in US implied volatility, probability of volatility spillovers from the Brazilian and Russian equity markets to the US equity market increases. In case of US−India spillover effects, the R-square value ranges from 13 to 25 percent (Table 6(a)) with classification results of around 87 percent (Table 6(b)). But all the regression parameters are not found to be statistically different from zero (Table 6(c)). This exhibit that volatility spillover effects between the US and Indian equity markets do not get influenced by overall US financial market conditions, rather some specific financial and/or economic events drive the said spillover effects. The results relating to the Brazilian and Russian equity markets are primarily due to a greater degree of openness observed in the respective economies. With increasing trade as well as financial linkages, the countries are becoming more prone to the international financial events.

In case of US-China spillover effects, the R-square value ranges from 8 to 12 percent (Table 7(a)) with classification results of around 75 percent (Table 7(b)). Coefficients relating to both contemporaneous and dynamic impacts are found to be statistically different from zero at 10 and 5 percent significance levels respectively (Table 7(c)). The magnitude of lagged impact is comparatively higher and positive as compared to contemporaneous impact with negative bias. This means that past financial market conditions in the US economy increase probability of volatility spillover effects from the latter to the Chinese equity market. The findings are quite similar to what reported earlier that both the US and Chinese equity markets share a strong bi-directional spillover relationship with each other. For instance, the same month impact of US FCI is reducing in nature, whereby probability of volatility spillovers from the

Chinese to US equity market increases with an improvement in the US financial market conditions, whereas on the other hand, one month lagged US FCI increases probability of volatility spillover effects from the US to Chinese equity market. This finding is consistent with the ones reported earlier. Lastly, Fig. 7 reports graphical presentation of spillover coefficients, whereby financial conditions in the US economy observe to be having a magnified impact on information transmissions across US-Russian equity markets both contemporaneously and dynamically. However, lagged impact of the same is relatively higher for the US-Chinese equity markets as compared to US-Brazilian equity markets.

In order to ensure goodness-of-fit, the study employs Receiver Operating Characteristic (ROC) framework.[52] The said framework allows measurement of sensitivity and specificity for different possible cutoff points simultaneously, i.e. measurement of true positive and true negative values supporting that the results generated are not by chance rather due to overall adequacy of the model. The graphical presentation of the same is regarded as ROC curve. Figs. 8—10 report ROC curves relating to the US-Brazil, US-Russia and US-China spillover effects. The area under curve is around 67, 68 and 67 percent with respect to the US-Brazil, US-Russia and US-China spillover effects respectively, and highly significant with 95 percent confidence interval (Tables 8—10). This ensures overall adequacy of the logistic regression models. Lastly, we plot ex-ante probabilities against the US overall financial conditions index (Fig. 11). For

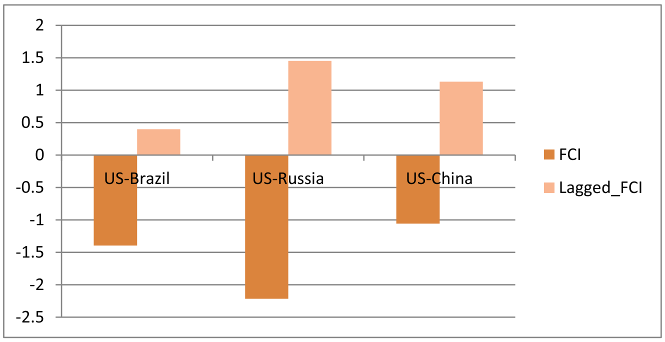

Fig. 7. Graphic presentation of spillover coefficients.
Source: Computed by the authors.

