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## CONDITIONAL CO-MOVEMENT AND DYNAMIC INTERACTIONS: US AND BRIC EQUITY MARKETS

**ABSTRACT:** *The present study attempts to capture conditional or time-varying co-movement and dynamic interactions between the US and BRIC (Brazil, Russia, India, and China) equity markets across the sample period 2004 to 2014 by employing diverse econometric models. The sample period is further divided into three different sub-periods concerning the US financial crisis period, viz. pre-crisis, crisis, and post-crisis periods. The vector autoregression–dynamic conditional correlation–multivariate asymmetric generalized autoregressive conditional heteroskedastic [VAR-DCC-MVAGARCH (1.1)] model and Toda-Yamamoto’s (1995) Granger causality tests are employed for the purpose of overall*

*analysis in a multivariate framework. The results report the existence of time-varying co-movement between the US and BRIC equity markets, whereby co-movement between the US and Brazilian markets is found to be the highest, followed by the Russian, Indian, and Chinese equity markets. Dynamic interactions are also registered between the respective US/BRIC co-movements during different sub-periods. The results have important implications for market participants and policymakers.*

**KEY WORDS:** *BRIC; co-movement; dynamic interactions; equity markets; time-varying; US*

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## **1. INTRODUCTION**

Since the seminal work of Grubel (1968) on the benefits of international portfolio diversification, the topic has become a contentious issue among researchers worldwide. The burgeoning literature on the financial crisis has increased researchers' interest in spillover effects, financial contagion, and interdependency between international stock markets. The level of interaction or interdependence between markets has important implications for portfolio allocation, diversification, and risk management decisions, because a higher level of interaction reduces diversification benefits. Furthermore, Markowitz (1952) argues that a higher degree of co-movement between asset prices (returns) undermines diversification benefits arising out of international portfolios. Thus, understanding spillover effects is imperative for international portfolio investors. Spillovers are reflected as changes in stock market returns or volatilities in one market owing to a transmission of information from another market through diverse transmission channels (Fleming et al. 1998; Rejeb & Boughrara 2015). Furthermore, co-movement among international equity markets reflects cross-country spillover effects existent in the underlying equity markets.

Ever since the unprecedented US sub-prime crisis, a wide body of literature has attempted to account for contagion or interdependence among markets (Hamao et al. 1990; Theodossiou & Lee 1993; Bekaert 1995; Yang 2005; Cappiello et al. 2006; Chiang et al. 2007; Dooley & Hutchison 2009; Kenourgios et al. 2011; Samarakoon, 2011; Kenourgios & Padhi 2012; Suardi 2012; Bianconi et al. 2013; Ahmad et al. 2014; Singh & Kaur 2015; Singh & Singh 2016; etc). Most studies relate to developed markets, but after the US financial crisis emerging markets are becoming investment avenues for international investors in search of risk premiums. However, the fundamental aspect of ascertaining these linkages is co-movement between foreign equity markets (Claessens & Forbes 2001; Forbes & Rigobon 2002). Consequently, an understanding of overall co-movement among different equity asset classes across international boundaries is essential for international investors. Moreover, an increase in co-movement also has an impact on the volatility of portfolios and asset prices (Karolyi & Stulz 1996). Thus, when constructing portfolios, co-movement is a considerable factor due to its impact on portfolio risk and returns.

Owing to liberalization in terms of both real and financial linkages across foreign boundaries, domestic equity markets experience co-movement with international markets. Furthermore, international capital flows have an impact on overall exchange rate movement, so accounting for linkages between the markets becomes an imperative task for multinational corporations. These cross-country financial flows are subject to a high degree of volatility and sudden withdrawals, thereby making economies very sensitive to them. In other words, co-movement between markets acts as a catalyst agent when framing macroeconomic policies.

Another important issue when accounting for market integration is country- or industry-based effects that channel co-movement between markets. These effects are challenging, because with the establishment of the European Union, the Association of Southeast Asian Nations (ASEAN), and other regional blocs, market integration has increased at an unstoppable rate, and this phenomenon has further increased interdependence between participant economies. The BRIC countries (Brazil, Russia, India, and China), however, constitute a geopolitical economic block in which the respective economies are heterogeneous and still directed by domestic fundamentals, and therefore country effects are likely to play a significant role in portfolio allocation decisions.

Existing studies have extensively documented spillover effects in the context of both stock market returns and volatility. Apart from these short-run linkages, considerable evidence is available with respect to long-run stochastic trends between countries (see, for instance, Hoque 2007; Menon et al. 2009). Despite these long-run linkages, the diversification benefits are not abruptly eroded as market returns can react very slowly to these common stochastic trends (Hyde et al. 2007). Consequently, precise measurement of time-varying correlation coefficients between the international markets is an inevitable task. Due to a higher degree of information asymmetry, emerging equity markets are somewhat more sensitive to financial contagion than mature markets (Celik 2012).

By and large, the methodology employed by empirical studies of co-movement among markets can be divided into two threads. The first relates to long-run co-

movement, captured through cointegration analysis, and the second to short-run linkages, employing the vector autoregression (VAR) model, GARCH-based models, and/or conventional correlation coefficients. Since the seminal work of King and Wadhvani (1990), researchers have extensively analysed time-varying correlation coefficients among the asset classes. A rich literature supports the use of dynamic conditional correlation (DCC) GARCH-based models to account for short-run time-varying co-movement, due to its ability to consider heteroskedasticity while modelling conditional correlation coefficients. According to Myers et al. (2014), if two variables are driven by common cyclical events, then the correlation will be equivalent to 1, and otherwise less than 1.

Emerging markets like the BRIC nations are becoming very attractive to international investors due to enormous opportunities in infrastructure, capital goods, health, education, retail, etc., In this regard, the present study attempts to capture conditional or short-run time-varying co-movement between the US and BRIC equity markets for the years 2004–2014 in an asymmetric multivariate framework where responses toward negative market shocks are computed simultaneously, and considering especially the US financial crisis period by employing vector autoregression (six days' lagged values) dynamic conditional correlation – the multivariate asymmetric generalized autoregressive conditional heteroskedastic [VAR (6) DCC-MVAGARCH (1.1)] model. Additionally, we attempt to capture the dynamic interactions between US and BRIC co-movement coefficients through the application of Toda-Yamamoto's (1995) Granger causality approach. The economic intuition behind this pertains to the growing investment in emerging equity markets in the wake of the interest rate differentials between rich and emerging world economies since the financial crisis. Therefore, it is interesting to understand the dynamic interactions between the co-movements of the US and BRIC markets, in order to glimpse how individual BRIC markets are moving in tandem with the US, while simultaneously considering their interaction with others. Overall, the results report time-varying co-movement coefficients between the US and BRIC equity markets, coupled with significant causality relationships between the co-movement coefficients.

