

Amanjot Singh; Manjit Singh

Article

Inter-linkages and causal relationships between US and BRIC equity markets: An empirical investigation

Arab Economic and Business Journal

Provided in Cooperation with:

Holy Spirit University of Kaslik

Suggested Citation: Amanjot Singh; Manjit Singh (2016) : Inter-linkages and causal relationships between US and BRIC equity markets: An empirical investigation, Arab Economic and Business Journal, ISSN 2214-4625, Elsevier, Amsterdam, Vol. 11, Iss. 2, pp. 115-145, <https://doi.org/10.1016/j.aebj.2016.10.003>

This Version is available at:

<https://hdl.handle.net/10419/187536>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0/>

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/aebj

Inter-linkages and causal relationships between US and BRIC equity markets: An empirical investigation

Amanjot Singh*, Manjit Singh

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

ARTICLE INFO

Article history:

Received 28 June 2016

Received in revised form

10 August 2016

Accepted 16 October 2016

Keywords:

Causal relationships

BRIC

Equity markets

Inter-linkages

US

ABSTRACT

The US and BRIC economies are sharing increasing trade as well as financial linkages since the last decade. In this regard, the present study attempts to capture long run and short run inter-linkages and causal relationships between the US and BRIC equity markets during different time frames, i.e., pre-crisis, crisis and post-crisis periods. The study employs Johansen cointegration, VAR, VECM, Toda-Yamamoto's Granger causality, generalized impulse responses, and variance decomposition models to account for the said linkages. For the full sample period analysis, Gregory-Hansen cointegration and Diebold and Yilmaz's (2011) spillover index approaches are also employed. Overall, the results report changing market dynamics and partial integration across the years 2004–2014.

© 2016 The Authors. Production and hosting by Elsevier B.V. on behalf of Holy Spirit University of Kaslik. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

The important issues in stock market integration are price discovery and return-volatility spillover effects due to increasing financial flows across foreign boundaries. Price discovery is the process by which a market attempts to react and reach its equilibrium price level in the short and long run (Booth, So, & Tse, 1999; Sehgal, Ahmad, & Deisting, 2015). The dynamic version of this price discovery process also describes how information produced in one-equity market transmits across the other equity markets owing to increasing trade and financial linkages among the foreign economies. An understanding of spillover or contagion effects support construction of optimal international portfolios and management of risks thereon. In short, the dynamics of price spillover effects support price prediction and arbitrage trading strategies to the market participants (Dimpfl & Jung, 2012; Pati & Rajib, 2011). Additionally, 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 (Aragó & Salvador, 2011).

According to the strong form of Efficient Market Hypothesis (EMH), stock markets reflect and discount every type of available and relevant information in stock prices. However, in practical scenarios, stock markets are not found to be efficient in reflecting every type of information, i.e. past, present and future owing to information asymmetry and certain behavioral aspects attached to the market participants. It is well documented that past events also have an impact on current stock prices. In addition to this,

* Corresponding author at: 303-C Rajguru Nagar, Ludhiana, Punjab 141012, India. Tel.: +91 9988075727.

E-mail address: amanjot_42@yahoo.com (A. Singh).

Peer review under responsibility of Holy Spirit University of Kaslik.

<http://dx.doi.org/10.1016/j.aebj.2016.10.003>

2214-4625/© 2016 The Authors. Production and hosting by Elsevier B.V. on behalf of Holy Spirit University of Kaslik. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

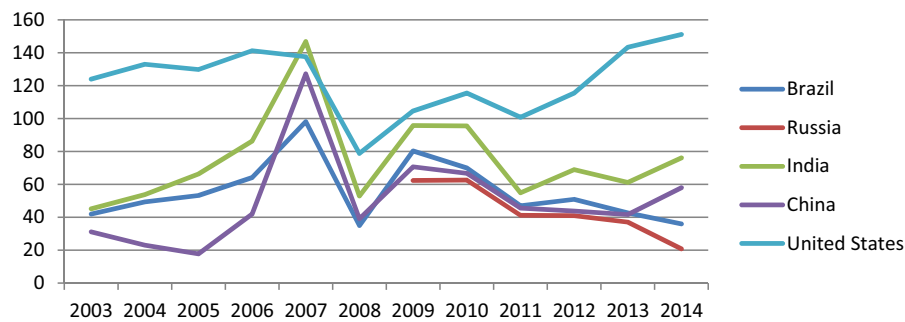


Fig. 1 – Market capitalization of listed domestic companies (% of GDP).

Source: IMF data.

cross market past events also have an impact on domestic stock prices, thereby making the markets inefficient and establishing lead-lag relationships. These cross market events further make the international equity markets to witness co-movement or greater degree of interdependence among themselves undermining diversification benefits. [Harvey \(1995\)](#) thus suggests inclusion of emerging market asset classes in an internationally diversified investment portfolio because the latter markets do not correlate strongly with developed markets and further have little exposure to global risk factors (see also, [Carrieri, Errunza, & Hogan, 2007](#); [Lagoarde-Segot & Lucey, 2007](#); [Lehkonen & Heimonen, 2014](#); [Singh & Singh, 2016](#); [Wuthisatian, 2014](#); etc.).

BRIC is a geopolitical, economic collection of Brazil, Russia, India and China; the most promising emerging markets' group. Owing to increasing economic ties within the bloc and with the mature markets, the decoupling hypothesis amongst the respective economies is under scanner. The unprecedented US financial crisis led to significant damage to investors' confidence across the worldwide markets. During the turbulent time period, i.e. from September 2008 to early March 2009, the US stock market fell by 43 percent and those in emerging markets witnessed a drastic fall of around 50 percent, and further frontier stock markets also witnessed a substantial fall of around 60 percent (see, [Samarakoon, 2011](#); [Zouhair, Lanouar, & Ajmi, 2014](#)). This clearly depicts the impact of the said financial crisis on other international economies. Moreover, according to IMF (April, 2014), emerging markets with higher exposure to volatile capital flows and current account deficits or fiscal imbalances, are likely to be more vulnerable to global financial shocks. Consequently, our objective is to capture inter-linkages and causal relationships between the US-BRIC equity markets during different time frames concerning the recent US financial crisis. Additionally, ever since the financial crisis, there has been a significant increase in equity asset allocations to the emerging markets, so, studies relating to equity market linkages holds an important place in financial economics (IMF CPIS, October 2014).

Fig. 1 reports graphical presentation of market capitalization of listed domestic companies as a percentage of GDP of the respective US-BRIC¹ economies. A very high value (generally above 100) indicates over-valuation of the concerned market. High market capitalization values in the US, Brazil, China and India during 2007–2008, spotlight buoyancy in the respective stock markets before the emergence of the global financial crisis. However, after this point, a significant decline in these values can be observed due to the emergence of the US financial crisis. Moreover, the time-varying movement of the market capitalization pattern point out toward strong co-movement among the respective equity markets, making a strong case for dynamic interactions among the said markets. Interestingly, since the financial crisis, market capitalization has even surpassed its previous highest level with respect to the US economy. Seemingly, the present study employs Johansen Cointegration, Vector Autoregression (VAR) and Vector Error Correction Model (VECM) approaches. The said approaches are widely used by the researchers in order to account for causal linkages among the markets (for instance, [Dekker, Sen, & Young, 2001](#); [Masih & Masih, 2001](#); [Royfaizal, Lee, & Azali, 2007](#); [Singh & Kaur, 2016](#); [Valadkhani & Chancharat, 2008](#); etc.).

The models are capable of studying the impact and magnitude of past events on current conditional returns. They also capture the speed and direction with which one variable respond to innovations in another variable. Apart these approaches, Granger causality test, generalized impulse responses, and variance decomposition analysis (VDA) models are also employed accounting for short run dynamic interactions among the concerned variables. Overall, the results report significant long run and short run dynamic interactions among the US-BRIC equity markets during different time horizons thereby impacting the degree of market integration over the years. The rest of the paper is organized as follows; Section 2 reports relevant literature review, Section 3 highlights rationale and objectives of the study, Section 4 reports empirical framework part, Section 5 discusses empirical findings and lastly Section 6 concludes the paper.

2. Relevant literature review

Investors allocating a part of their portfolio in internationally diversified emerging markets' portfolios enjoy increased ex-ante portfolio returns with managed increase in risk ([Syriopoulos, Makram, & Boubaker, 2015](#)). According to [Wang and Ye \(2016\)](#),

¹ The market capitalization values with respect to the Russian economy are available with effect from 2009 only.

Harvey's (1995) recommendation has prompted a growing body of research on comprehending degree of global financial integration in emerging equity markets. In a partially integrated market structure, the expected returns are function of global as well as local risk factors further having an impact on different asset allocation decisions and risk-return relationship in the said markets (Karolyi & Stulz, 2002). There are three different possible scenarios in this case; when capital markets are partially segmented, both local and world risk factors influence asset returns in equilibrium; when markets are fully integrated then global risk factors influence asset returns; whereas when the markets are found to be fully segmented or independent then asset returns are greatly influenced by local risk factors only. Consequently, co-movement among different equity asset classes is expected to be lower in order to garner diversification benefits: advocated by Markowitz (1952). When the markets are perfectly integrated, then the arbitrage opportunities are hard to exist.

The stock markets are regarded as perfectly integrated when assets with perfectly correlated returns commands same price, irrespective of the trading location (Palamalai, Kalaivani, & Devakumar, 2013; Stulz, 1981). But in practical scenarios, the degree of integration varies over a period of time, especially during a crisis period. During a crisis like event, the markets are generally found to be highly integrated. A voluminous literature supports greater degree of integration in developed markets, whereas the case is different for the emerging markets, wherein the latter markets are found to be partially segmented (Abid, Kaabia, & Guesmi, 2014; Adler & Qi, 2003; Bekaert & Harvey, 1995; Cheung & Mak, 1992; Lamba, 2005; Wang & Liu, 2016; etc.). This partial segmentation between the emerging and mature equity markets favors construction of internationally diversified portfolios having stocks from the emerging equity markets.

Arshanapalli, Doukas, and Lang (1995) documented that the "cointegrating structure" that ties the U.S. and the Asian stock market movements increased substantially ever since October 1987. The authors also reported that the Asian equity markets are less integrated with the Japanese equity market compared to the U.S. market. On a similar note, Chen, Firth, and Rui (2002) investigated dynamic interdependence of the major stock markets in Latin America i.e., Argentina, Brazil, Chile, Colombia, Mexico and Venezuela by employing cointegration and error correction models. Overall, the results reported the existence of one cointegrating vector, thereby suggesting limited diversification benefits attached to different Latin American markets in the long run. Cheng and Glascock (2006) investigated stock market linkages between the US and three stock markets of China, Hong Kong, and Taiwan, before and after the 1997 Asian financial crisis. The Granger causality results indicated increased feedback relationships between the said markets in the post-crisis period. Additionally, results from variance decomposition analysis also suggest that stock markets are more responsive to shocks emanating from foreign markets after the crisis.

Diamandis (2009) examined long-run relationships between four Latin American stock markets (Argentina, Brazil, Chile and Mexico) and the US using VAR frameworks. The results reported that there is one long-run cointegrating relationship among the five equity markets; however, there are still small long-run diversification benefits due to slow adjustments to these common trends. Menon, Subha, and Sagar (2009) investigated linkages between the Indian subcontinent and major stock markets of China, Singapore, America, and Hong Kong by employing Engle-Granger test of cointegration. The results evidenced that the Indian equity market is related to some of the undertaken markets in the long run. Using regime-switching cointegration tests and Monte Carlo simulation approach, Kenourgios and Samitas (2011) examined long-run relationships among five Balkan emerging stock markets (Turkey, Romania, Bulgaria, Croatia, and Serbia), the US and three developed European markets (UK, Germany, Greece). The results provide evidence in favor of the existence of common stochastic trends between the Balkan emerging markets within the regime and globally.

Recently, Singh and Kaur (2015) investigated stock market linkages between the US, India and China, especially during the US subprime crisis by employing tri-variate vector autoregression approach. The results reported that there is uni-directional causality running from the US market to the Indian and Chinese market and from the Chinese market to the Indian market in the short run. A large number of studies have examined long run as well as short run linkages among emerging and mature equity markets. However, studies relating to emerging equity markets are quite limited and that too with a special focus on crisis and post crisis periods. Accordingly, long run linkages have an impact on portfolio diversification benefits in the long run. Similarly, short run linkages seek to understand dynamic interactions and behavior of cross market fluctuations in different countries in the short run. It is quite obvious that a crisis like event further has an impact on the degree of integration among the markets.

Our study contributes to the literature in three senses; firstly, the present study employs relatively longer and more recent time period ranging from 2004 to 2014; secondly, different econometric models are employed in order to capture long and short run causality linkages among the markets across different time horizons, i.e. pre-crisis, crisis and post-crisis period in a multivariate framework; lastly, the study considers US-BRIC equity markets, whereby the BRIC equity markets are regarded as the most promising emerging markets' group. These time-varying linkages account for varying degrees of market integration among the US-BRIC equity markets.

3. Rationale and objectives

The present study attempts to understand both long run as well as short run linkages between the US-BRIC equity markets during different time horizons, i.e. pre-crisis period, crisis period and post-crisis period in a multivariate framework. In other words, our focus is on the behavior of stock market integration between US-BRIC markets in the wake of US subprime crisis (2007-2009). To date, numerous studies have tried to capture inter-linkages and causal relationships between the US-BRIC equity market returns and volatility (for instance, Ahmad, Sehgal, & Bhanumurthy, 2013; Bhar & Nikolova, 2009; Bianconi, Yoshino, & Machado de Sousa,

2013; Kenourgios, Samitas, & Paltalidis, 2011; Syriopoulos et al., 2015; Xu & Hamori, 2012; etc.). However, our objective is to capture both long run and short run first moment, i.e. stock market returns' linkages among the US-BRIC equity markets across a relatively longer period of time concerning the financial crisis period and in a single interaction framework.

Moreover, post crisis period (from 2009) is marked by the existence of increasing flows to the emerging markets in the wake of unconventional monetary policy initiatives undertaken in major emerged markets. So, it is quite pertinent to account for the said linkages among these economically important economies during different time horizons. Both economic as well as financial integrations are increasing between the respective BRIC economies. The efforts undertaken in the context of 'BRICS Bank', infrastructure funding, trade initiatives, etc. are surely adding up to market integration phenomenon. Our study is a one stop shop covering both long run and short run linkages among the respective US-BRIC economies in a much more calibrated and comprehensive manner considering different time horizons and econometric models. The results bear strong implications for international portfolio managers in their act of managing portfolios and asset allocation decisions.