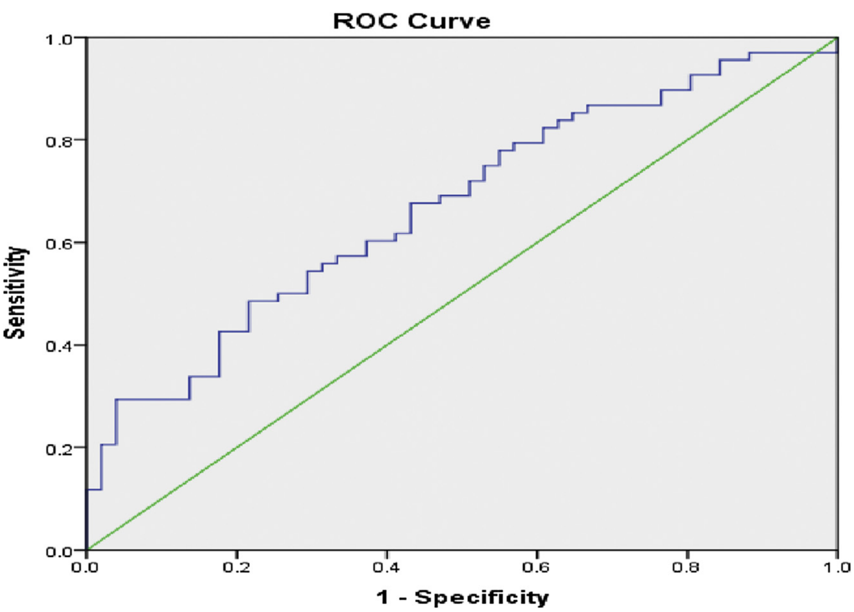

Fig. 8. Receiver operating characteristic (ROC) curve (US—Brazil).

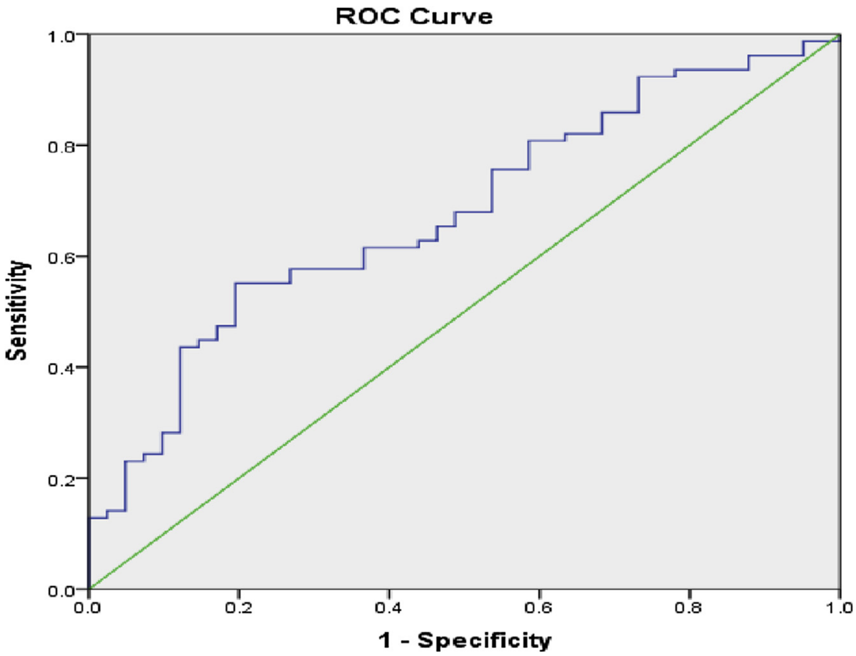

Fig. 9. Receiver operating characteristic (ROC) curve (US–Russia).

creating a scatter plot concerning the US FCI and respective probabilities, US FCI index values are arranged in an ascending order with an interval of 0.25 and similarly, VIX index values are arranged in an ascending order but with an interval of 1.50. There is no specific reason for taking these interval values, rather these are considered on the basis of convenience and overall differences between the successive values.

In case of the US-Brazil and US-Russia markets, probability of positive spillover effects reduces with increase in the US FCI values. As soon as the US financial system starts witnessing improvement, probability of volatility

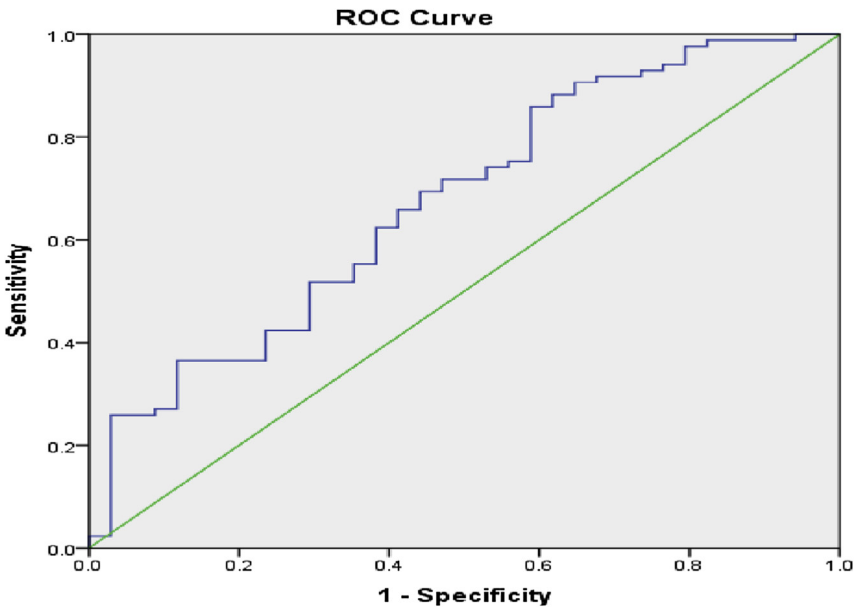

Fig. 10. Receiver operating characteristic (ROC) curve (US–China).