Our study contributes to the literature in three ways. Firstly, complex simultaneous asymmetric interactions are modelled using a 5-dimensional

multivariate framework with an attempt to generate conditional correlations. Secondly, conditional correlations are analysed with special reference to the recent global financial crisis. Thirdly, an attempt is made to understand dynamic interactions between US-BRIC co-movement coefficients, stipulating the investment philosophies of investors in the wake of the portfolio rebalancing approach. The results are critically relevant to different market participants because these time-varying co-movements highlight the importance and implementation of different active portfolio management strategies to maintain portfolio values. Even policymakers are interested in comprehending spillover effects across foreign boundaries.

The rest of the paper is organized as follows. Section 2 presents the empirical framework, section 3 the results and discussion, and section 4 concludes.

## **2. EMPIRICAL FRAMEWORK**

Local daily closing values of the respective benchmark indices are taken from the Bloomberg terminal and the Yahoo finance database, as per their availability, from 01/01/2004 to 30/11/2014, a relatively long period of time. The benchmark indices used in the study are S&P 500 (US), IBOVESPA (Brazil), RTS (Russia), NIFTY (India), and the Shanghai composite index SSE (China). For the purpose of analysis, following the Business Cycle Dating Committee of the National Bureau of Economic Research (2010) and Bekaert et al. (2011), the present study considers 1st January 2004 to 30th June 2007 to be the pre-crisis period; 1st July 2007 to 30th June 2009 to be the crisis period; and 1st July 2009 to 30th November 2014 to be the post-crisis period. Daily continuously compounding gross index returns  $[R_t = \text{Log}(P_t / P_{t-1}) * 100]$  are used in the analysis. Only common trading days are considered for the overall analysis. Owing to non-convergence issues in a multivariate framework, the study has employed a simpler version of the DCC model under the VAR framework, due to non-existence of common stochastic trends or long-run co-movement between the US and BRIC equity markets.

### **2.1 VAR (6) DCC-AMGARCH (1.1) model**

The application of the GARCH-based models requires a mean equation at the beginning. The present study employs Akaike's information criterion (AIC) for

the purpose of determining appropriate lag lengths, because the AIC values are normally found to be less restrictive than other criteria. Under the VAR framework, a dependent variable is a function of its own lags as well as the lags of other variables (Sims 1980). The coefficients of the lagged variables justify the existence of return spillovers across the selected variables.

$$\begin{aligned}
 r_t^B &= u^B + a^B r_{t-1}^B + b^B r_{t-1}^R + c^B r_{t-1}^I + d^B r_{t-1}^C + e^B r_{t-1}^U + \varepsilon_t^B \\
 r_t^R &= u^R + b^R r_{t-1}^B + a^R r_{t-1}^R + c^R r_{t-1}^I + d^R r_{t-1}^C + e^R r_{t-1}^U + \varepsilon_t^R \\
 r_t^I &= u^I + b^I r_{t-1}^B + c^I r_{t-1}^R + a^I r_{t-1}^I + d^I r_{t-1}^C + e^I r_{t-1}^U + \varepsilon_t^I \\
 r_t^C &= u^C + b^C r_{t-1}^B + c^C r_{t-1}^R + d^C r_{t-1}^I + a^C r_{t-1}^C + e^C r_{t-1}^U + \varepsilon_t^C \\
 r_t^U &= u^U + b^U r_{t-1}^B + c^U r_{t-1}^R + d^U r_{t-1}^I + e^U r_{t-1}^C + a^U r_{t-1}^U + \varepsilon_t^U
 \end{aligned} \tag{1}$$

where  $r_t^B, r_t^R, r_t^I, r_t^C$  and  $r_t^U$  are the logarithmic returns of Brazil, Russia, India, China, and the US respectively [equation (1)]. The residuals are assumed to be serially uncorrelated. The coefficients  $a^B, a^R, a^I, a^C$  and  $a^U$  capture own-market return spillovers and the rest of the coefficients capture cross-market return spillovers, assuming one-day lagged values for the sake of brevity, which otherwise can be extended up to  $p$  lags. The residuals derived from the ‘mean’ equation are factored into GARCH-based models to account for conditional variances. The DCC-MVAGARCH model accounts for dynamic conditional correlations considering heteroskedasticity in the error terms. At the same time, the DCC-MVAGARCH model ensures implied adjustments with respect to time gaps between the markets, because the conditional correlations are modelled under a dynamic framework wherein lagged values are used for the purpose of computation.

The DCC-MVAGARCH (1.1) model is part of the multivariate GARCH family, whereby positive covariance definiteness, flexibility, and parsimony are ensured in an implied sense. Moreover, the empirical evidence suggests that models capturing correlation in the second moment (stock market volatility) of the stock markets are more efficient than the models working on the first moment (stock market returns) (Syriopoulos et al. 2015). As proposed by Engle (2002),

the model is estimated through a two-step procedure. In the first step, univariate GARCH (1.1) models for each of the return series are fitted out, and in the next step conditional correlations are computed. As there are only five endogenous variables we will be resorting to the full system estimation technique in RATS version 9.0 instead of the two-step procedure, wherein univariate models will be expressed as in equation (2). The joint-estimation system pertains to joint-country estimation of the correlation parameters.

### Univariate model

$$\sigma_t^2 = C + A_1 \varepsilon_{t-1}^2 + B_1 \sigma_{t-1}^2 + \delta \varepsilon_{t-1}^2 D_{t-1} + \varepsilon_t \quad (2)$$

where  $A_1$  and  $B_1$  capture the impact of the news component and lagged volatility respectively on the current conditional variance, and  $\delta$  captures the asymmetric response of the conditional variance towards negative shocks in the own-market. If  $\varepsilon_{t-1} < 0$ , then value 1 is assigned to the indicator function ( $D$ ), and otherwise it is 0, following Glosten et al. (1993).