4. Empirical framework

There are basically two main approaches for measuring cross border financial linkages: (i) price-based approach and (ii) volume-based approach (Lane, 2014). Under price-based approach, correlations in asset prices and financial market returns are captured across the countries. To note, the price-based approach is relatively silent on the extent of international financial flows required to generate the said co-movements. However, on the other hand, volume-based approach accounts for international financial flows as well as international investment positions to capture cross border financial linkages. Further, price-based approach can be demarcated into two different perspectives, i.e. asset pricing perspective and statistical perspective (Abbes & Trichilli, 2015; Naranjo & Aris, 1997). As per the first perspective, if different stock markets are perfectly integrated then the securities exposed to similar type of risk factors command similar prices across the concerned markets (Naranjo & Aris, 1997). However, this phenomenon reduces potential diversification benefits arising out of international portfolios. The second perspective suggests that owing to integration, markets tend to move together and share stable, long run equilibrium relationship with short run dynamic adjustments thereon (Cheng, 2000). Thus, a proper understanding of stock market integration holds an utmost important place for the potential investors. The existence of a long run stochastic trend among the variables does not undermine diversification benefits all abruptly because adjustment forces react quite slowly to restore the equilibrium path (Hyde, Bredin, & Nguyen, 2007). So, considerable evidences report short run dynamic interactions among the international markets through static and dynamic correlation coefficients highlighting portfolio diversification benefits.

Studies relating to stock market linkages attempt to capture long run stochastic trends through cointegration analysis and further short run interactions among the undertaken markets by specifically working on first as well as second moments. To explore linkages and causal relationships, the present study employs benchmark stock market indices of the respective nations. A respective broader stock market index reflects a combination of different sectors of the concerned economy. The stock market indices used for the purpose of analysis are NIFTY (for India), BOVESPA (for Brazil), RTS (for Russia), SSE Shanghai Composite Index (for China) and S&P 500 (for the US). Daily closing local values of the respective benchmark indices are used for the purpose of analysis, ranging from 01/01/2004 to 30/11/2014; relatively longer period of time. The source of data is Bloomberg and Yahoo² financial databases as per availability of data on a continuous basis. The respective common trading days are taken into consideration. The time period is special with respect to its coverage of pre-crisis, crisis and post global financial crisis period events. 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, Ehrmann, Fratzscher, and Mehl (2011). So, for the purpose of analysis, the present study considers; 1st JANUARY 2004–30th JUNE 2007 as pre-crisis period; 1st JULY 2007–30th JUNE 2009 as crisis period; 1st JULY 2009–30th NOVEMBER 2014 as post crisis period. The study employs different econometric models comprising, Johansen cointegration, VECM, VAR, Granger causality, Toda-Yamamoto's Granger causality, generalized impulse responses and VDA models.

4.1. Long run linkages

The present study employs Johansen cointegration approach to account for long run co-movement and causal linkages among the variables in a multivariate framework. The said model is found to be an appropriate model analyzing short run and long run causal relationships among the variables in question; evidenced from literature. It may be noted that for the application of Johansen approach, the variables are required to be integrated of order one, i.e. the same should be non stationary at level, but becomes stationary after taking first difference. The Johansen method is a maximum likelihood approach based on two likelihood test statistics as proposed by Johansen (1991, 1995). The said approach provides two alternate test statistics to examine cointegration allowing for intercept and trend in cointegrating equations: the Trace Test and the Maximum Eigenvalue Test. Under the Trace

² We have duly cross-checked the dataset (Chinese equity market) by comparing it with the available dataset from Bloomberg.

test, the null hypothesis is there is no cointegrating vector ($h_0:r=0$). whereas the alternative hypothesis of cointegration is n cointegrating vectors ($h_1:r>0$). The Maximum Eigenvalue test, tests the null hypothesis that the number of cointegrating vectors is equal to r , whereas the alternative hypothesis tests the number of cointegrating vectors as $r>1$.

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \lambda_i^{\wedge}) \quad (1)$$

$$\lambda_{\text{max}}(r, r+1) = -T \ln(1 - \lambda_{r+1}^{\wedge}) \quad (2)$$

where r =number of cointegrating vectors and λ_i^{\wedge} is the estimated eigenvalue from the $\alpha\beta'$ matrices, T is the number of usable observations. The Johansen test of cointegration requires that the lag lengths should be appropriate and consequently, the present study uses Akaike's information criterion values (AIC) to ascertain the lag lengths by employing VAR models at level across different time frames. The method finds out the cointegrating vectors, which are further appended into VAR models, imposing certain restrictions known as VECM approach. The VECM model analyzes both short run as well as long run equilibrium relationships among the variables undertaken. The existence of a cointegrating vector exhibits the existence of a long run equilibrium relationship among the markets. The VECM equation is defined as follows:

$$\Delta x_t = \sum_{i=1}^{p-1} \pi_i \Delta x_{t-i} + \alpha \beta' u_{t-1} + \epsilon_t \quad (3)$$

where x_t is a non stationary series in its first differentiation (stock indices), π_i is a matrix of coefficients, α is the speed of adjustment parameter, p is the lag order of the first differenced series, β' is cointegrating vector, u is the lagged error correction term and ϵ_t is the residual term; as in [Enders \(2014\)](#). The residual terms should not be autocorrelated, however, the same can be cross correlated to an extent. In a formal sense, $E(\epsilon_t)=0$ and $E(\epsilon_t \epsilon_t') = \Omega$, with Ω as a symmetric matrix of variance-covariance, definite positive ([Rejeb & Boughrara, 2015](#)). Under VECM, an endogenous variable is a function of its own lagged values as well as lagged values of other variables. Apart from this, error correction terms also factored into the equations to ascertain disequilibrium adjustments. The cointegrating vector ascertains long run causality relationship between the markets, whereas the coefficients of respective error correction terms indicate the speed of adjustments in the event of any disequilibrium. However, if the results report non-existence of any cointegrating vectors, then the VAR model is employed to capture short run dynamic linkages among the endogenous variables.

4.2. Short run linkages

Non-existence of common stochastic trends further pertains to the application of models capturing short run linkages. The study employs unrestricted VAR models to account for the same. It must be remembered that the coefficient matrix π_i , (as in Eq. (3)), also captures short run dynamic interactions among the variables. [Sims \(1980\)](#) proposed a VAR model to capture dynamic interactions among the endogenous variables. Under the unrestricted VAR framework, a dependent variable is a function of its own lagged values as well as lagged values of other variables only. The variables are required to be stationary, so, daily continuously compounding gross index returns are used for the said purpose: $R_t = \ln(P_t/P_{t-1}) * 100$, where R_t is daily gross index return, P_t is current day's closing price and P_{t-1} is previous day's closing price. Say, there are two variables Y_1 and Y_2 , the VAR model equation shall be defined as follows:

$$\begin{aligned} Y_{1,t} &= c_1 + A_{1,1}Y_{1,t-1} + A_{1,2}Y_{2,t-1} + e_{1,t} \\ Y_{2,t} &= c_2 + A_{2,1}Y_{1,t-1} + A_{2,2}Y_{2,t-1} + e_{2,t} \end{aligned} \quad (4)$$

where Y_i is a $k \times 1$ vector of the endogenous variables (stock market returns), c_i is a $k \times 1$ vector that represents the constant term ($i=1, 2$), A_i is a $k \times k$ coefficient matrix (for every $i=1, 2$) and e_t is a $k \times 1$ vector representing the residual terms at time t . The A_i coefficients capture dynamic (lagged) impact of endogenous variables, i.e. lagged impact of domestic as well as international stock market returns on current conditional returns. The error terms are expected to be white noise. The joint significant tests under F-statistics framework help in accounting for short run causality dynamic relationships between the variables. The short run dynamics are studied under three different frameworks; Toda-Yamamoto's Granger causality, generalized impulse response functions (GIRF) and VDA. All of these tests are important part/branches of VECM/VAR models as the case may be.

Under the Granger causality test, when past values (lagged) of one variable help in predicting future values of another variable, then the former variable is said to be granger causing the latter. 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 \(1995\)](#)³ proposed estimation of an augmented VAR model without pre-testing the existence of any cointegrating vectors among the variables guaranteeing thereon

³ It may be noted that the exact nature of Toda-Yamamoto's Granger causality approach relating to its long run or short run instrument is under debate. However, considering the 'lagged' impact of variables and daily indices' values, it is quite reasonable to consider it as a short run test accounting for dynamic linkages between the markets concerned.

the asymptotic distribution of the Wald test statistic. Initially, a VAR(p) process is estimated without considering the integration of the series. The optimal lag lengths are determined through AIC values. Then the estimation of the augmented VAR($p+m$) model is done, where m is the maximum order of integration determined as per unit root analysis. The resultant analysis of the past values' impact of one variable on another assures asymptotic distribution of the Wald test statistic. So, in the present study, we employ normal Granger non-causality tests in the event of non-existence of cointegrating vectors and Toda-Yamamoto's Granger non-causality approach in the event of cointegrated variables.

Due to the dynamic nature of the VECM/VAR, we can further comprehend the dynamic movement of the variables, whenever a shock is subjected to an error term in the system. Both GIRF and VDA capture response of an endogenous variable when a shock equivalent to one standard deviation is subjected to a variable's error term in the system. The impulse response functions capture the response of variables toward one standard deviation shock to the error terms of other variables. However, in order to overcome the problem of ordering of variables in structural impulse response functions, Pesaran and Shin (1998) proposed the generalized version of the responses free from ordering requirements.

$$X_t = \sum_{j=1}^p A_j X_{t-j} + u_t = \sum_{j=0}^{\infty} \Phi_j u_{t-j} \quad (5)$$

where X_t is an $m \times 1$ vector of the endogenous variables and $\Phi_j = A_1 \Phi_{j-1} + A_2 \Phi_{j-2} + \dots + A_p \Phi_{j-p}$, $j = 1, 2, \dots$ is an infinite moving average representation of the VAR model. Let us denote the generalized impulse response function (G) for a shock to the entire system, u_t^0 , as:

$$G_s = E \left(\frac{X_{t+N}}{u_t = u_t^0, \Omega_{t-1}^0} \right) - E \left(\frac{S_{t+N}}{\Omega_{t-1}^0} \right) \quad (6)$$

where Ω_{t-1}^0 is the information set upto $t-1$. Assume $u_t \sim N(0, \Sigma)$ and $E(u_t/u_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \dots, \sigma_{mj})' \sigma_{jj}^{-1} \delta_j$, $\delta_j = (\sigma_{jj})^{-1/2}$ denotes a one standard error shock. Furthermore, e_i is $m \times 1$, with i th element equal to one and all other elements equal to zero. The generalized impulse response function for a one standard deviation shock to the i th equation in the VAR model on the j th variable at horizon N is defined as (Ewing & Wunnava, 2004; Singh, 2016):

$$G_{ij,N} = \frac{e_j' \Phi_N \Sigma e_i}{(\sigma_{ii})^{1/2}}, i, j = 1, 2, \dots, m \quad (7)$$

The GIRFs are non-linear estimations and are based on the idea of mean impulse response functions. The GIRFs provide more robust results as compared to structural IRFs. The responses are drawn for the coming 10 days.

On a similar note, VDA approach exhibits that when a shock is given to one variable, then that accounts for what percentage in the forecasted error distribution of another variable as well as own variable. The responses are drawn for the coming 5 days. Overall the long run and first moment linkages are modeled as in Fig. 2.

5. Empirical findings and discussion

Fig. 3 reports the graphical presentation of the logged indices across the years 2004-2014. The highlighted portion clearly depicts the impact of the US subprime crisis on all of the BRIC equity markets. There was a sudden decrease in all of the BRIC stock indices in response to the financial turmoil triggered in the US financial system.

A general view of the indices highlights the existence of some common forces that brings the markets to co-movement over a period of time. As mentioned earlier, for the application of the cointegration based models, the indices are required to be integrated of order one (1), i.e., they should be non stationary at level, but becomes stationary after taking the first difference of the same. As

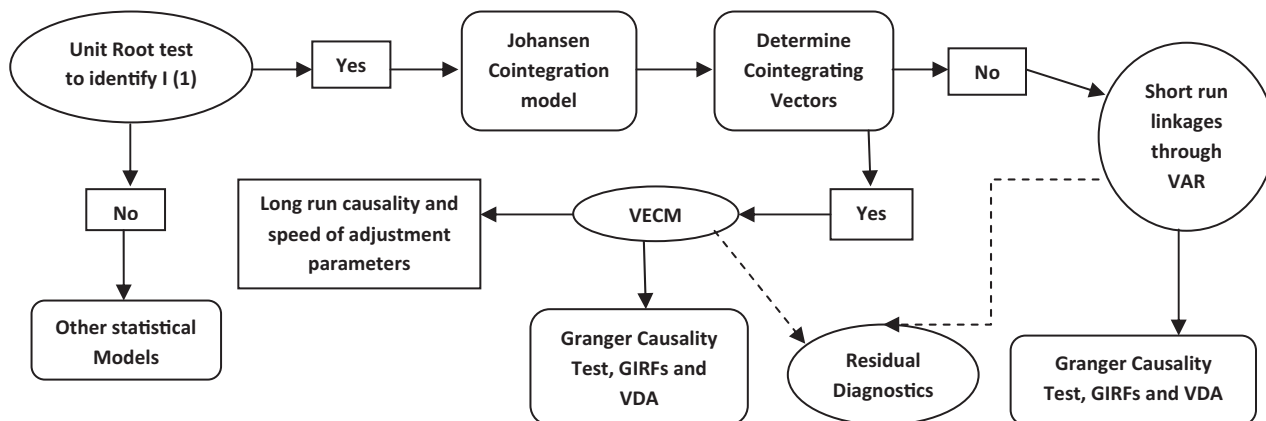


Fig. 2 – Outline of long run and short run linkages among equity markets.

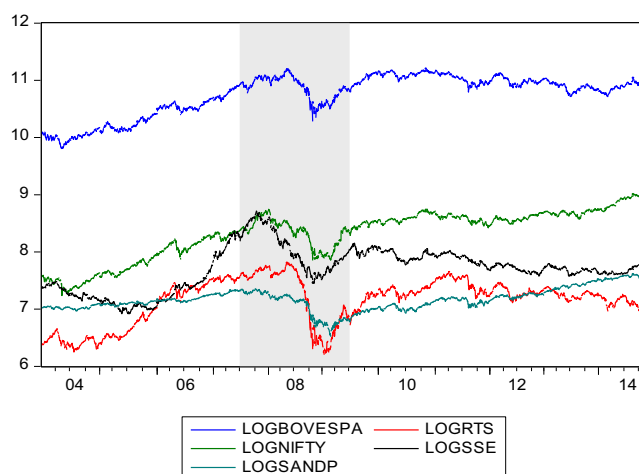


Fig. 3 – Graphical presentations of logged indices.