Table 8
Area under curve (US–Brazil).

Test result variable(s): predicted probability				
Area	Std. error[a]	Asymptotic sig.[b]	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.670	0.049	0.002*	0.574	0.766

*Significant at 5% level.
[a] Under the nonparametric assumption.
[b] Null hypothesis: true area = 0.5.

Table 9
Area under curve (US–Russia).

Test result variable(s): predicted probability				
Area	Std. error[a]	Asymptotic sig.[b]	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.677	0.050	0.002*	0.579	0.776

*Significant at 5% level.
[a] Under the nonparametric assumption.
[b] Null hypothesis: true area = 0.5.

Table 10
Area under curve (US–China).

Test result variable(s): predicted probability				
Area	Std. error[a]	Asymptotic sig.[b]	Asymptotic 95% confidence interval	
			Lower bound	Upper bound
0.673	0.055	0.003*	0.565	0.781

*Significant at 5% level.
[a] Under the nonparametric assumption.
[b] Null hypothesis: true area = 0.5.
Source: Computed by the authors.

spillover effects from the US to Brazilian and Russian equity markets starts reducing. Technically, probability of volatility spillover effects from the Brazilian and Russian equity markets to the US market increases with improvements in the US financial market conditions. But, a possible explanation for this can be that during improved US financial market conditions, volatility reduces in the US equity market as investors' confidence increases, so, the contribution of other equity markets increases under the VAR framework. During the lowest point of US FCI (Lehman Brothers' episode), probability of volatility spillovers from the US to Brazilian and Russian equity markets is near to one. On the other hand, during the highest point of US FCI, probability of the same is near to zero, rather the contribution of other equity markets increases. Expectedly, probability also reduces in case of the Chinese equity market, but the same reduces quite slowly and on a linear basis. As both contemporaneous and dynamic impacts are found to be significant, so, probability does not reduce at a faster pace as compared to US-Brazil and US-Russia markets. Notably, in case of the Chinese equity market, probability of positive spillovers is not very high as compared to the US-Brazil and US-Russia markets. These findings bear strong implications for investors having stocks in the US-BRIC equity markets.

4. Conclusions

The study attempts to capture the impact of US overall financial market conditions on information transmissions, i.e. volatility spillover effects among the US-BRIC equity markets by employing different econometric models