### Conditional correlation

The dynamic conditional correlations are computed over a period of time in an ARMA-like framework, wherein the current conditional correlation is a function of its recent market shock as well as past conditional correlation.  $D_t$  is the diagonal matrix of conditional variances.  $R_t$  is the time-varying matrix of conditional correlation.  $H_t$  is the variance covariance matrix [equations (3), (4), and (5)].

$$H_t = D_t R_t D_t \quad (3)$$

$$R_t [p_j^{ij}] = \text{diag} \left( Q_t^{-\frac{1}{2}} \right) Q_t \text{diag} \left( Q_t^{-\frac{1}{2}} \right) \quad (4)$$

$$Q_t = (1 - \lambda_1 - \lambda_2) Q^0 + \lambda_1 u_{t-1} u_{t-1} + \lambda_2 Q_{t-1} \quad (5)$$

where  $Q_t$  is a function of squared standardized residuals  $u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$  and  $Q^0$  an unconditional variance-covariance matrix.  $\lambda_1$  and  $\lambda_2$  are non-negative

scalars such that  $\lambda_1 > 0, \lambda_2 > 0$  and  $\lambda_1 + \lambda_2 < 1$ . The correlation between two variables, say the US and Brazil,  $p_t^{UB}$  at time  $t$ , is given by:

$$p_t^{UB} = \frac{E_{t-1}[\varepsilon_t^U \varepsilon_t^B]}{\sqrt{E_{t-1}[(\varepsilon_t^U)^2]} * \sqrt{E_{t-1}[(\varepsilon_t^B)^2]}} \quad (6)$$

where  $[\varepsilon_t^i \varepsilon_t^j]$  is the conditional covariance and  $[(\varepsilon_t^{ii})^2]$  is the conditional variance at  $t-1$ . The estimation of the model follows the Quasi Maximum Likelihood (QML) approach [equation (7)], where  $u_t$  is assumed to follow a joint Gaussian log-likelihood function for a sample of  $T$  observations and  $k = 5$  in a 5-variable model.

$$\log L = -\frac{1}{2} \sum_{t=1}^T [K \log(2\pi) + \ln |H_t| + u_t' H_t^{-1} u_t] \quad (7)$$

The optimization algorithm for estimation of the maximum likelihood functions is carried out using the BFGS approach (500 iterations), coupled with preliminary iterations by the Simplex method (20 iterations).

## 2.2 Dynamic Interactions

Dynamic interactions between different US-BRIC co-movements are captured through the application of Toda-Yamamoto's (1995) Granger causality approach. This approach is an important branch of the VAR-based models. Dynamic interactions are modelled amongst the co-movement coefficients generated by the application of a GARCH-based model. Notwithstanding, these time-varying coefficients capture spillover effects between the studied markets. However, the ultimate objective is to come up with time-varying co-movement indices (correlation indices) while controlling heteroskedastic error terms. Therefore, in this second part of the study, dynamic interactions are modelled considering dynamic coefficients as a separate set of individual indices spotlighting co-movement between the various studied markets. In pursuit of the latter objective, the existence of unit roots is checked for each of the correlation indices to ascertain their degree of integration. Under the Granger causality test, when past (lagged) values of one variable help to predict the future values of another variable, the former variable is said to be Granger-causing the latter. In other words, the results establish a lead-lag relationship between the

variables. The Granger causality test ascertains the exogenous quality of the endogenous variables by the application of joint significance tests on the coefficients of the latter variables in the equation. However, due to the existence of non-stationary series, the standard Wald-test statistic does not follow its usual asymptotic chi-square distribution under the null of zero restrictions. Consequently, Toda and Yamamoto (1995) propose estimation of an augmented VAR model without pre-testing the existence of any cointegrating vectors among the variables, guaranteeing asymptotic distribution of the Wald test statistic. Initially, a VAR ( $p$ ) process is estimated without considering the integration of the series, i.e., at level per se. Optimal lag lengths are determined on the basis of AIC values. Later, the augmented VAR ( $p+m$ ) model is estimated, where  $m$  is the maximum order of integration determined as per unit root analysis introduced as an exogenous variable. The resultant analysis of the past values' impact of one variable on another assures asymptotic distribution of the Wald test statistic.

### 3. EMPIRICAL FINDINGS AND DISCUSSION

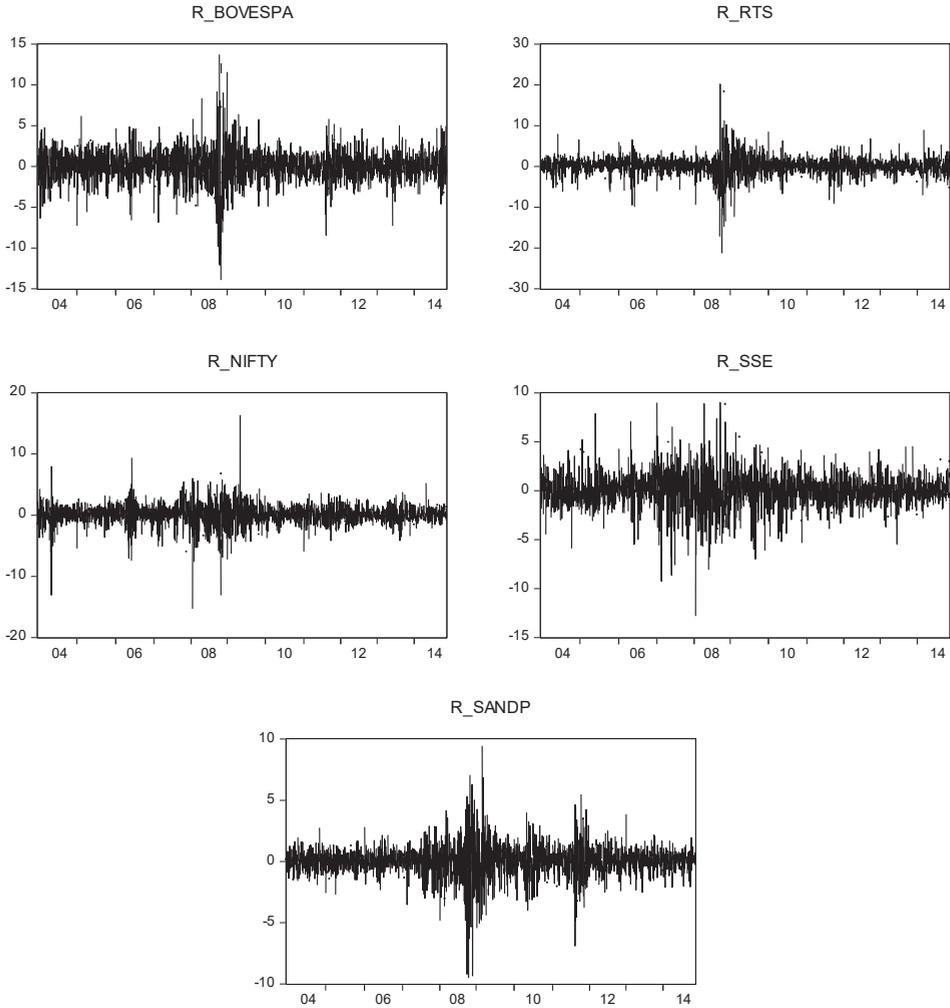
Figure 1 presents a graph of the respective index returns. All the markets witnessed a substantial increase in volatility during the Lehman Brothers episode, i.e., in the last quarter of the year 2008. This confirms the existence of the volatility-clustering phenomenon in the respective markets, whereby periods of small volatility are followed by smaller ones, and periods of large volatility are followed by larger ones.