Source: Computed by the Authors.

expected, all of the US-BRIC equity indices are found to be integrated of order one at logged levels across different time frames. Table 1 reports unconditional correlation coefficient results during different time frames at logged level.

During the pre-crisis period, co-movement between the US-Brazilian, US-Russian and US-Indian markets is found to be very high, whereas co-movement between the US and Chinese equity markets is found to be the lowest amongst others. Interestingly, co-movement of the Chinese equity market is also found to be relatively lower with the other BRIC markets. However, co-movement between the US-Russian and US-Chinese markets increased during the crisis period. Moreover, integration of the Chinese equity market with the other BRIC equity markets also increased during the crisis period. There has been a substantial increase in correlation coefficients among the latter markets during that period. Interestingly, correlation coefficients between the US and other BRIC equity markets are observed to be negative in nature after the US financial crisis except for the Indian equity

Table 1 – Unconditional correlation coefficients.

Indices	LogBovespa	LogRTS	LogNifty	LogSSE	LogSandP
Panel A: Pre-crisis period; Bovespa (Brazil), RTS (Russia), Nifty (India), SSE (China) and SandP (US)					
LogBovespa	1.0000				
LogRTS	0.9592	1.0000			
LogNifty	0.9775	0.9740	1.0000		
LogSSE	0.6442	0.6358	0.6065	1.0000	
LogSandP	0.9586	0.9138	0.9535	0.7144	1.0000
Panel B: Crisis Period					
LogBovespa	1.0000				
LogRTS	0.9371	1.0000			
LogNifty	0.9065	0.9072	1.0000		
LogSSE	0.7341	0.7908	0.8347	1.0000	
LogSandP	0.8357	0.9472	0.8628	0.8178	1.0000
Panel C: Post-Crisis Period					
LogBovespa	1.0000				
LogRTS	0.5775	1.0000			
LogNifty	-0.2556	-0.1697	1.0000		
LogSSE	0.6891	0.2473	-0.4535	1.0000	
LogSandP	-0.5830	-0.1984	0.8382	-0.7405	1.0000
Panel: D Full Sample Period					
LogBovespa	1.0000				
LogRTS	0.7982	1.0000			
LogNifty	0.9144	0.7315	1.0000		
LogSSE	0.7713	0.6894	0.6414	1.0000	
LogSandP	0.2849	0.4630	0.5622	0.1462	1.0000

Source: Computed by the Authors; analyses done at logged level of indices.

market. This means that barring the Indian equity market, the rest of the BRIC equity markets are found to be favorable in the context of lower co-movement with the US equity market. On the other hand, co-movement between the Indian and the rest of the BRIC equity markets is also negative in nature since the financial crisis period. So, amongst the BRIC economies, the Indian equity market is found to be a segmented or independent market ever since the crisis period. Lastly, when we consider the correlation coefficients during the full sample period, then the results report another interesting stance that co-movement between the US-Russia and US-India is found to be higher as compared to US-Brazil and US-China. Co-movement amongst the BRIC equity markets is also positive in nature, whereby an increase in one market is followed by another market and vice versa. These unconditional correlation coefficients provide an important understanding of degree of integration among the US-BRIC equity markets during different time frames. It is pertinent to mention that these correlation coefficients are not robust in nature, but generally are found to be quite informative in analyzing the extent of linkages among the variables undertaken.

5.1. Long run co-movement

Now, we move on to Johansen cointegration model results in a multivariate framework (Table 2). During the pre-crisis period, the results report a common stochastic trend among the US-BRIC equity markets. It means that during the pre-crisis period there was a long run co-movement among the said markets.⁴

The pre-crisis time period or great moderation period witnessed a substantial increase in financial flows from emerged to the developing economies in the wake of risk premiums. However, during the crisis period, we could not find an evidence of long run co-movement or common stochastic trend among the variables undertaken. This further supports the existence of short run dynamic interactions among the US-BRIC equity markets during that period. During the post crisis period, the results report the existence of a common stochastic trend among the US-BRIC equity markets. Only the Trace test results confirm the existence of long run co-movement among the equity markets during the post crisis period. Notably, the Johansen approach primarily supports the results reported by Trace test. So, the results relating to the existence of a common stochastic trend are valid. On a similar note, we could not find any evidence of a long run co-movement during the full sample period. It may be noted that, the full sample period is relatively a very long period of time comprising US financial crisis, so, the existence of any structural break can substantially reduce the power of any test accounting for cointegrating relationship. Subsequently, the present study also employs Gregory-Hansen cointegration test, wherein the null hypothesis of no cointegration is tested against the alternative hypothesis of existence of cointegration with endogenously determined single structural break (Gregory & Hansen, 1996). The Gregory-Hansen cointegration test considering trend and full break in the coefficients is modeled as follows:

$$\log \text{index}_{\text{US},t} = c + a_1 D_t + a_2 \log \text{indices}_{\text{BRIC},t} + a_3 D_t \log \text{indices}_{\text{BRIC},t} + e_t \quad (8)$$

where c is the constant term, a_1 , a_2 , and a_3 are the coefficients and e_t is the error term. Structural change is captured through the dummy variable D :

$$D_t = \begin{cases} 1 & \text{if } t > \tau \\ 0 & \text{if } t \leq \tau \end{cases}$$

where τ is the relative timing of a structural change. The break point is determined by finding the minimum value for the Augmented Dickey Fuller (ADF) unit root test statistic on the residuals derived from the said regression (Fig. 4). The results report minimum t-statistic value of -6.225 with the 1 percent and 5 percent critical values being reported as -7.310 and -6.840 . So, the Gregory-Hansen test also did not support the existence of any common stochastic trend among the US-BRIC equity markets even allowing for a structural break because minimum t-statistic is not as negative as the critical values at the 1 percent and 5 percent significance levels. The markets are driven by independent factors in the long run.

The graph shows the ADF test statistics while considering different breakpoints. The grid value highlights minimum ADF test value. Expectedly, the structural change occurred during the Lehman Brothers' episode in September 2008. These results are critically important for long run investors in their act of portfolio and risk management.

5.1.1. Long run causality relationships

The Johansen cointegration model reports the existence of long run co-movement only during the pre-crisis and post-crisis periods. So, the long run causality relationships are checked during the said periods only.

Table 3 reports normalized cointegrating coefficients taking the US equity market as the dependent variable. The results show that the Indian and Chinese markets have an increasing long run impact on the US market, whereas the Brazilian and Russian markets have a decreasing long run impact on the US market. It may be noted that the signs get changed after converting the equation. Theoretically, the US market exerts a greater degree impact on the Indian equity market, followed by Russian market in the long run. Additionally, we have also checked the contribution of individual variables in maintaining long run equilibrium relationship among the US-BRIC equity markets during the pre-crisis period. Technically, this technique is termed as 'exclusion tests'. The exclusion tests spotlight the contribution of the respective variables to the long run causation through asymptotic chi-square restrictions model. We fail to reject the null hypothesis: Brazilian market does not contribute to the long run equilibrium relationship with the US market at the 5 percent significance level ($1.9736, p > 0.05$). However, the rest of the markets significantly

⁴ The results are similar even after allowing for the existence of only intercept in the cointegrating equation.

Table 2 – Johansen cointegration model results.**Panel: A pre-crisis period**

Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Probability
None [*]	0.070748	113.6907	88.80380	0.0003 [*]
At most 1	0.033939	57.77901	63.87610	0.1464
At most 2	0.023206	31.46808	42.91525	0.4176
At most 3	0.009977	13.57654	25.87211	0.6923
At most 4	0.007759	5.935600	12.51798	0.4685

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability
None ^{**}	0.070748	55.91166	38.33101	0.0002 ^{**}
At most 1	0.033939	26.31093	32.11832	0.2167
At most 2	0.023206	17.89154	25.82321	0.3855
At most 3	0.009977	7.640940	19.38704	0.8524
At most 4	0.007759	5.935600	12.51798	0.4685

Panel: B Crisis Period

Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
None	0.063978	74.26715	88.80380	0.3486
At most 1	0.043764	46.63035	63.87610	0.5704
At most 2	0.038617	27.92477	42.91525	0.6266

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability
None	0.063978	27.63680	38.33101	0.4808
At most 1	0.043764	18.70558	32.11832	0.7511
At most 2	0.038617	16.46169	25.82321	0.5039

Panel: C Post-Crisis Period

Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
None [*]	0.023997	88.85079	88.80380	0.0496 [*]
At most 1	0.020336	60.96656	63.87610	0.0858
At most 2	0.014643	37.38058	42.91525	0.1603
At most 3	0.011784	20.44586	25.87211	0.2042
At most 4	0.005939	6.837989	12.51798	0.3617

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability
None	0.023997	27.88423	38.33101	0.4634
At most 1	0.020336	23.58599	32.11832	0.3767
At most 2	0.014643	16.93472	25.82321	0.4632

(continued on next page)

Table 2 (continued)**Panel: D Full Sample Period**

Lags interval (in first differences): 1 to 6

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
------------------------------	------------	--------------------	------------------------	-------------

Lags interval (in first differences): 1 to 6

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
------------------------------	------------	--------------------	------------------------	-------------

None	0.012613	63.09695	88.80380	0.7651
At most 1	0.007940	33.54712	63.87610	0.9767
At most 2	0.004509	14.98790	42.91525	0.9985

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

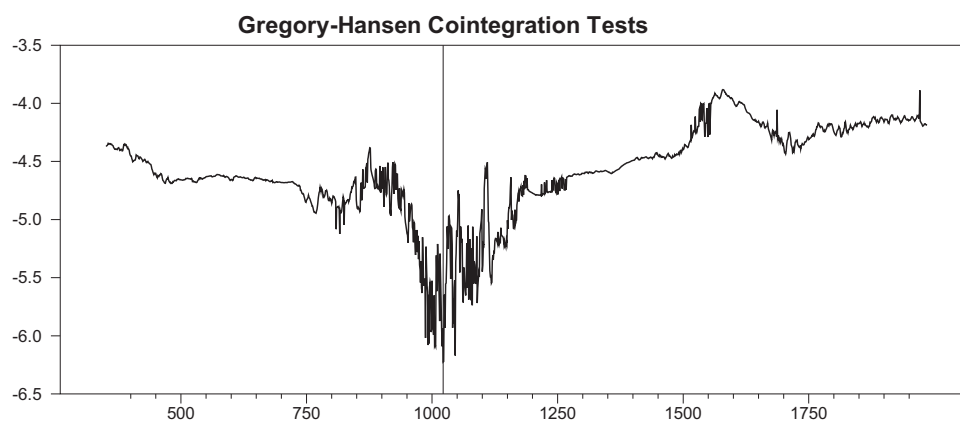
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability
------------------------------	------------	------------------------	------------------------	-------------

None	0.012613	29.54983	38.33101	0.3538
At most 1	0.007940	18.55922	32.11832	0.7616
At most 2	0.004509	10.52143	25.82321	0.9459

Source: Computed by the Authors; CE(s) stands for Cointegrating Equation(s).

* Trace test indicates 1 cointegrating eqn(s) at the 0.05 level.

** Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level. Trace test indicates no cointegration at the 0.05 level. Max-eigenvalue test indicates no cointegration at the 0.05 level.

**Fig. 4 – Gregory-Hansen cointegration test with ADF statistics.**

Source: Computed by the Authors.

contribute in maintaining long run equilibrium relationship with the US market at the 5 percent significance level [Russia 22.6443, $p < 0.05$; India 24.8973, $p < 0.05$; China 26.6148, $p < 0.05$]. The joint test of all the variables also supports significant impact of all the BRIC equity markets in maintaining long run equilibrium relationship with the US market at the 5 percent significance level (37.3217, $p < 0.05$).

Table 3 – Normalized cointegrating coefficients (standard error in parentheses). Pre-crisis period.

LogSandP	LogBovespa	LogRTS	LogNifty	LogSSE	TREND
1.000000	0.090404 (0.05230)	0.174617 (0.02729)	−0.440925 (0.05287)	−0.082935 (0.01053)	−0.000117 (0.00004)

Source: Computed by the Authors; US equity market taken as dependent variable.

Table 4 – Coefficients of error correction terms (Pre-crisis period).

Parameter	D(LogSandP)	D(LogBovespa)	D(LogRTS)	D(LogNifty)	D(LogSSE)
Error correction	−0.0378 [*] (0.0130) [−2.9143]	0.0071 (0.0312) [0.2280]	0.0049 (0.0313) [0.1586]	0.1562 [*] (0.0286) [5.4510]	0.0655 [*] (0.0307) [2.1321]

Source: Computed by the Authors; Standard errors in () & t-statistics in [].

^{*} Reject null hypothesis of no significant relationship at the 5% significance level.

Table 5 – Normalized cointegrating coefficients (standard error in parentheses). Post-crisis period.

LogSandP	LogBovespa	LogRTS	LogNifty	LogSSE	TREND
1.000000	0.561270 (0.19656)	−0.075031 (0.09053)	−0.214489 (0.17135)	−0.471574 (0.16608)	−0.000600 (0.00013)

Source: Computed by the Authors; US equity market taken as dependent variable.

The presence of cointegrating vectors further support the employment of VECM models to examine short run and long run causal linkages among the equity markets. The lag lengths are determined on the basis of AIC values. The error correction terms (ECT) are not found to be statistically different from zero in the context of Brazilian and Russian equity markets at the 5 percent significance level (Table 4). This means that the said markets are statistically exogenous and dominant to the system and followed an autonomous path during the pre-crisis period. Interestingly, ECT coefficient is found to be negative and significant with respect to the US market, thereby highlighting corrective stance of the US equity market in the event of any disequilibrium situation. In other words, during the pre-crisis period, the Brazilian and Russian markets were following an independent dominant trend, whereby the US equity market was acting as a restoring agent toward the long run equilibrium path in the event of a short run deviation. Around 4 percent of the disequilibrium adjustments used to take place in one day and rest in the coming days. Moreover, the significant ECT parameters imply the long run causation impact of other markets on the respective equity markets. For instance, the US, Indian and Chinese equity markets were affected by the other equity markets in the long run during that period.

Table 5 reports normalized cointegrating coefficients during the post crisis period. A 1 percent increase in the Brazilian equity market causes 0.5612 percent decrease in the US equity market in the long run. On the other hand, the Russian, Indian and Chinese equity markets have a long run increasing impact on the US equity market. Theoretically, the US market exerts a greater degree impact on the Brazilian equity market followed by the Chinese, Indian and Russian equity markets in the long run. On a similar note, we have employed certain exclusion tests to account for the contribution of the said markets in maintaining equilibrium in the long run. We fail to reject the null hypothesis: the respective Russian, Indian and Chinese equity markets do not contribute to the long run equilibrium relationship with the US market at even 10 percent significance level [Russia 0.2334, $p > 0.10$; India 0.5212, $p > 0.10$; China 1.4332, $p > 0.10$]. However, on the other hand, the Brazilian equity market contributes to the cointegrating relationship with the US equity market at the 10 percent significance level (3.0606, $p < 0.10$). Moreover, all the BRIC equity markets collectively contribute to the long run equilibrium relationship at the 5 percent significance level (14.4519, $p < 0.05$).