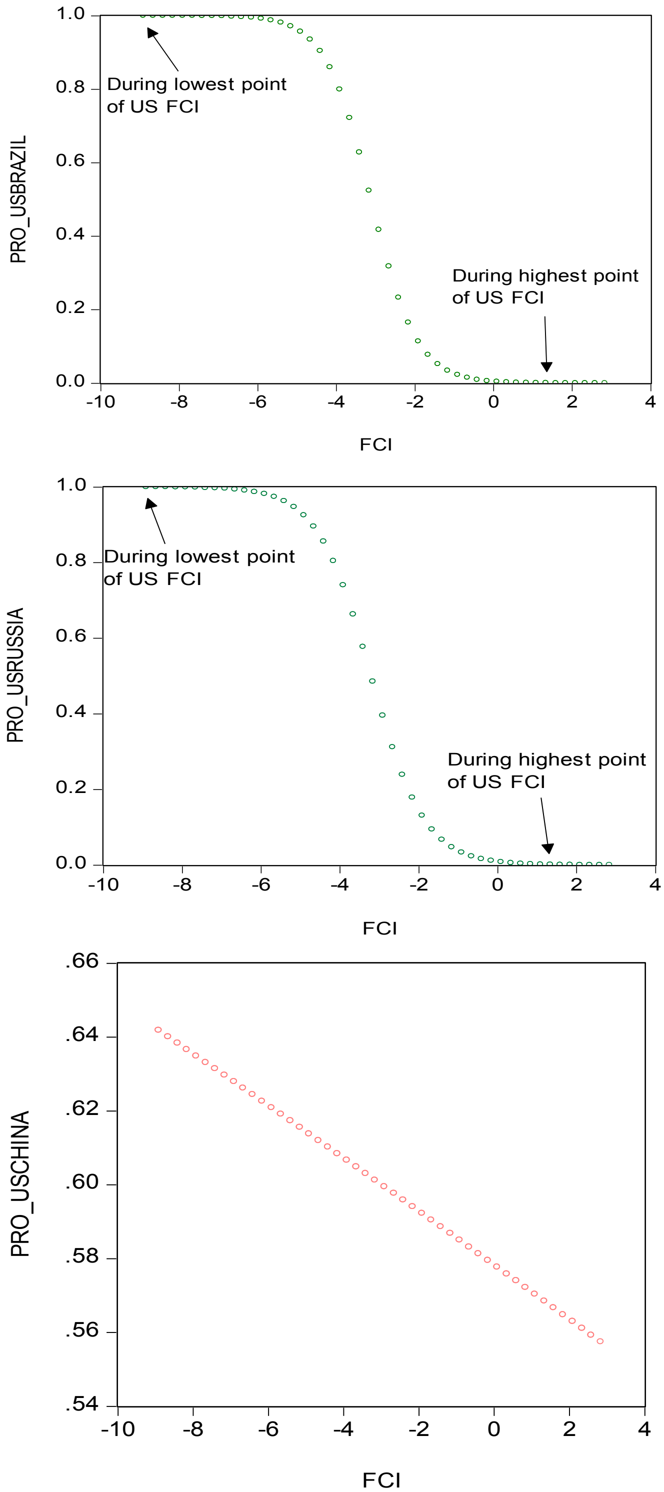

Fig. 11. Ex-ante probabilities (Positive spillovers) vis-à-vis US financial conditions.
Source: Computed by the authors.

ranging from univariate ARMA (1,1) EGARCH-M (1,1) model, Diebold and Yilmaz's[18] spillover index framework to binary logistic regression models; extension of Singh and Kaur.[46] Our hypothesis was that the equity markets discount domestic as well as international information contents supporting cross market interactions, so, how the same shall get affected in the event of deterioration or improvement in the overall US financial market conditions. Our results raise serious concerns over decoupling hypothesis generally expected between the emerged and emerging economies. To quote, all the markets witnessed an increased level of volatility during the US financial crisis period. There are bi-directional volatility spillover effects recorded between the US and other BRIC equity markets. Interestingly, both the US and Chinese equity markets share strong bi-directional relationships, whereby the Chinese equity market is also observed to be having a greater magnitude impact on the US equity market. With the increase in the US overall financial market conditions, probability of spillover effects from the US to Brazilian and Russian equity markets reduces, whereas on the other hand, probability reduces but at a slower pace in the context of the Chinese equity market. Moreover, both the Brazilian and Russian equity markets share a strong co-movement with the US equity market.[2]

Interestingly, lagged US FCI is observed to be having an increasing impact on the probability of volatility spillover effects from the US to other BRIC equity markets with respect to all US−Brazil, US−Russia, US−India (though insignificant) and US−China markets (Fig. 7). This exhibits that information transmissions are greatly affected by past financial conditions in the US financial market, whereby volatility increases in the BRIC equity markets with improvement in the US financial market conditions. This could be due to increasing confidence of the investors in the US equity market over the period. On the other, improving US financial conditions reduce probability of positive spillover effects contemporaneously. As soon as the US FCI reaches its zero level, i.e. equilibrium level, probability of positive spillovers reduces to zero. But this is not the case with respect to the Chinese equity market because the probability of the same reduces at a very slower pace registering strong bi-directional spillover effects. China holds a dominant place in the worldwide export market along with mammoth financial reserves justifying the existence of strong bi-directional spillover effects.

Ever since 2001, portfolio investment liabilities of the Chinese economy have been increasing, especially after the financial crisis, thereby making the said economy sensitive to international macroeconomic events as well (IMF data). These findings are critically relevant for the market participants and policy makers in their attempt to manage portfolio risks, financial contagion phenomenon and asset allocation decisions. US−India spillover effects are not significantly influenced by the US financial market conditions; as reported by statistical evidences. Information about volatility spillover effects is also found to be helpful for option pricing, portfolio optimization, computation and management of value-at-risk, and risk hedging.[3] Keeping in view the importance of these volatility spillover effects, it is pertinent to account for the impact of some macroeconomic events in channelizing the said information transmissions. Our study attempts to fill this gap. As a future scope, some other financial or macroeconomic variables can be considered while accounting these information transmissions.

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