This phenomenon further supports the application of a GARCH-based model that accounts for conditional variances and co-movements. Table 1 presents descriptive statistics of the respective index returns during the full sample period. The Russian equity market has the lowest average daily gross index returns along with the highest level of variations, while during the same period the Indian equity market has the highest average returns. The remainder of the index returns fall within this continuum.

The skewness values show a greater probability of negative returns than positive returns with respect to all the studied markets. Further, Kurtosis and Jarque-Bera test statistics confirm leptokurtic and non-normal distribution of the

respective index returns. This highlights the existence of the abnormal returns available to investors in the US-BRIC equity markets.

**Figure 1.** Index Returns



**Source:** Computed by the authors

**Table 1.** Descriptive statistics: Index returns (Full sample period)

Parameters	R-Bovespa	R-RTS	R-Nifty	R-SSE	R-SandP
Mean	0.0361	0.0217	0.0634	0.0230	0.0261
Sigma	1.9592	2.3359	1.7157	1.7504	1.2636
ADF test	-37.126*	-42.501*	-48.209*	-47.713*	-53.989*
Philips-Perron	-50.837*	-42.403*	-48.213*	-47.744*	-54.008*
KPSS test	0.1884**	0.2784**	0.0627**	0.1683**	0.2137**
L.Box (1)	3.9622***	36.770***	0.0054	0.2935	28.952***
L.Box (12)	30.355***	53.254***	12.856	25.703***	57.343***
L.Box (36)	88.641***	114.43***	47.806	63.249***	148.43***
Zivot-Andrews	-19.398****	-19.022****	-18.635****	-18.735****	-19.457****

**Source:** Computed by the authors

\*Rejects null hypothesis of non-stationary time series at the 5% significance level; \*\*Data does not provide evidence to reject null hypothesis of stationary time series with asymptotic critical value 0.4630 at the 5% significance level; \*\*\*Rejects null hypothesis of independent distribution of the index returns at the 5% significance level; \*\*\*\*Rejects null hypothesis of non-stationary series with a structural break at the 5% significance level.

**Table 2.** DCC-Multivariate Asymmetric GARCH (1.1) model results

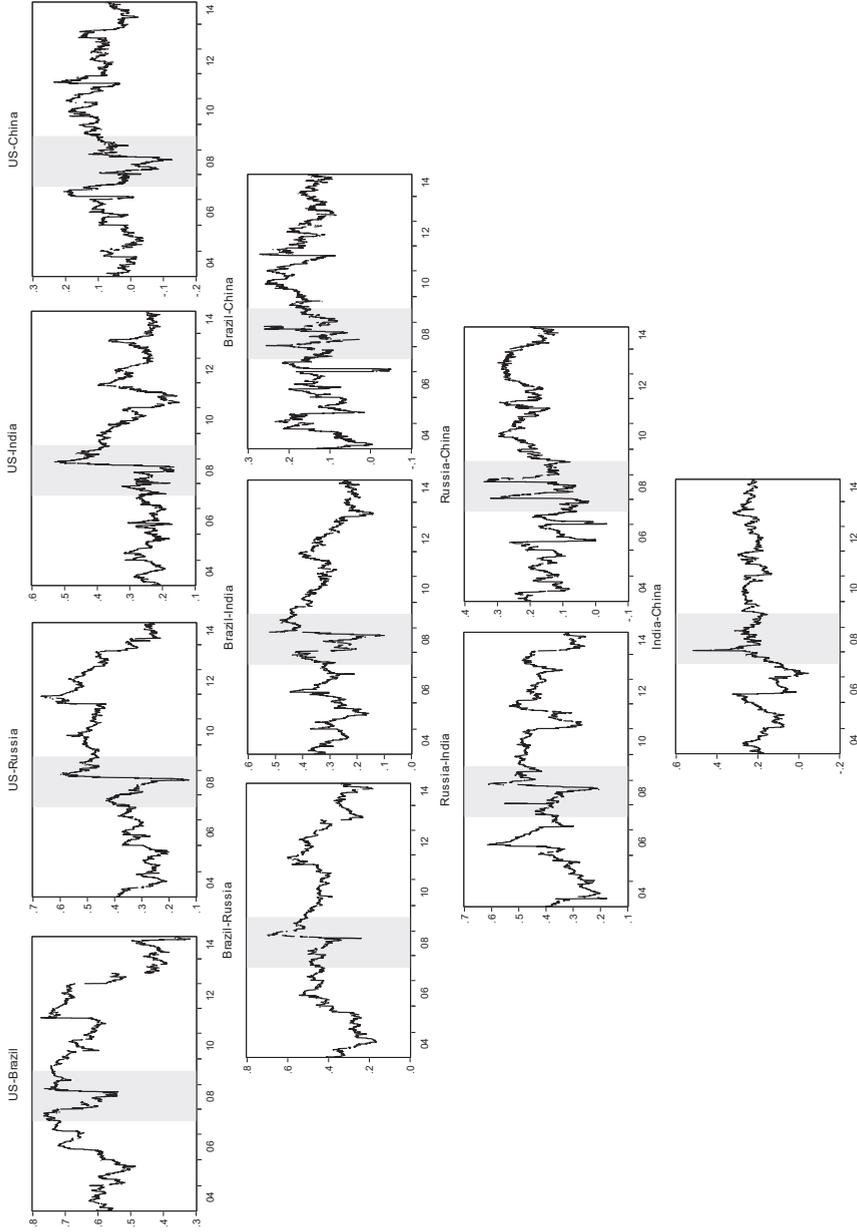
Parameter	Coefficients	Parameter	Coefficients
C (US)	0.021127*	B (US)	0.926914*
C (Brazil)	0.076901*	B (Brazil)	0.930196*
C (Russia)	0.092937*	B (Russia)	0.913845*
C (India)	0.039474**	B (India)	0.900617*
C (China)	0.017183*	B (China)	0.956563*
A (US)	-0.01589*	$\delta$ (US)	0.132891*
A (Brazil)	-0.001626	$\delta$ (Brazil)	0.09332*
A (Russia)	0.016787*	$\delta$ (Russia)	0.088142*
A (India)	0.049213**	$\delta$ (India)	0.080041**
A (China)	0.040844*	$\delta$ (China)	-0.00554
$\lambda_1 = 0.0101^*$ ; $\lambda_2 = 0.9860^*$			