Only the US and Brazilian equity markets are found to be affected by the other equity markets in the long run (Table 6). The rest of the markets, i.e. the Russian, Indian and Chinese equity markets are observed to be independent following a dominant path in the long run during the post crisis period. Around 2 percent of the adjustments take place in one day in the event of any disequilibrium, whereby the US and Brazilian are the only markets acting as restoring agents during this period. For instance, an increase in the Indian equity market is counterbalanced by a corresponding increase in the US and Brazilian equity market.

5.2. Short run linkages and causality relationships

The long run linkages do not undermine diversification benefits all abruptly owing to slow adjustments to the equilibrium path. So, now we move on to short run linkages and causal relationships under VAR/VECM frameworks. Fig. 5 is the graphical presentation of the index returns during the period 2004–2014. All the index returns are volatile in nature, especially during the Lehman

Table 6 – Coefficients of error correction terms (Post-crisis period).

Parameter	D(LogSandP)	D(LogBovespa)	D(LogRTS)	D(LogNifty)	D(LogSSE)
Error correction	−0.020553 [*] (0.00579) [−3.54993]	−0.025015 [*] (0.00821) [−3.04769]	0.007083 (0.00982) [0.72100]	0.002913 (0.00622) [0.46856]	0.010650 (0.00722) [1.47446]

Source: Computed by the Authors; Standard errors in () & t-statistics in [].

^{*} Reject null hypothesis of no significant relationship at the 5% significance level.

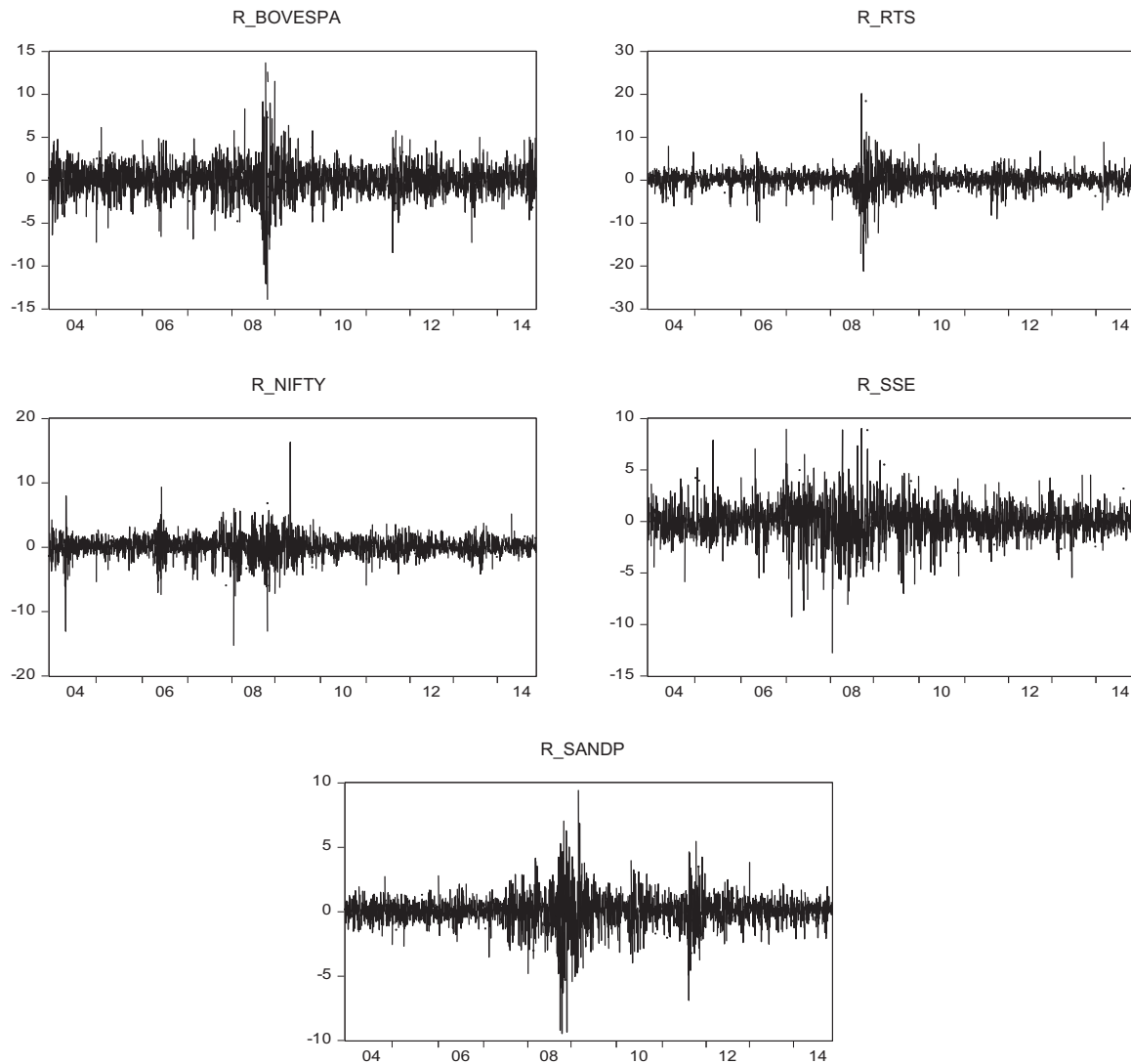


Fig. 5 – Graphical presentation of index returns.
Source: Computed by the Authors.

Brothers' episode (a high point of the crisis). Further [Table 7](#) reports descriptive characteristics of the respective index returns during different time frames. During the pre-crisis period, the Russian equity market witnessed highest daily average returns (0.1539%) followed by China, Brazil, India and US. However, the highest level of volatility (sigma) is also observed in the Russian market during this period, whereas the US equity market is found to be the least volatile market. The skewness values are negative with respect to all of the countries undertaken except for the Chinese equity market. The negative values report greater probability of negative returns in comparison to positive. For the Chinese market, the skewness value is near to zero depicting symmetric distribution of the index returns. Both the Kurtosis and Jarque-Bera test statistic values report leptokurtic and non-normal distribution of the index returns with respect to all the US-BRIC equity markets.

This further highlights the existence of abnormal returns available to the investors in the respective markets. The financial time series are required to be mean reverting i.e. stationary for the application of the statistical models. For this, the study employs three different stationarity tests comprising, ADF, Philips-Perron and KPSS tests allowing for intercept only. All of the stationarity tests support stationary distribution of the index returns.

However, the Russian, Indian and Chinese equity markets are not found to be efficient in the context of impact of lagged values on current index returns; evidenced from significant autocorrelation Ljung-Box test statistic values at the 5% significance level. During the crisis period, all the equity markets witnessed negative returns, whereby the Russian equity market registered largest negative returns for its investors followed by the US market. The relative lowest negative returns are observed in the Indian equity market with 0.0012%. Similarly, the Russian equity market was found to be the highest volatile market during that period followed by the Brazilian equity market. The skewness values are negative except for the Brazilian equity market. A positive value denotes greater probability of positive returns in comparison to negative. Again, the Kurtosis and Jarque-Bera test values report leptokurtic and non-normal distribution of index returns. All the index return series are found to be stationary, wherein the Indian and

Table 7 – Index returns: descriptive statistics.

Parameters	R_Bovespa	R_RTS	R_Nifty	R_SSE	R_SandP
Panel A: pre-crisis period					
Mean	0.1098	0.1539	0.1038	0.1166	0.0383
Median	0.1698	0.2887	0.2264	0.0118	0.0708
Maximum	6.1499	7.8878	9.3329	8.9433	2.7728
Minimum	-7.2268	-9.8403	-13.0538	-9.2561	-3.5342
Sigma	1.7205	1.8087	1.6605	1.6971	0.7211
Skewness	-0.4765	-0.7649	-1.0809	0.0057	-0.2138
Kurtosis	4.4638	6.6553	11.6768	7.5233	4.4921
Jarque-Bera	97.0130	499.1923	2542.110	650.4702	76.6034
Probability	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]
Observations	763	763	763	763	763
ADF test	-27.467 ^{**}	-25.343 ^{**}	-22.006 ^{**}	-28.209 ^{**}	-22.064 ^{**}
Philips-Perron	-27.700 ^{**}	-25.389 ^{**}	-26.719 ^{**}	-28.205 ^{**}	-29.957 ^{**}
KPSS test	0.1889 ^{***}	0.1065 ^{***}	0.1747 ^{***}	1.2527	0.1097 ^{***}
L.Box (1)	0.0102	5.4184 ^a	0.7734	0.4551	3.3826
L.Box (12)	20.939	24.655 ^a	26.709 ^a	16.104	18.190
L.Box (36)	50.593	47.191	55.997 ^a	55.525 ^a	48.354
Panel B: crisis period					
Mean	-0.0174	-0.1574	-0.0012	-0.0617	-0.1196
Median	0.1223	0.1160	0.1261	0.0190	0.0050
Maximum	13.6782	20.2039	16.3343	9.0342	9.4008
Minimum	-13.8819	-21.1994	-15.2303	-12.7635	-9.4695
Sigma	3.0898	3.8188	2.7127	2.5817	2.1613
Skewness	0.0388	-0.3801	-0.3061	-0.1834	-0.3048
Kurtosis	7.0807	9.7845	8.8372	5.1271	6.2000
Jarque-Bera	291.5218	815.6311	602.8517	81.5374	185.7123
Probability	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]
Observations	420	420	420	420	420
ADF test	-14.625 ^{**}	-17.236 ^{**}	-21.220 ^{**}	-19.604 ^{**}	-17.563 ^{**}
Philips-Perron	-22.000 ^{**}	-17.072 ^{**}	-21.225 ^{**}	-19.625 ^{**}	-24.094 ^{**}
KPSS test	0.1387 ^{***}	0.2101 ^{***}	0.2046 ^{***}	0.3131 ^{***}	0.1169 ^{***}
L.Box (1)	1.2743	11.728 ^a	0.6446	0.7199	9.3388 ^a
L.Box (12)	31.552 ^a	26.152 ^a	10.031	11.110	24.212 ^a
L.Box (36)	73.535 ^a	73.249 ^a	25.085	38.269	73.570 ^a
Panel C: post-crisis period					
Mean	0.0052	-0.0003	0.0593	-0.0099	0.0701
Median	0.0097	0.0339	0.0825	0.0000	0.0946
Maximum	5.7681	8.8909	5.1846	4.6789	5.4580
Minimum	-8.4305	-9.0052	-5.8679	-6.9827	-6.8958
Sigma	1.5307	1.8893	1.2093	1.3677	1.0880
Skewness	-0.0678	-0.1134	-0.0866	-0.3627	-0.3409
Kurtosis	5.0350	5.1809	4.3894	5.5379	7.0095
Jarque-Bera	199.1555	230.1762	93.8623	333.5646	791.9264
Probability	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]
Observations	1149	1149	1149	1149	1149
ADF test	-36.002 ^{**}	-31.019 ^{**}	-32.573 ^{**}	-33.719 ^{**}	-36.765 ^{**}
Philips-Perron	-36.063 ^{**}	-30.979 ^{**}	-32.547 ^{**}	-33.719 ^{**}	-37.360 ^{**}
KPSS test	0.1148 ^{***}	0.3821 ^{***}	0.1280 ^{***}	0.1632 ^{***}	0.0471 ^{***}
L.Box (1)	4.3418 ^a	8.0358 ^a	1.6625	0.0075	7.1923 ^a
L.Box (12)	20.797	18.149	25.942 ^a	16.845	30.931 ^a
L.Box (36)	38.354	41.796	56.126 ^a	51.370 ^a	72.632 ^a
Panel D: full sample period					
Mean	0.0361	0.0217	0.0634	0.0230	0.0261
Median	0.0789	0.1470	0.1378	0.0050	0.0773
Maximum	13.6782	20.2039	16.3343	9.0342	9.4008
Minimum	-13.8819	-21.1994	-15.2303	-12.7635	-9.4695
Sigma	1.9592	2.3359	1.7157	1.7504	1.2636
Skewness	-0.1160	-0.5298	-0.5826	-0.2131	-0.5345
Kurtosis	9.6275	14.4865	13.7825	7.5718	11.7188
Jarque-Bera	4276.849	12,940.36	11,438.71	2050.342	7503.920
Probability	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]	0.0000 [*]

(continued on next page)

Table 7 (continued)

Parameters	R_Bovespa	R_RTS	R_Nifty	R_SSE	R_SandP
Observations	2334	2334	2334	2334	2334
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 ^a	36.770 ^a	0.0054	0.2935	28.952 ^a
L.Box (12)	30.355 ^a	53.254 ^a	12.856	25.703 ^a	57.343 ^a
L.Box (36)	88.641 ^a	114.43 ^a	47.806	63.249 ^a	148.43 ^a

Source: Computed by the Authors.

* Reject null hypothesis of normal distribution at the 5% significance level.

** Reject null hypothesis of non-stationary time series at the 5% significance level.

*** Data do not provide evidence to reject null hypothesis of stationary time series with asymptotic critical value 0.4630 at the 5% significance level.

^a Reject null hypothesis of independent distribution of the index returns at the 5% significance level; L.Box stands for Ljung Box test statistics.

Chinese markets are the only markets found to be efficient in nature in the context of insignificant impact of the past values on current returns. Since the financial crisis period, only the Indian and US equity markets are witnessing substantial positive returns. On a similar note, volatility in the Russian market is found to be the highest followed by the Brazilian equity market. The skewness values are negative with respect to all the US-BRIC equity markets. The index returns are found to be non-normal and leptokurtic because the values of the fourth moment are greater than three. All the index returns are observed to be stationary. However, since the financial crisis, all the equity markets are found to be inefficient owing to the significant impact of past values. On an average, the Indian equity market witnessed the highest level of returns coupled with lesser levels of standard deviation during the full sample period. The lowest daily average returns are observed in the Russian market along with the highest level of volatility. This shows that the investors in the Russian market encounter a negative relationship between the risk and return. The next best returns are observed for the Brazilian, US and Chinese market. However, the skewness values are negative with respect to each of the countries. The fat-tailed and non-normal distribution of index returns spotlight the existence of abnormal returns in the markets. The index returns are found to be stationary. Barring the Indian equity market, all other equity markets are found to be inefficient in the context of the impact of past returns on current returns. After discussing about the descriptive statistics, now we move on to short run causal linkages among the markets. These linkages promulgate dynamic short run interactions among the markets, thereby making a case for the international portfolio managers to analyze the same. Table 8 reports VECM results during the pre-crisis period.

Table 8 – VECM model results (Pre-crisis period).

Parameters	D(LogSandP)	D(LogBovespa)	D(LogRTS)	D(LogNifty)	D(LogSSE)
Error correction	-0.037893 [*] (0.01300) [-2.91437]	0.007126 (0.03124) [0.22809]	0.004969 (0.03133) [0.15862]	0.156215 [*] (0.02866) [5.45109]	0.065532 [*] (0.03074) [2.13214]
D(LOGSANDP(-1))	-0.060021 (0.04652) [-1.29035]	0.111015 (0.11177) [0.99324]	0.320867 [*] (0.11207) [2.86314]	0.413543 [*] (0.10252) [4.03365]	0.009727 (0.10996) [0.08846]
D(LOGBOVESPA(-1))	0.016021 (0.02031) [0.78874]	-0.011005 (0.04881) [-0.22548]	0.224736 [*] (0.04894) [4.59219]	0.035772 (0.04477) [0.79901]	0.017920 (0.04802) [0.37320]
D(LOGRTS(-1))	-0.010186 (0.01596) [-0.63809]	-0.031892 (0.03836) [-0.83139]	0.024783 (0.03846) [0.64435]	0.002541 (0.03519) [0.07221]	0.006606 (0.03774) [0.17507]
D(LOGNIFTY(-1))	-0.005161 (0.01711) [-0.30155]	-0.025571 (0.04112) [-0.62182]	-0.079545 ^{**} (0.04123) [-1.92920]	-0.020009 (0.03772) [-0.53045]	-0.003065 (0.04046) [-0.07576]
D(LOGSSE(-1))	0.007154 (0.01552) [0.46106]	0.002167 (0.03728) [0.05811]	-0.035516 (0.03738) [-0.95004]	-0.006631 (0.03420) [-0.19389]	-0.030301 (0.03668) [-0.82611]
Constant	0.000400 (0.00026) [1.52729]	0.001139 ^{**} (0.00063) [1.80979]	0.001244 [*] (0.00063) [1.97139]	0.000885 (0.00058) [1.53310]	0.001169 ^{**} (0.00062) [1.88856]

Source: Computed by the Authors.

* Reject null hypothesis of insignificant impact at the 5% significance level.

** Reject null hypothesis of insignificant impact at the 10% significance level; Standard errors in () & t-statistics in []; One day lagged values are employed considering AIC values.

One day lagged price change in the US and Brazilian equity market has a positive and statistically significant impact on the current conditional return in the Russian equity market. A 1 percent increase in the US and Brazilian market causes 0.32 and 0.22 percent increase in the Russian equity market respectively.

However, on the other hand, the impact of the Indian equity market is negative in nature, whereby an increase in the Indian market causes 0.08 percent fall in the Russian market. The Indian equity market also gets influenced by one day lagged price change in the US equity market in positive terms (0.4135, $p < 0.05$). In nutshell, during the pre-crisis period, only the Russian and Indian equity markets are found to be influenced by the US equity market, whereas the rest of the markets are observed to be resilient from the same. Table 9 reports Granger causality results under Toda-Yamamoto framework during the pre-crisis period. In this case, the Toda-Yamamoto approach is suitable owing to the existence of integrated series. The results show that during this period there is a uni-directional causality running from the US, Brazilian and Indian equity markets to the Russian equity market. On a similar note, there is another uni-directional impact of the US market on the Indian market.

Fig. 6 graphically reports generalized impulse responses during the pre-crisis period. The response of the US market is initially positive toward one standard deviation shock to the Brazilian equity market. But, overall, the response is following a downward trend throughout coming 10 days. The US equity market is marginally impacted by the Russian and Chinese equity markets, whereas there is a positive relationship between the Indian and US equity markets. The response of the Brazilian equity market toward market shocks in other equity markets is more or less flattish with marginal increments. Interestingly, the response of the Russian equity market toward market shocks in the US and Brazilian equity market is positive initially, approaching further augmented levels after two days. The Russian market is marginally influenced by the Chinese equity market. The Indian equity market is substantially influenced by the US, Brazilian and Russian equity markets, whereby it is following a similar kind of pattern as in the case of the Russian equity market. Lastly, the Chinese equity market is also substantially influenced by the US equity

Table 9 – Toda-Yamamoto's Granger causality test (Pre-crisis period).

Excluded	Chi-sq	df	Prob.
Dependent variable: LOGSANDP			
LOGBOVESPA	1.603373	2	0.4486
LOGRTS	0.127615	2	0.9382
LOGNIFTY	2.483144	2	0.2889
LOGSSE	0.216663	2	0.8973
All	4.172531	8	0.8412
Dependent variable: LOGBOVESPA			
LOGSANDP	3.211590	2	0.2007
LOGRTS	1.878087	2	0.3910
LOGNIFTY	2.495144	2	0.2872
LOGSSE	0.778896	2	0.6774
All	6.841678	8	0.5538
Dependent variable: LOGRTS			
LOGSANDP	10.25562	2	0.0059*
LOGBOVESPA	21.97254	2	0.0000*
LOGNIFTY	5.272104	2	0.0716**
LOGSSE	1.363108	2	0.5058
All	76.39413	8	0.0000*
Dependent variable: LOGNIFTY			
LOGSANDP	32.57099	2	0.0000*
LOGBOVESPA	0.968439	2	0.6162
LOGRTS	0.544241	2	0.7618
LOGSSE	0.132659	2	0.9358
All	67.23462	8	0.0000*
Dependent variable: LOGSSE			
LOGSANDP	0.297925	2	0.8616
LOGBOVESPA	0.541070	2	0.7630
LOGRTS	2.410202	2	0.2997
LOGNIFTY	0.189373	2	0.9097
All	3.668673	8	0.8857

Source: Computed by the Authors.

* Reject null hypothesis of non Granger causality at the 5% significance level.

** Reject null hypothesis of non Granger causality at the 10% significance level; Significant values denote Granger causality or impact of respective variable on dependent.

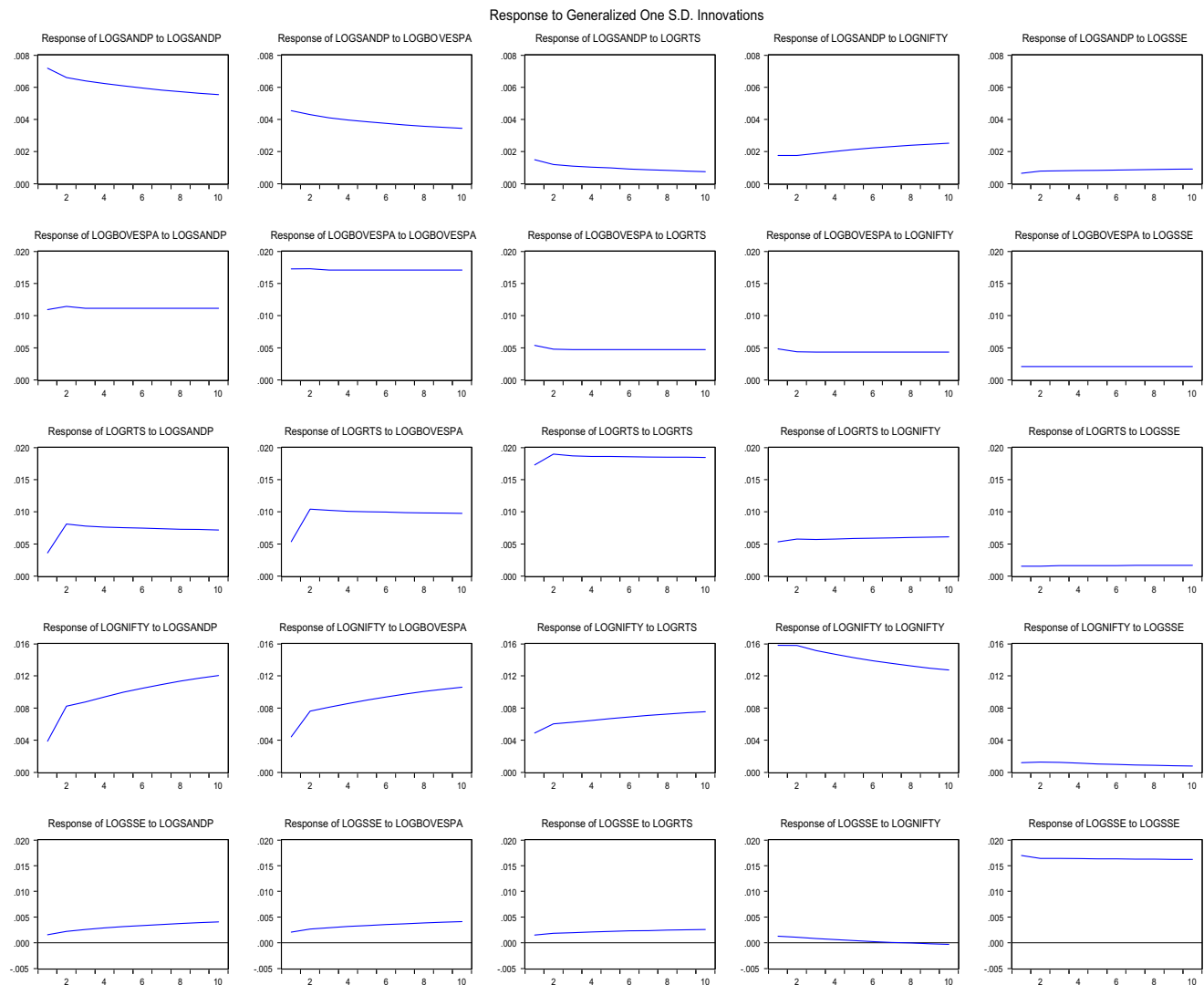


Fig. 6 – Generalized impulse responses (Pre-Crisis Period).

Source: Computed by the Authors.

market comparing to other markets. Generally, the responses are positive in nature, wherein a positive relationship is expected between the undertaken markets throughout the coming 10 days. However, the Chinese equity market is found to be more or less segmented because its responses are highly transitory in nature toward market shocks in other countries, whereas the rest of the BRIC equity markets display a permanent effect of a market shock in the US equity market highlighting a shift in long run equilibrium.

Table 10 reports VDA results during the pre-crisis period. The VDA results are sensitive to ordering of the variables. So, the ordering of the variables is done considering the Granger causality results. The variables which are ordered first in the sequence are found to be most resilient from other markets. In all of the cases, when a shock is subjected to the error terms of the US equity market, then its contribution to the forecasted error variances increases over the 5 days' horizon with respect to all of the BRIC equity markets. On the other hand, the extent of information explained by the BRIC equity markets is found to be negligible in the US equity market. Moreover, the contribution of own market shocks is very high in all of the US-BRIC equity markets. Similarly, during this period, the Chinese equity market is found to be the most resilient market from the cross market shocks as compared to other equity markets. The contribution of the Brazilian equity market is also considerably higher in forecasted error variances in the Russian equity market. In nutshell, during this pre-crisis period, the Chinese equity market is observed to be the least affected market amongst US-BRIC equity markets. Its impulse responses are also found to be transitory and short term in nature (consistent with, [Shachmurove, 2006](#)). Moreover, the latter market did not have any considerable impact on other US-BRIC equity markets during this period. A possible reason for this could be closed economic system relative to other markets during that time period. As expected, the US market is found to be the dominant market followed by the Brazilian equity market.

Table 10 – Variance decomposition analyses (Pre-crisis period).

Period	S.E.	LOGSANDP	LOGBOVESPA	LOGRTS	LOGNIFTY	LOGSSE
Variance decomposition of LOGSANDP						
1	0.007181	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.009771	99.86197	0.021877	0.075153	0.012245	0.028757
3	0.011690	99.70502	0.018066	0.143019	0.082402	0.051498
4	0.013264	99.49395	0.014650	0.213129	0.203324	0.074945
5	0.014617	99.23418	0.012082	0.287757	0.366466	0.099517
Variance decomposition of LOGBOVESPA						
1	0.017255	40.10953	59.89047	0.000000	0.000000	0.000000
2	0.024471	41.81465	58.09391	0.039857	0.051520	6.41E–05
3	0.029858	42.05758	57.82131	0.057225	0.063806	8.01E–05
4	0.034411	42.19753	57.66777	0.065350	0.069276	7.84E–05
5	0.038430	42.28203	57.57508	0.070260	0.072555	7.78E–05
Variance decomposition of LOGRTS						
1	0.017301	4.272716	5.325333	84.89751	5.230887	0.273558
2	0.026213	11.40244	9.139515	75.89007	3.438169	0.129806
3	0.032599	13.09395	10.31333	73.54262	2.954824	0.095274
4	0.037868	13.75848	10.85156	72.52552	2.783909	0.080527
5	0.042460	14.08891	11.16972	71.94742	2.721023	0.072928
Variance decomposition of LOGNIFTY						
1	0.015828	5.988000	2.572740	0.000000	91.27513	0.164134
2	0.022831	15.90975	3.046381	0.043348	80.90648	0.094049
3	0.027935	20.47318	3.409107	0.091295	75.96024	0.066174
4	0.032168	23.94815	3.665003	0.161646	72.17530	0.049906
5	0.035875	26.95661	3.881722	0.248333	68.87180	0.041535
Variance decomposition of LOGSSE						
1	0.016975	0.822398	0.649942	0.000000	0.000000	98.52766
2	0.023661	1.308466	0.808466	0.014787	0.030297	97.83798
3	0.028841	1.674269	0.891993	0.031183	0.092628	97.30993
4	0.033225	2.000118	0.949923	0.050765	0.176046	96.82315
5	0.037102	2.309922	0.996735	0.072823	0.275318	96.34520

Ordering: US, Brazil, China, India, Russia.

Source: Computed by the Authors; S.E. stands for standard error; Table shows contribution of the respective market shocks in explaining forecasted error variations in another.

During a crisis period, dynamic interactions among the equity markets, increase owing to financial instability and propagation of shocks via equity markets (Bekaert & Harvey, 1995). The Johansen model does not support the existence of a common stochastic trend among the equity markets during the crisis period. So, only short run dynamic interactions are modeled via VAR model during this period. At the very outset, the VAR model requires dataset to be stationary, subsequently, the study factors continuously compounding gross index returns into the model framework. The optimal lag lengths (two in this case) are determined through AIC values. Table 11 reports VAR model results during the crisis period. The US equity market is significantly influenced by one day lagged returns in the US market per se, however, the impact is found to be negative in nature (-0.1387 , $p < 0.10$). A negative impact justifies the existence of financial instability during this period in the US economy.