**Source:** Computed by the authors

\* Rejects null hypothesis of no significant relationship at the 5% significance level; \*\* Rejects null hypothesis of no significant relationship at the 10% significance level; Log likelihood: -19733.6539; Convergence in 85 iterations.

The financial time series are required to be ‘mean’ reverting, i.e., stationary for the application of different econometric models. For this, the study employs three different stationarity tests, augmented Dickey-Fuller (ADF), Philips-Perron, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) allowing for intercept only. All the stationarity tests support stationary distribution of the index returns. We also checked for the presence of structural breaks in the data by adopting the Zivot-Andrews (1992) testing procedure. All the index returns were found to be stationary, but with a structural break in the intercept during the financial crisis period.

Figure 2. Conditional correlation coefficients



Source: Computed by the authors

**Table 3.** Conditional correlation coefficients: Descriptive statistics

**A: Full sample period**

Co-movements	Mean	Sigma	Skewness	Kurtosis	Jarque-Bera	Obs.
US–Brazil	0.619306	0.101466	-0.70064	2.660937	201.0127*	2,321
US–Russia	0.397836	0.109247	0.052793	1.914755	114.977*	2,321
US–India	0.275718	0.06733	1.055713	3.808512	494.3549*	2,321
US–China	0.07061	0.061261	-0.1418	2.829763	10.58096*	2,321
Brazil–Russia	0.414016	0.099663	-0.30334	2.623254	49.32008*	2,321
Brazil–India	0.30954	0.073086	0.088147	2.451973	32.05043*	2,321
Brazil–China	0.145695	0.051849	-0.52152	3.811218	168.8542*	2,321
Russia–India	0.396425	0.085173	-0.23616	2.246222	76.52187*	2,321
Russia–China	0.179988	0.067036	-0.20704	2.471306	43.61336*	2,321
India–China	0.20188	0.068669	-0.78551	4.164163	369.7503*	2,321

**B: Pre-crisis period**

Co-movements	Mean	Sigma	Skewness	Kurtosis	Jarque-Bera	Obs.
US–Brazil	0.610864	0.064906	0.432071	2.203212	43.17538*	750
US–Russia	0.303142	0.04869	-0.07999	1.851719	42.00443*	750
US–India	0.241553	0.027991	0.273038	2.503499	17.0223*	750
US–China	0.052368	0.056206	0.761993	2.972142	72.60347*	750
Brazil–Russia	0.357732	0.098237	-0.0497	1.752442	48.94629*	750
Brazil–India	0.293066	0.051597	0.008512	3.242401	1.845247	750
Brazil–China	0.12067	0.060651	-0.49755	2.719166	33.40891*	750
Russia–India	0.353131	0.092985	0.63215	2.821882	50.94313*	750
Russia–China	0.14515	0.052834	-0.44498	3.451153	31.11126*	750
India–China	0.145814	0.077557	-0.03239	2.206254	19.81969*	750

**C: Crisis period**

Co-movements	Mean	Sigma	Skewness	Kurtosis	Jarque-Bera	Obs.
US–Brazil	0.685075	0.066227	-0.73394	2.082562	52.56079*	421
US–Russia	0.401508	0.104144	-0.26416	2.452554	10.15351*	421
US–India	0.312453	0.099497	0.491114	1.852104	40.03773*	421
US–China	0.025123	0.061469	-0.41964	2.343456	19.91739*	421
Brazil–Russia	0.486901	0.078286	0.465152	3.11425	15.41066*	421

<b>Brazil–India</b>	0.34501	0.094451	-0.43517	2.061618	28.73422*	421
<b>Brazil–China</b>	0.134161	0.041107	0.591571	3.458898	28.24927*	421
<b>Russia–India</b>	0.406937	0.077052	-0.04181	3.236247	1.101691	421
<b>Russia–China</b>	0.135824	0.075159	1.046292	3.340284	78.84447*	421
<b>India–China</b>	0.22149	0.059285	0.895188	7.490247	409.9095*	421

#### D: Post-crisis period

Co-movements	Mean	Sigma	Skewness	Kurtosis	Jarque-Bera	Obs.
<b>US–Brazil</b>	0.600735	0.120256	-0.58397	1.90064	123.2736*	1,150
<b>US–Russia</b>	0.458249	0.095275	-0.76618	3.034229	112.5713*	1,150
<b>US–India</b>	0.284551	0.060742	0.147021	2.060605	46.42758*	1,150
<b>US–China</b>	0.099159	0.048437	-0.02622	2.580047	8.582367*	1,150
<b>Brazil–Russia</b>	0.424042	0.086079	-0.52375	2.621729	59.43308*	1,150
<b>Brazil–India</b>	0.3073	0.071735	-0.10156	2.150325	36.57023*	1,150
<b>Brazil–China</b>	0.166237	0.03915	0.326861	2.580426	28.91271*	1,150
<b>Russia–India</b>	0.420812	0.070584	-0.80091	2.398699	140.2705*	1,150
<b>Russia–China</b>	0.218876	0.04657	-0.33986	2.26491	48.02983*	1,150
<b>India–China</b>	0.231266	0.035473	-0.26537	2.731614	16.94844*	1,150

Source: Computed by the authors

\*Rejects null hypothesis of normal distribution of correlation coefficients at the 5% significance level

However, application of a GARCH-based empirical model will keep in check these respective structural changes. All the index returns are significantly influenced by their past conditional returns except for the Indian equity market, thereby implying inefficiency existent in other US-BRIC equity markets, evidenced by significant Ljung-Box test statistics taking 1, 12, and 36 days' lagged values. As per the efficient market hypothesis (EMH), stock prices reflect all available information floated in the respective or cross-markets; however, the significant impact of past events on current ones refutes these claims. Now we move to DCC-MVAGARCH model results for the purpose of computing conditional correlation coefficients.