Talking about the Brazilian market, both one day and two days' lagged returns in the US equity market are having a statistically significant impact on the current Bovespa returns at the 5 and 10 percent significance levels. On a similar note, the Russian equity market also gets influenced by one day lagged returns in the US equity market. Interestingly, during this period, the Brazilian equity market is having a greater magnitude impact on the Russian index returns as compared to the US equity market. The coefficient is found to be 0.3202, whereby one percent change in the Brazilian equity market causes 0.3202 percent change in the Russian equity market. Similarly, the Indian equity market is also influenced by one and two days' lagged returns in the US equity market during the crisis period. The magnitude of two days' lagged impact is lesser as compared to one day lagged impact. The Indian equity market is also positively influenced by two days' lagged returns in the Chinese equity market at the 10 percent significance level. A positive impact spotlights increasing integration among the said markets because a change in one market brings a parallel change in another. Lastly, the results also report a statistically significant impact of one day lagged returns in the US equity market on the current Chinese index returns at the 5 percent significance level. It is pertinent to mention that all of these dynamic interactions also display stock market return spillovers that took place during the period of global financial meltdown.

Table 11 – VAR model results (Crisis Period).

Parameters	R_SANDP	R_BOVESPA	R_RTS	R_NIFTY	R_SSE
R_SANDP(–1)	–0.138750 ^{**} (0.07161) [–1.93753]	0.214991 [*] (0.10292) [2.08883]	0.257847 [*] (0.12035) [2.14250]	0.396336 [*] (0.08683) [4.56447]	0.310658 [*] (0.08330) [3.72956]
R_SANDP(–2)	–0.097277 (0.07221) [–1.34716]	0.201190 ^{**} (0.10378) [1.93857]	–0.083451 (0.12135) [–0.68767]	0.161815 ^{**} (0.08755) [1.84816]	–0.009072 (0.08399) [–0.10801]
R_BOVESPA(–1)	–0.039836 (0.05186) [–0.76812]	–0.163342 [*] (0.07454) [–2.19143]	0.320207 [*] (0.08716) [3.67396]	0.016687 (0.06288) [0.26537]	0.021935 (0.06032) [0.36363]
R_BOVESPA(–2)	–0.057103 (0.05282) [–1.08105]	–0.169591 [*] (0.07592) [–2.23388]	0.070453 (0.08877) [0.79366]	0.055274 (0.06405) [0.86303]	0.037132 (0.06144) [0.60436]
R_RTS(–1)	0.031312 (0.03760) [0.83284]	–0.020206 (0.05404) [–0.37394]	–0.010688 (0.06318) [–0.16915]	–0.021192 (0.04559) [–0.46488]	–0.061673 (0.04373) [–1.41030]
R_RTS(–2)	0.020192 (0.03451) [0.58513]	–0.037842 (0.04960) [–0.76302]	–0.035107 (0.05799) [–0.60536]	0.028489 (0.04184) [0.68088]	–0.008884 (0.04014) [–0.22133]
R_NIFTY(–1)	–0.037866 (0.04663) [–0.81203]	–0.011871 (0.06702) [–0.17712]	–0.001789 (0.07837) [–0.02283]	–0.145299 [*] (0.05654) [–2.56979]	0.064901 (0.05424) [1.19657]
R_NIFTY(–2)	0.022414 (0.04629) [0.48416]	0.029931 (0.06654) [0.44985]	0.065069 (0.07780) [0.83634]	–0.055521 (0.05613) [–0.98910]	–0.014780 (0.05385) [–0.27448]
R_SSE(–1)	0.006900 (0.04370) [0.15789]	0.047756 (0.06281) [0.76031]	–0.101104 (0.07344) [–1.37660]	–0.073526 (0.05299) [–1.38755]	0.045028 (0.05083) [0.88580]
R_SSE(–2)	–0.059475 (0.04333) [–1.37270]	–0.067103 (0.06227) [–1.07759]	–0.015207 (0.07281) [–0.20885]	0.100099 ^{**} (0.05253) [1.90539]	–0.022180 (0.05040) [–0.44012]
Constant	–0.145700 (0.10563) [–1.37939]	0.013298 (0.15181) [0.08759]	–0.154170 (0.17751) [–0.86850]	0.067663 (0.12807) [0.52831]	–0.021631 (0.12286) [–0.17607]

Source: Computed by the Authors; R stands for index returns.

^{*} Reject null hypothesis of insignificant impact at the 5% significance level.

^{**} Reject null hypothesis of insignificant impact at the 10% significance level; Standard errors in () & t-statistics in [].

Overall, the impact of one day lagged US equity market return is observed to be the highest for the Indian equity market followed by the Chinese equity market.

Table 12 reports Granger causality results during the crisis period. There is uni-directional causality running from the US equity market to the BRIC equity markets due to the existence of US financial crisis during this period. Apart from this, there is also uni-directional impact of the Brazilian equity market on the Russian during this period. Similarly, the Chinese equity market is also having a uni-directional impact on the Indian equity market (consistent with, Singh & Kaur, 2015). Moving ahead with the generalized impulse responses (Fig. 7), all the US-BRIC equity markets respond positively toward market shocks on the first day, however, approaching zero after four days. Similar to the pre-crisis period results, the impulse responses of the Chinese equity market toward other equity markets are found to be marginal. Even other equity markets are also found to be somewhat resilient from the error shocks in the Chinese equity market. Overall, we can say that the impulse responses are transitory in nature instead of having a permanent impact on the long run equilibrium relationship observed during the pre-crisis period. Lastly, Table 13 reports VDA results. The contribution of the BRIC equity markets in explaining movements in the US equity market is found to be marginal throughout the coming 5 days. When a shock is subjected to the error terms of the US equity market, then its contribution to the forecasted error variances in the Brazilian equity market reduces over a period of time. Similar to the pre-crisis period results, the contribution of the Brazilian equity market increases in the error variances of the Russian equity market. During the crisis period also, the Chinese equity market is found to be independent, however, the contribution of the US equity market is somewhat greater in magnitude.

Overall, the results report dominant stance of the US economy on the BRIC equity markets during the subprime crisis period. Now, we move on to post crisis period's short run dynamic interactions. As discussed earlier, ever since the financial crisis, the underlying markets are witnessing a common stochastic trend, meaning that there are some common forces which bring the markets to co-move in the long run. Apart from these long run linkages, there are also short run dynamic interactions that guide the behavior and prediction power of the markets. Table 14 reports VECM model results. One day lagged price change in the

Table 12 – Granger causality results (Crisis period).

Excluded	Chi-sq	df	Prob.
Dependent variable: R_SANDP			
R_BOVESPA	1.529920	2	0.4654
R_RTS	1.050927	2	0.5913
R_NIFTY	1.015259	2	0.6019
R_SSE	1.892599	2	0.3882
All	4.741375	8	0.7848
Dependent variable: R_BOVESPA			
R_SANDP	6.782240	2	0.0337*
R_RTS	0.730786	2	0.6939
R_NIFTY	0.259278	2	0.8784
R_SSE	1.663257	2	0.4353
All	10.11549	8	0.2570
Dependent variable: R_RTS			
R_SANDP	5.878485	2	0.0529**
R_BOVESPA	13.53862	2	0.0011*
R_NIFTY	0.717530	2	0.6985
R_SSE	1.971415	2	0.3732
All	50.34129	8	0.0000*
Dependent variable: R_NIFTY			
R_SANDP	21.76048	2	0.0000*
R_BOVESPA	0.761039	2	0.6835
R_RTS	0.670318	2	0.7152
R_SSE	5.310434	2	0.0703**
All	50.85669	8	0.0000*
Dependent variable: R_SSE			
R_SANDP	14.65713	2	0.0007*
R_BOVESPA	0.437799	2	0.8034
R_RTS	2.047799	2	0.3592
R_NIFTY	1.622044	2	0.4444
All	33.49345	8	0.0001*

Source: Computed by the Authors.

* Reject null hypothesis of non Granger causality at the 5% significance level.

** Reject null hypothesis of non Granger causality at the 10% significance level; Significant values denote Granger causality or impact of respective variable on dependent.

Brazilian equity market has a statistically significant impact on the current US equity index return at the 5 percent significance level. The Russian equity market also gets influenced by one day lagged price change in the US and Brazilian equity markets at the 5 percent significance level. A 1 percent increase in the US and Brazilian market causes 0.21 and 0.25 percent increase in the Russian equity market respectively. On a similar note, the Indian equity market also gets influenced by one day lagged price change in the US, Brazilian and Russian equity markets, whereby the impact of the US equity market is found to be greater in magnitude terms. Moreover, the impact of the Russian equity market is negative in nature. For instance, a 1 percent decrease in the Russian equity market causes around 0.05 percent increase in the Indian equity market. The Chinese equity market also gets influenced by one day lagged price change in the US and Brazilian equity markets at the 5 percent significance level. Similar to the Indian equity market, the US equity market has a greater magnitude impact on the Chinese equity market (0.1487, $p < 0.05$).

Interestingly, since the US financial crisis, there is uni-directional causality running between the Brazilian and US equity markets, whereby the Brazilian equity market is Granger causing US equity market (Table 15); evidenced from Toda-Yamamoto Granger causality test. As expected, the rest of the markets are strongly influenced by the US equity market uni-directionally. Apart from this, there is also uni-directional impact of the Brazilian equity market on the Russian equity market during this period and further Brazilian and Russian equity markets on the Indian equity market.

Lastly, there is another uni-directional impact of the Brazilian market on the Chinese equity market. Overall, since the US financial crisis, the Brazilian equity market is observed to be playing a leading role impacting other BRIC equity markets. Comparing to the US equity market, the chi-square values also support the dominant impact of the Brazilian equity market on the Indian and Russian equity markets. Fig. 8 graphically reports generalized impulse responses of the respective equity markets. The US equity market responds positively to the market shocks in the BRIC equity markets. However, the stimulated responses start following a downward trend in the coming days. All the US, Brazilian, Russian and Indian equity markets largely remain resilient from the Chinese equity market, whereby the responses are largely transitory in nature. All the markets generally exhibit a shift in

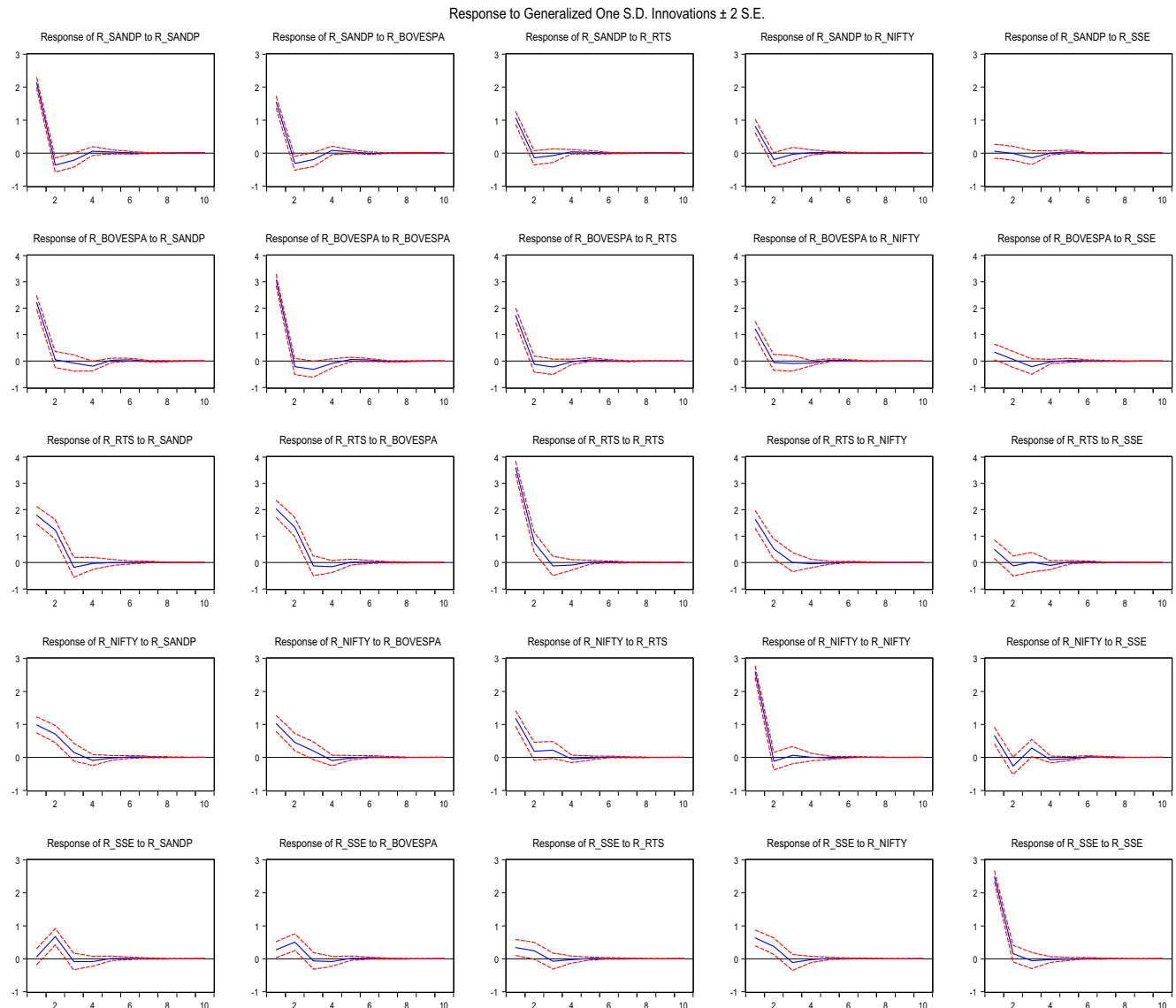


Fig. 7 – Generalized impulse responses (Crisis Period).

Source: Computed by the Authors.

the long run equilibrium relationship, when a shock is subjected to the error terms of other variables. But the response of the Chinese equity market though positive remains somewhat transitory toward error shocks in other US-BRIC equity markets. Table 16 reports VDA results highlighting a greater degree impact of the Brazilian equity market with respect to all other equity markets since the US financial crisis. The contribution of the US equity market is also observed to be higher with respect to the Russian, Indian and Chinese equity markets. However, the magnitude of the impact is lesser comparing to the Brazilian equity market. Overall, we can say that ever since the US financial crisis, the Brazilian equity is found to be playing a significant role in directing movements in other BRIC equity markets and in some sense the US equity market as well.