The multivariate autoregressive conditional heteroskedastic (MVARCH) effects test supports the existence of the volatility-clustering phenomenon in empirical terms in the residuals derived from the 'mean' equation. For brevity, VAR model results with six days' lagged values are not reported. Table2 reports the

DCC-MVAGARCH model results. Almost all the coefficients are found to be statistically different from zero at the 5% and 10% significance levels. As expected, all the equity markets are substantially influenced by their past conditional variances, irrespective of recent market shocks. The conditional volatility has an asymmetric response to negative market shocks. This implies that falling returns add to the conditional volatility in the respective markets, except for China (Christie 1982). In other words, falling returns or negative market shocks add to conditional variance in the market on account of the augmenting level of financial risk with the decrease in equity valuations. It also highlights negative relationship between current returns and future volatility further channelling various portfolio-management-based decisions. Both the DCC parameters are found to be significant, whereby past co-movements significantly influence current conditional correlation. Residual diagnostic tests confirm the overall adequacy of the DCC-MVAGARCH model.

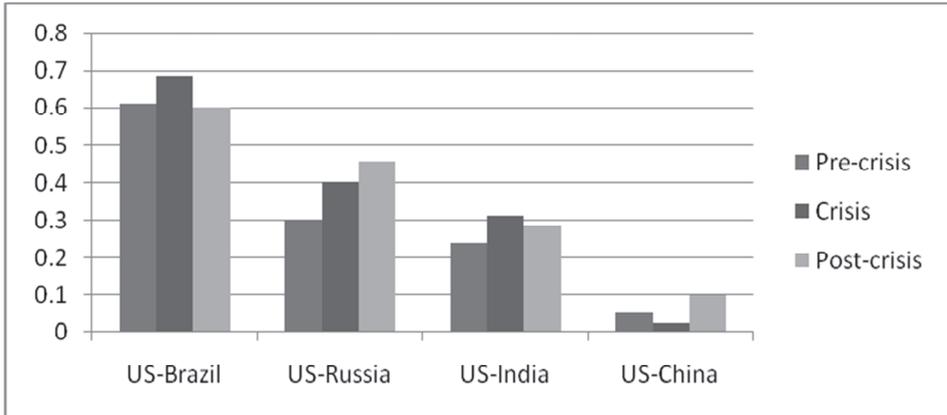
Figure 2 presents a graph of the respective co-movements. Perhaps these time-varying correlation coefficients report spillover interactions between the US-BRIC equity markets during the period 2004 to 2014. All the correlation coefficients signify the existence of the US subprime crisis during the period 2007 to 2009. The correlation coefficients further support active portfolio management strategies in the wake of varying portfolio risk and return. The coefficients highlight the fact that integration between the US-BRIC equity markets varies over a period of time: the markets do not share a static relationship with each other. All the correlation coefficients report a substantial increase in co-movement during the period 2007 to 2009, i.e., during the US subprime crisis period. These co-movements imply a direct or indirect impact of the financial crisis on other BRIC economies. Additionally, co-movement between these markets increased during the third quarter of the year 2011, i.e. during the Eurozone debt crisis. This means that there are significant information transmissions between the US-BRIC equity markets during adverse market scenarios.

Table 3 presents descriptive statistics of conditional correlation coefficients from the years 2004 to 2014 and across different sub-periods. On average (full sample period), the US and Brazilian markets share the highest level of co-movement (0.6193) and the US and Chinese markets the lowest (0.0706). These

results are consistent with the findings of Aloui et al. (2011), who also argue that the highest degree of co-movement is between the US and Brazilian equity markets, followed by Russian and Indian equity markets, but with a sample period ending much before ours. According to these authors, both Brazil and Russia are commodity-dependent markets, which are normally expressed in US dollar terms; therefore strong co-movement between the US and these markets is to be expected. The rest of the correlation coefficients range between 0.0706 and 0.6193. The correlation coefficients between the US and Russian equity markets are found to be highly volatile compared to the rest of the coefficients. Some of the skewness values are positive and some are negative. The positive values signify a greater probability of a positive co-movement among the variables, and vice-versa for the negative values. The distribution of all the correlation coefficients is observed to be non-normal.

Furthermore, the distributions are mostly platykurtic in nature. Even during the crisis period, the correlation coefficients between the US and Brazilian (0.6850) and Chinese (0.0251) equity markets are found to be the highest and the lowest respectively. The next-highest correlation coefficients are observed for the US-Russian and US-Indian equity markets. Similar levels of correlation coefficients are observed for the pre-crisis and post-crisis periods. Interestingly, almost all the skewness values since the financial crisis (post-crisis period) are found to be negative, signifying a greater probability of reduced co-movement between the equity markets. Co-movement between Brazil-Russia and Russia-India is also found to be higher during different sub-periods. The rest of the parameters are self-explanatory.

**Figure 3.** Average co-movement coefficients between the US and BRIC equity markets



Source: Computed by the authors

To comprehend co-movement between the US-BRIC equity markets in a more calibrated manner, in Figure 3 graphical bars are created for different sub-periods relative to average correlation coefficients. It is evident that co-movement between the US and Brazilian equity markets is the highest, followed by the Russian, Indian, and Chinese equity markets. During the crisis period all the co-movement coefficients witnessed a substantial increase compared to pre-crisis levels, except for US-China. More interestingly, co-movement increased between US-Russia and between US-China after the financial crisis period.