Lastly, we have tried to analyze short run linkages among the US-BRIC equity markets during the full sample period. Owing to non-existence of long run co-movement among the US-BRIC equity markets during the full sample period, VAR model is employed to account for short run dynamic interactions among the variables. Table 17 reports VAR model results. The AIC values support the usage of six days lagged values in the VAR framework. All the markets are significantly affected by their own past values except the Russian equity market. It may be reported as the efficiency of the Russian equity market because the past index returns do not have a statistically significant impact on the current index returns. The said market efficiency reflects past domestic information in the asset prices. Two, four, five and six days' lagged returns in the Brazilian equity market have a significant impact on the current US equity index returns. Moreover, six and five days' lagged returns in the Russian and Chinese equity markets also have a significant impact on the US equity market returns at the 5 percent significance level respectively. It may be noted that the impact is negative

Table 13 – Variance decomposition analyses (Crisis period).

Period	S.E.	R_SANDP	R_BOVESPA	R_RTS	R_NIFTY	R_SSE
Variance decomposition of R_SANDP						
1	2.138169	100.0000	0.000000	0.000000	0.000000	0.000000
2	2.172897	99.66223	0.093085	0.097209	0.146989	0.000489
3	2.190616	99.01923	0.174716	0.197307	0.261455	0.347294
4	2.192082	98.94834	0.238589	0.199709	0.264051	0.349309
5	2.192639	98.91857	0.244381	0.199638	0.264670	0.372740
Variance decomposition of R_BOVESPA						
1	3.073069	52.12545	47.87455	0.000000	0.000000	0.000000
2	3.096919	51.35448	48.47848	0.045832	0.007111	0.114103
3	3.126176	50.45868	49.01983	0.095882	0.047460	0.378148
4	3.133344	50.59115	48.83899	0.127129	0.056160	0.386571
5	3.134162	50.57232	48.84963	0.132586	0.056239	0.389226
Variance decomposition of R_RTS						
1	3.593329	24.76026	8.657404	65.84689	0.000000	0.735441
2	3.860722	31.67387	10.20919	57.04865	0.000104	1.068178
3	3.866637	31.79775	10.17810	56.89160	0.066307	1.066242
4	3.872237	31.71874	10.37089	56.72938	0.071442	1.109554
5	3.872453	31.71559	10.37497	56.72377	0.075887	1.109781
Variance decomposition of R_NIFTY						
1	2.592562	14.29141	2.987390	5.756181	72.01156	4.953457
2	2.723158	19.55193	2.786070	5.529576	66.64819	5.484229
3	2.747195	19.51102	2.925774	5.585863	65.67643	6.300911
4	2.750786	19.57060	2.955304	5.574277	65.56684	6.332984
5	2.751223	19.57085	2.954409	5.574003	65.54602	6.354717
Variance decomposition of R_SSE						
1	2.487032	0.064688	1.749734	0.000000	0.000000	98.18558
2	2.586548	6.751364	1.627273	0.290712	0.304738	91.02591
3	2.589749	6.834612	1.626982	0.303120	0.383538	90.85175
4	2.591640	6.924913	1.646521	0.317428	0.384141	90.72700
5	2.591694	6.925178	1.647942	0.317508	0.384251	90.72512

Ordering: US, Brazil, China, Russia, India.

Source: Computed by the Authors; Table shows contribution of the respective market shocks in explaining forecasted error variations in another.

Table 14 – VECM model results (Post-crisis period).

Parameters	D(LogSandP)	D(LogBovespa)	D(LogRTS)	D(LogNifty)	D(LogSSE)
Error correction	−0.020553 [*] (0.00579) [−3.54993]	−0.025015 [*] (0.00821) [−3.04769]	0.007083 (0.00982) [0.72100]	0.002913 (0.00622) [0.46856]	0.010650 (0.00722) [1.47446]
D(LOGSANDP(−1))	−0.129557 [*] (0.03768) [−3.43804]	0.000561 (0.05342) [0.01051]	0.213177 [*] (0.06394) [3.33393]	0.214278 [*] (0.04047) [5.29465]	0.148796 [*] (0.04701) [3.16500]
D(LOGBOVESPA(−1))	0.068125 [*] (0.02551) [2.67030]	−0.079471 [*] (0.03617) [−2.19732]	0.251457 [*] (0.04329) [5.80881]	0.155860 [*] (0.02740) [5.68855]	0.101875 [*] (0.03183) [3.20078]
D(LOGRTS(−1))	0.005240 (0.02124) [0.24674]	0.033372 (0.03011) [1.10850]	−0.055507 (0.03603) [−1.54040]	−0.051755 [*] (0.02281) [−2.26927]	0.006640 (0.02649) [0.25064]
D(LOGNIFTY(−1))	0.007432 (0.03013) [0.24670]	0.046763 (0.04271) [1.09496]	−0.006628 (0.05112) [−0.12966]	−0.024150 (0.03235) [−0.74645]	−0.027735 (0.03758) [−0.73796]
D(LOGSSE(−1))	0.029409 (0.02475) [1.18839]	0.029103 (0.03508) [0.82955]	0.012356 (0.04199) [0.29425]	−0.015442 (0.02658) [−0.58101]	−0.027895 (0.03087) [−0.90354]
Constant	0.000814 [*] (0.00032) [2.55774]	4.01E−05 (0.00045) [0.08893]	−0.000145 (0.00054) [−0.26751]	0.000447 (0.00034) [1.30753]	−0.000213 (0.00040) [−0.53623]

Source: Computed by the Authors.

^{*} Reject null hypothesis of insignificant impact at the 5% significance level. Standard errors in () & t-statistics in []; One day lagged values are employed considering AIC values.

Table 15 – Toda-Yamamoto's Granger causality test (Post crisis period).

Excluded	Chi-sq	df	Prob.
Dependent variable: LOGSANDP			
LOGBOVESPA	5.087265	2	0.0786**
LOGRTS	2.184858	2	0.3354
LOGNIFTY	0.084420	2	0.9587
LOGSSE	2.253363	2	0.3241
All	9.842713	8	0.2762
Dependent variable: LOGBOVESPA			
LOGSANDP	1.145501	2	0.5640
LOGRTS	0.463328	2	0.7932
LOGNIFTY	0.900578	2	0.6374
LOGSSE	0.908663	2	0.6349
All	5.847573	8	0.6643
Dependent variable: LOGRTS			
LOGSANDP	12.94740	2	0.0015*
LOGBOVESPA	37.95706	2	0.0000*
LOGNIFTY	0.718417	2	0.6982
LOGSSE	1.144252	2	0.5643
All	89.62472	8	0.0000*
Dependent variable: LOGNIFTY			
LOGSANDP	32.56882	2	0.0000*
LOGBOVESPA	35.92665	2	0.0000*
LOGRTS	9.251273	2	0.0098*
LOGSSE	0.676004	2	0.7132
All	123.5427	8	0.0000*
Dependent variable: LOGSSE			
LOGSANDP	13.53158	2	0.0012*
LOGBOVESPA	11.30286	2	0.0035*
LOGRTS	2.468664	2	0.2910
LOGNIFTY	1.443385	2	0.4859
All	56.46843	8	0.0000*

Source: Computed by the Authors.

* Reject null hypothesis of non-Granger causality at the 5% significance level.

** Reject null hypothesis of non-Granger causality at the 10% significance level; Significant values denote Granger causality or impact of respective variable on dependent.

in nature, whereby an increase in one market causes another market to witness a downward phase. One and two days' lagged returns in the US equity market have a positive and statistically significant impact on the current Brazilian equity index returns. Even three days' lagged returns in the Indian equity market also have a significant impact on the Brazilian equity market returns. The impact is negative in nature, whereby a 1 percent increase in the Indian equity market causes the Brazilian equity market to witness around 0.05 percent decrease in the market returns. The rest of the BRIC equity markets are also influenced by one day lagged returns in the US equity market. In case of the Russian equity market, even four, five and six days' lagged returns in the US equity market have a statistically significant impact on the current index returns at the 5 and 10 percent significance levels. One and five days' lagged returns in the Brazilian equity market also have a significant impact on the Russian equity market. The impact is positive in nature, whereby a 1 percent increase in the lagged returns causes the Russian market to observe 0.28 and 0.13 percent increase in the market returns respectively. The Russian equity market is also influenced by one and three days' lagged returns in the Indian equity market, however, the said impact is negative in nature.

On a similar note, one and five days' lagged returns in the Chinese equity market have a negative and significant impact on the Russian equity market returns. Interestingly, the Indian equity market is influenced by up to four days' lagged returns in the US equity market, wherein the impact of one day lagged return is greater in magnitude. One, two and five days' lagged returns in the Brazilian equity market also have a significant impact on the current Nifty index returns in positive terms. Even one day lagged returns in the Russian and Chinese equity markets also have a negative impact on the Indian equity market returns. A 1 percent decrease in the Russian and Chinese equity markets causes 0.03 and 0.04 percent increase in the Indian equity market returns respectively. One and four days' lagged returns in the Brazilian equity market have a statistically significant positive impact on the current Chinese market returns. Even four and three days' lagged returns in the Russian and Indian equity markets have a significant impact on the Chinese equity market returns respectively and that too with a similar magnitude of 0.04 percent.

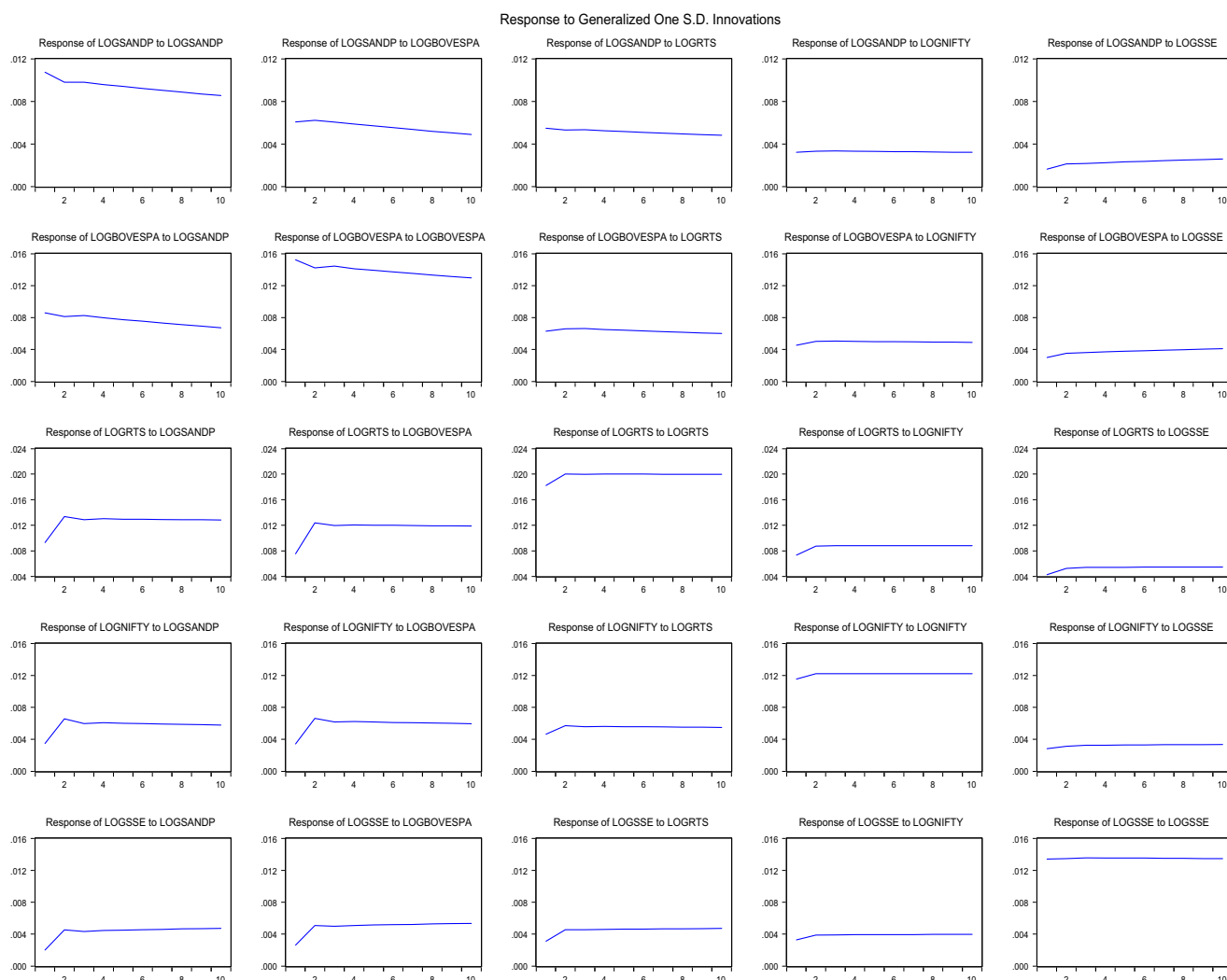


Fig. 8 – Generalized impulse responses (Post-Crisis Period).

Source: Computed by the Authors.

It is pertinent to mention that these dynamic interactions also exhibit stock market return spillovers across the US-BRIC equity markets during the full sample period. Table 18 reports Granger causality results. It is observed that there is a bi-directional causality relationship running between the US-Brazilian and US-Russian equity markets. There is a feedback relationship in existence among the said markets. On the other hand, there is uni-directional causality running from the Brazilian to Russian equity market, Chinese market to Russian, US market to Indian, Brazilian market to Indian, US market to Chinese and Brazilian market to Chinese market during the full sample period. The generalized impulse responses (Fig. 9) report that initially the response of all the markets is positive on the first day, however, the stimulated responses start approaching zero after two to three days. This means that all of the market shocks are transitory in nature, whereby the responses last for only two to three days. As mentioned earlier, the Chinese equity market is found to be an independent market because the rest of the markets do not get affected by the market shocks in the Chinese equity market in substantial terms. Moreover, the response of the Chinese equity market toward one standard deviation shock in other equity markets remains marginal throughout the 10 days horizon. Similar types of results are observed in the context of VDAs during the full sample period like in the pre-crisis, crisis and post-crisis periods (Table 19). All the markets are largely influenced by their own market innovations rather than cross market innovations. On a similar note, the Chinese equity market is found to be independent in the context of contribution of cross market shocks in its forecasted error variations. The contribution of the Brazilian equity market is found to be greater as compared to the US equity market in explaining forecasted error variances in the rest of the BRIC equity markets during the sample period. All the models are found to be adequate and consistent because the inverse roots of AR characteristic polynomial lie inside the circle with respect to all the models. Moreover, the models also support non-existence of serial autocorrelation in the residuals derived from the respective models.

Table 16 – Variance decomposition analyses (Post-crisis period).