**Table 4.** Toda-Yamamoto Granger causality results (Pre-crisis period)

Dependent variable: US-BRAZIL			
Excluded	Chi-sq	df	Prob.
US-RUSSIA	5.230530	2	0.0731**
US-INDIA	0.791768	2	0.6731
US-CHINA	5.900615	2	0.0523**
RUSSIA-INDIA	14.93958	2	0.0006*
RUSSIA-CHINA	2.293262	2	0.3177
INDIA-CHINA	0.537144	2	0.7645
BRAZIL-RUSSIA	5.694162	2	0.0580**
BRAZIL-INDIA	0.606867	2	0.7383
BRAZIL-CHINA	0.868689	2	0.6477
All	34.31136	18	0.0115*

US-BRIC CONDITIONAL CO-MOVEMENT

<b>Dependent variable: US-RUSSIA</b>			
Excluded	Chi-sq	Df	Prob.
US-BRAZIL	1.298580	2	0.5224
US-INDIA	1.268034	2	0.5305
US-CHINA	2.515344	2	0.2843
RUSSIA-INDIA	23.65301	2	0.0000*
RUSSIA-CHINA	4.052552	2	0.1318
INDIA-CHINA	2.341527	2	0.3101
BRAZIL-RUSSIA	1.380833	2	0.5014
BRAZIL-INDIA	0.142701	2	0.9311
BRAZIL-CHINA	0.172743	2	0.9173
All	40.09141	18	0.0020*
<b>Dependent variable: US-INDIA</b>			
Excluded	Chi-sq	df	Prob.
US-BRAZIL	1.567210	2	0.4568
US-RUSSIA	0.503803	2	0.7773
US-CHINA	6.322925	2	0.0424*
RUSSIA-INDIA	14.71668	2	0.0006*
RUSSIA-CHINA	1.315932	2	0.5179
INDIA-CHINA	0.322387	2	0.8511
BRAZIL-RUSSIA	1.971132	2	0.3732
BRAZIL-INDIA	8.598667	2	0.0136*
BRAZIL-CHINA	1.647507	2	0.4388
All	38.81061	18	0.0030*
<b>Dependent variable: US-CHINA</b>			
Excluded	Chi-sq	df	Prob.
US-BRAZIL	2.588070	2	0.2742
US-RUSSIA	4.758834	2	0.0926**
US-INDIA	0.729963	2	0.6942
RUSSIA-INDIA	25.96096	2	0.0000*
RUSSIA-CHINA	6.520281	2	0.0384*
INDIA-CHINA	1.770830	2	0.4125
BRAZIL-RUSSIA	3.943850	2	0.1392
BRAZIL-INDIA	0.086187	2	0.9578
BRAZIL-CHINA	0.081258	2	0.9602
All	49.00923	18	0.0001*

Source: Computed by the authors

\*Rejects null hypothesis of insignificant Granger causality at the 5% significance level. \*\*Rejects null hypothesis of insignificant Granger causality at the 10% significance level.

China is slowly opening up its economy to foreign players, thereby witnessing increasing co-movement with the US equity market. On the other hand, co-movement between US-Brazil and between US-India has decreased since the financial crisis period. This reaffirms the decoupling hypothesis in the latter emerging equity markets. Overall, all the BRIC equity markets are partially integrated with the US market, providing diversification benefits to international investors.

**Table 5.** Toda-Yamamoto Granger causality results (Crisis period)

<b>Dependent variable: US–BRAZIL</b>			
Excluded	Chi-sq	df	Prob.
US–RUSSIA	10.70024	4	0.0301*
US–INDIA	9.071202	4	0.0593**
US–CHINA	3.126814	4	0.5368
RUSSIA–INDIA	2.673449	4	0.6139
RUSSIA–CHINA	11.75278	4	0.0193*
INDIA–CHINA	14.18383	4	0.0067*
BRAZIL–RUSSIA	18.30458	4	0.0011*
BRAZIL–INDIA	6.979712	4	0.1370
BRAZIL–CHINA	3.702283	4	0.4478
All	84.30485	36	0.0000*
<b>Dependent variable: US–RUSSIA</b>			
Excluded	Chi-sq	df	Prob.
US–BRAZIL	11.18559	4	0.0246*
US–INDIA	3.599150	4	0.4630
US–CHINA	2.768978	4	0.5972
RUSSIA–INDIA	0.672101	4	0.9547
RUSSIA–CHINA	2.972859	4	0.5624
INDIA–CHINA	18.29551	4	0.0011*
BRAZIL–RUSSIA	30.34267	4	0.0000*
BRAZIL–INDIA	6.258830	4	0.1806
BRAZIL–CHINA	2.112771	4	0.7150
All	98.41141	36	0.0000*

<b>Dependent variable: US-INDIA</b>			
Excluded	Chi-sq	df	Prob.
US-BRAZIL	2.287571	4	0.6830
US-RUSSIA	4.456940	4	0.3477
US-CHINA	3.036880	4	0.5517
RUSSIA-INDIA	2.457036	4	0.6523
RUSSIA-CHINA	3.830357	4	0.4295
INDIA-CHINA	1.109265	4	0.8928
BRAZIL-RUSSIA	3.230689	4	0.5200
BRAZIL-INDIA	2.552450	4	0.6353
BRAZIL-CHINA	1.509402	4	0.8250
All	35.26334	36	0.5034
<b>Dependent variable: US-CHINA</b>			
Excluded	Chi-sq	df	Prob.
US-BRAZIL	11.03368	4	0.0262*
US-RUSSIA	17.25509	4	0.0017*
US-INDIA	2.290288	4	0.6825
RUSSIA-INDIA	2.781335	4	0.5951
RUSSIA-CHINA	9.414334	4	0.0515**
INDIA-CHINA	4.833908	4	0.3048
BRAZIL-RUSSIA	22.02974	4	0.0002*
BRAZIL-INDIA	3.157886	4	0.5318
BRAZIL-CHINA	2.204691	4	0.6982
All	84.35338	36	0.0000*

**Source:** Computed by the authors

\*Rejects null hypothesis of insignificant Granger causality at the 5% significance level \*\*Rejects null hypothesis of insignificant Granger causality at the 10% significance level

Lastly, we attempt to capture dynamic interactions between the US-BRIC co-movement coefficients, considering one developed equity market (the US) on the one hand and an emerging markets bloc (BRIC nations) on the other, but in a multivariate framework. All the correlation indices are integrated of order 1, i.e.,  $I(1)$ , thereby justifying the application of the Toda-Yamamoto approach to capture interactions. Table 4 presents Toda-Yamamoto Granger causality

results for the pre-crisis period. During the pre-crisis period there is a significant uni-directional causality running from US-Russia and US-China to US-Brazil, US-China to US-India, and US-Russia to US-China.

**Table 6.** Toda-Yamamoto Granger causality results (Post-crisis period)

<b>Dependent variable: US–BRAZIL</b>			
Excluded	Chi-sq	df	Prob.
US–RUSSIA	2.012993	3	0.5697
US–INDIA	9.995299	3	0.0186*
US–CHINA	2.760070	3	0.4301
RUSSIA–INDIA	2.108987	3	0.5501
RUSSIA–CHINA	2.584930	3	0.4601
INDIA–CHINA	2.466486	3	0.4814
BRAZIL–RUSSIA	5.639929	3	0.1305
BRAZIL–INDIA	4.425801	3	0.2190
BRAZIL–CHINA	2.359309	3	0.5013
All	59.41740	27	0.0003*
<b>Dependent variable: US–RUSSIA</b>			
Excluded	Chi-sq	df	Prob.
US–BRAZIL	53.73327	3	0.0000*
US–INDIA	3.499148	3	0.3209
US–CHINA	5.318613	3	0.1499
RUSSIA–INDIA	3.363340	3	0.3389
RUSSIA–CHINA	2.754425	3	0.4311
INDIA–CHINA	0.544498	3	0.9090
BRAZIL–RUSSIA	5.655413	3	0.1296
BRAZIL–INDIA	6.018003	3	0.1107
BRAZIL–CHINA	5.131823	3	0.1624
All	89.28179	27	0.0000*
<b>Dependent variable: US–INDIA</b>			
Excluded	Chi-sq	df	Prob.
US–BRAZIL	5.235014	3	0.1554
US–RUSSIA	12.18562	3	0.0068*
US–CHINA	3.722712	3	0.2930
RUSSIA–INDIA	5.673408	3	0.1286

RUSSIA-CHINA	6.066131	3	0.1084
INDIA-CHINA	0.682011	3	0.8774
BRAZIL-RUSSIA	0.899555	3	0.8255
BRAZIL-INDIA	6.215054	3	0.1016
BRAZIL-CHINA	6.998520	3	0.0719**
All	47.65790	27	0.0084*
<b>Dependent variable: US-CHINA</b>			
Excluded	Chi-sq	df	Prob.
US-BRAZIL	20.85890	3	0.0001*
US-RUSSIA	8.370566	3	0.0389*
US-INDIA	8.670723	3	0.0340*
RUSSIA-INDIA	2.460523	3	0.4825
RUSSIA-CHINA	1.108690	3	0.7750
INDIA-CHINA	2.939401	3	0.4011
BRAZIL-RUSSIA	6.528504	3	0.0885**
BRAZIL-INDIA	0.535930	3	0.9109
BRAZIL-CHINA	9.925283	3	0.0192*
All	58.13755	27	0.0005*

**Source:** Computed by the authors

\*Rejects null hypothesis of insignificant Granger causality at the 5% significance level; \*\*Rejects null hypothesis of insignificant Granger causality at the 10% significance level

The Russian equity market is found to be independent and uninfluenced by other BRIC co-movements with the US equity market. However, during the crisis period (Table 5) significant bi-directional causality relationships are observed between US-Brazil and US-Russia co-movements. This may be due to strong integration with the US economy. During this period there is also a uni-directional causality relationship running from US-India to US-Brazil, and US-Brazil and US-Russia to US-China. Interestingly, co-movement between the US and Indian equity markets was not influenced by any other co-movement coefficients during the financial crisis period. During the post-crisis period (Table 6) other uni-directional causality relationship are observed: from US-India to US-Brazil, US-Brazil to US-Russia, US-Russia to US-India, and from US-Brazil, US-Russia and US-India to US-China. These dynamic relationships highlight the significant interactions between different market investment philosophies/environments, because since the financial crisis foreign players

have significantly increased equity allocations to the BRIC equity markets (Papageorgiou 2014). Seemingly, the probability of a common set of investors increases in this kind of scenario, and consequently significant interactions can be observed between the US (global leader) and the co-movements of other BRIC equity markets. China is still on the way to achieving ‘market economy’ status, so the significant impact of other co-movements on the latter’s co-movement is expected. The investment environment in the other BRIC equity markets channels investments in the Chinese equity market. These results clearly imply growing financial integration between the US and BRIC equity markets, with strong economic implications for the market participants and policymakers.

#### **4. CONCLUDING REMARKS**

The present study attempts to capture conditional co-movement and dynamic interactions between the US and BRIC equity markets across the sample period 2004 to 2014 by employing diverse econometric models. Co-movement analysis has significant implications for both long-and short-run investors (Candelon et al. 2008). Generally, there are two types of investors: those who believe in short-run arbitrage opportunities available in the respective markets and cross-markets, and those who believe in investing for a longer period of time in the respective markets. Our results are critically relevant to the former, as time-varying co-movement and dynamic interactions between the markets highlight investors’ employment of different active portfolio management strategies. The results show that co-movement between the US and Chinese equity markets is the lowest, so Chinese equity market stocks are a strong investment candidate, for the purpose of enjoying diversification benefits (consistent with Bianconi et al. 2013, Zhang et al. 2013, Syriopoulos et al. 2015, etc.).

The results provide an overall understanding of the co-movement of the BRIC equity markets vis-a-vis US and other markets. It may be noted that highly integrated markets reduce diversification benefits arising out of country-based factors and put more emphasis on industry-based factors. However, the present study shows partial integration among the BRIC equity markets, thereby highlighting the greater role of country-based factors in portfolio construction. For instance, owing to its lesser degree of openness, China’s equity market has a lower level of co-movement with the other studied markets. During a crisis,

policymakers, especially monetary authorities, respond to the global financial instability, thereby making monetary policy initiatives extremely dependent on global financial stress. Thus, policymakers like central bankers and the IMF are also interested in co-movement among the international equity markets because of spillover and contagion effects from one economy to another.

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