Period	S.E.	LOGSANDP	LOGBOVESPA	LOGRTS	LOGNIFTY	LOGSSE
Variance decomposition of LOGSANDP						
1	0.010738	68.09892	31.90108	0.000000	0.000000	0.000000
2	0.014570	64.34106	35.49810	0.008677	0.006984	0.145187
3	0.017584	63.53559	36.20725	0.015696	0.013440	0.228029
4	0.020053	63.20526	36.44079	0.021043	0.019632	0.313267
5	0.022171	63.12988	36.41472	0.026320	0.026299	0.402779
Variance decomposition of LOGBOVESPA						
1	0.015223	0.000000	100.0000	0.000000	0.000000	0.000000
2	0.020851	0.003435	99.69968	0.106189	0.066097	0.124596
3	0.025382	0.005443	99.60662	0.123994	0.084868	0.179072
4	0.029079	0.004294	99.50976	0.142324	0.102376	0.241245
5	0.032277	0.005597	99.41693	0.156584	0.117353	0.303536
Variance decomposition of LOGRTS						
1	0.018220	11.24471	17.18964	69.62215	0.000000	1.943498
2	0.027487	12.80872	27.74371	57.76620	0.000929	1.680437
3	0.034254	12.95589	30.00640	55.30444	0.000996	1.732267
4	0.039924	13.08397	31.19985	53.97064	0.000894	1.744645
5	0.044868	13.13716	31.85491	53.24649	0.000892	1.760546
Variance decomposition of LOGNIFTY						
1	0.011532	2.596838	8.834170	5.704876	79.52049	3.343628
2	0.017191	5.099775	18.80787	3.783852	69.82139	2.487114
3	0.021303	5.351930	20.60143	3.430397	68.16667	2.449573
4	0.024757	5.537964	21.56665	3.235433	67.24066	2.419293
5	0.027772	5.612489	22.04910	3.130129	66.78635	2.421932
Variance decomposition of LOGSSE						
1	0.013396	0.236496	3.861806	0.000000	0.000000	95.90170
2	0.019219	1.222719	8.907281	1.01E-05	0.025803	89.84419
3	0.023676	1.408165	10.30931	0.001901	0.027078	88.25354
4	0.027421	1.546193	11.14863	0.002278	0.028884	87.27402
5	0.030712	1.634451	11.69004	0.002474	0.030271	86.64276
Ordering: Brazil, US, China, Russia, India.						
Source: Computed by the Authors; Table shows contribution of the respective market shocks in explaining forecasted error variations in another.						

Table 17 – VAR model results (Full sample period).

Parameters	R_SANDP	R_BOVESPA	R_RTS	R_NIFTY	R_SSE
R_SANDP(–1)	–0.111128 (0.02773) [–4.00776]	0.120369 (0.04341) [2.77309]	0.274314 (0.04901) [5.59711]	0.305892 (0.03650) [8.38116]	0.211845 (0.03803) [5.56979]
R_SANDP(–2)	–0.034119 (0.02876) [–1.18648]	0.118157 [*] (0.04502) [2.62476]	0.047611 (0.05083) [0.93671]	0.147602 [*] (0.03785) [3.89951]	0.028725 (0.03945) [0.72823]
R_SANDP(–3)	0.014575 (0.02894) [0.50359]	–0.001827 (0.04531) [–0.04032]	0.034596 (0.05116) [0.67628]	0.088239 [*] (0.03810) [2.31622]	–0.007837 (0.03970) [–0.19740]
R_SANDP(–4)	0.032633 (0.02897) [1.12634]	–0.022903 (0.04535) [–0.50498]	0.114820 [*] (0.05121) [2.24215]	0.082222 [*] (0.03814) [2.15602]	0.022321 (0.03974) [0.56166]
R_SANDP(–5)	–0.062721 [*] (0.02889) [–2.17108]	–0.035116 (0.04522) [–0.77649]	–0.098182 ^{**} (0.05106) [–1.92281]	–0.012282 (0.03803) [–0.32298]	–0.052545 (0.03963) [–1.32598]
R_SANDP(–6)	–0.005403 (0.02806) [–0.19254]	–0.021049 (0.04393) [–0.47920]	–0.090069 ^{**} (0.04960) [–1.81606]	–0.022834 (0.03693) [–0.61825]	–0.004656 (0.03849) [–0.12097]
R_BOVESPA(–1)	–0.004816 (0.01804) [–0.26699]	–0.105964 [*] (0.02824) [–3.75264]	0.283732 [*] (0.03188) [8.89926]	0.105611 [*] (0.02374) [4.44810]	0.053319 [*] (0.02474) [2.15492]

Table 17 (continued)

Parameters	R_SANDP	R_BOVESPA	R_RTS	R_NIFTY	R_SSE
R_BOVESPA(-2)	-0.038889 (0.01861) [-2.08986]	-0.119419 (0.02913) [-4.09954]	0.045684 (0.03289) [1.38898]	0.046604 [*] (0.02449) [1.90277]	0.005389 (0.02552) [0.21114]
R_BOVESPA(-3)	-0.014826 (0.01869) [-0.79313]	-0.050500 ^{**} (0.02926) [-1.72573]	0.033001 (0.03304) [0.99880]	0.017977 (0.02461) [0.73061]	0.017404 (0.02564) [0.67876]
R_BOVESPA(-4)	-0.034008 ^{**} (0.01864) [-1.82424]	-0.048822 ^{**} (0.02918) [-1.67296]	-0.008528 (0.03295) [-0.25882]	0.001655 (0.02454) [0.06743]	0.061599 (0.02557) [2.40888]
R_BOVESPA(-5)	0.050135 [*] (0.01856) [2.70104]	0.009240 (0.02906) [0.31802]	0.135658 [*] (0.03281) [4.13502]	0.095568 [*] (0.02443) [3.91168]	0.027784 (0.02546) [1.09125]
R_BOVESPA(-6)	-0.053583 [*] (0.01845) [-2.90362]	-0.014712 (0.02889) [-0.50930]	0.051572 (0.03262) [1.58114]	0.037433 (0.02429) [1.54111]	0.037766 (0.02531) [1.49196]
R_RTS(-1)	0.012076 (0.01414) [0.85419]	-0.003860 (0.02213) [-0.17440]	-0.018096 (0.02499) [-0.72418]	-0.035600 ^{**} (0.01861) [-1.91312]	-0.020796 (0.01939) [-1.07238]
R_RTS(-2)	0.004288 (0.01412) [0.30373]	0.008206 (0.02210) [0.37128]	-0.030247 (0.02496) [-1.21203]	0.004848 (0.01858) [0.26085]	-0.000575 (0.01937) [-0.02969]
R_RTS(-3)	0.012311 (0.01411) [0.87275]	0.021244 (0.02208) [0.96209]	0.002992 (0.02493) [0.12001]	-0.021703 (0.01857) [-1.16890]	-0.020212 (0.01935) [-1.04464]
R_RTS(-4)	0.013328 (0.01410) [0.94557]	0.029899 (0.02206) [1.35506]	-0.027905 (0.02491) [-1.12009]	0.014632 (0.01855) [0.78869]	0.042359 [*] (0.01933) [2.19089]
R_RTS(-5)	0.017861 (0.01409) [1.26751]	0.011473 (0.02206) [0.52012]	-0.000468 (0.02491) [-0.01878]	-0.000871 (0.01855) [-0.04694]	0.024910 (0.01933) [1.28874]
R_RTS(-6)	-0.040756 [*] (0.01335) [-3.05385]	-0.016654 (0.02089) [-0.79716]	-0.036957 (0.02359) [-1.56670]	-0.005376 (0.01757) [-0.30604]	-0.005600 (0.01831) [-0.30590]
R_NIFTY(-1)	-0.008834 (0.01768) [-0.49972]	0.010916 (0.02767) [0.39445]	-0.051991 ^{**} (0.03125) [-1.66390]	-0.103521 [*] (0.02327) [-4.44885]	0.013759 (0.02425) [0.56739]
R_NIFTY(-2)	0.016927 (0.01772) [0.95525]	-0.003457 (0.02774) [-0.12461]	-0.006893 (0.03132) [-0.22009]	-0.089422 [*] (0.02332) [-3.83386]	-0.012160 (0.02431) [-0.50029]
R_NIFTY(-3)	-0.022680 (0.01777) [-1.27668]	-0.050766 ^{**} (0.02781) [-1.82549]	-0.072705 [*] (0.03140) [-2.31545]	-0.013377 (0.02338) [-0.57209]	0.041480 ^{**} (0.02437) [1.70222]
R_NIFTY(-4)	-0.016411 (0.01778) [-0.92319]	0.001235 (0.02783) [0.04437]	-0.017658 (0.03142) [-0.56202]	-0.032434 (0.02340) [-1.38621]	-0.023575 (0.02438) [-0.96686]
R_NIFTY(-5)	0.015815 (0.01760) [0.89855]	0.030764 (0.02755) [1.11657]	-0.018225 (0.03111) [-0.58582]	-0.053764 [*] (0.02317) [-2.32067]	0.002671 (0.02414) [0.11065]
R_NIFTY(-6)	0.026414 (0.01734) [1.52333]	0.034723 (0.02714) [1.27924]	0.029553 (0.03065) [0.96428]	-0.004942 (0.02282) [-0.21651]	0.029890 (0.02378) [1.25668]
R_SSE(-1)	0.013349 (0.01559) [0.85634]	0.030069 (0.02440) [1.23225]	-0.059028 [*] (0.02755) [-2.14240]	-0.045333 [*] (0.02052) [-2.20940]	-0.006033 (0.02138) [-0.28214]
R_SSE(-2)	-0.003498 (0.01562) [-0.22398]	-0.002164 (0.02444) [-0.08853]	0.027387 (0.02760) [0.99229]	0.033552 (0.02055) [1.63240]	0.002911 (0.02142) [0.13592]
R_SSE(-3)	0.008501 (0.01555) [0.54672]	0.013223 (0.02434) [0.54326]	0.027937 (0.02748) [1.01656]	-0.002956 (0.02047) [-0.14444]	0.050825 [*] (0.02133) [2.38303]
R_SSE(-4)	-0.008916 (0.01549) [-0.57546]	-0.009450 (0.02425) [-0.38964]	0.034168 (0.02738) [1.24774]	0.003714 (0.02039) [0.18214]	-0.032914 (0.02125) [-1.54878]

(continued on next page)

Table 17 (continued)

Parameters	R_SANDP	R_BOVESPA	R_RTS	R_NIFTY	R_SSE
R_SSE(-5)	-0.033904 [*] (0.01551) [-2.18608]	-0.028483 (0.02428) [-1.17322]	-0.085484 [*] (0.02741) [-3.11846]	-0.023977 (0.02041) [-1.17457]	-0.043029 [*] (0.02127) [-2.02265]
R_SSE(-6)	0.024436 (0.01546) [1.58016]	0.029039 (0.02421) [1.19960]	0.033706 (0.02733) [1.23317]	-0.005189 (0.02035) [-0.25495]	-0.020813 (0.02121) [-0.98120]
Constant	0.032467 (0.02595) [1.25120]	0.040754 (0.04062) [1.00329]	0.006316 (0.04586) [0.13771]	0.057343 [*] (0.03416) [1.67892]	0.007002 (0.03559) [0.19671]

Source: Computed by the Authors; R stands for index returns.

^{*} Reject null hypothesis of insignificant impact at the 5% significance level.

^{**} Reject null hypothesis of insignificant impact at the 10% significance level; Standard errors in () & t-statistics in [].

Table 18 – Granger causality results (Full sample period).

Excluded	Chi-sq	df	Prob.
Dependent variable: R_SANDP			
R_BOVESPA	26.86791	6	0.0002 [*]
R_RTS	13.31943	6	0.0382 [*]
R_NIFTY	7.398753	6	0.2855
R_SSE	8.887657	6	0.1800
All	55.63068	24	0.0003 [*]
Dependent variable: R_BOVESPA			
R_SANDP	13.47792	6	0.0360 [*]
R_RTS	3.795313	6	0.7044
R_NIFTY	6.523983	6	0.3671
R_SSE	4.856893	6	0.5623
All	29.77274	24	0.1924
Dependent variable: R_RTS			
R_SANDP	45.08672	6	0.0000 [*]
R_BOVESPA	96.56838	6	0.0000 [*]
R_NIFTY	8.922527	6	0.1780
R_SSE	18.61911	6	0.0049 [*]
All	282.1722	24	0.0000 [*]
Dependent variable: R_NIFTY			
R_SANDP	81.48391	6	0.0000 [*]
R_BOVESPA	36.63886	6	0.0000 [*]
R_RTS	5.691893	6	0.4586
R_SSE	8.632326	6	0.1953
All	247.7881	24	0.0000 [*]
Dependent variable: R_SSE			
R_SANDP	33.72710	6	0.0000 [*]
R_BOVESPA	11.60128	6	0.0715 ^{**}
R_RTS	8.976831	6	0.1749
R_NIFTY	6.581361	6	0.3613
All	131.4271	24	0.0000 [*]

Source: Computed by the Authors.

^{*} Reject null hypothesis of non-Granger causality at the 5% significance level.

^{**} Reject null hypothesis of non-Granger causality at the 10% significance level; Significant values denote Granger causality or impact of respective variable on dependent.

Table 19 – Variance decomposition Analyses (Full Sample Period).

Period	S.E.	R_SANDP	R_BOVESPA	R_RTS	R_NIFTY	R_SSE
Variance decomposition of R_SANDP						
1	1.245586	59.12870	40.87130	0.000000	0.000000	0.000000
2	1.253345	59.07903	40.85222	0.030749	0.010721	0.027283
3	1.255784	58.86031	41.01481	0.039023	0.056641	0.029213
4	1.256610	58.80554	40.96459	0.047028	0.151305	0.031533
5	1.257513	58.76181	40.95111	0.064874	0.176334	0.045872
Variance decomposition of R_BOVESPA						
1	1.949858	0.000000	100.0000	0.000000	0.000000	0.000000
2	1.956637	0.343439	99.57713	0.000146	0.006717	0.072567
3	1.963162	0.597443	99.31449	0.005387	0.008819	0.073859
4	1.967365	0.635401	99.10980	0.021879	0.157389	0.075532
5	1.969449	0.651453	98.99736	0.106226	0.165380	0.079578
Variance decomposition of R_RTS						
1	2.201580	4.085419	20.86976	75.04482	0.000000	0.000000
2	2.331358	4.759465	27.91101	67.00162	0.107322	0.220580
3	2.332830	4.753818	27.87579	66.94559	0.107206	0.317596
4	2.335178	4.768253	27.82780	66.81194	0.257903	0.334111
5	2.337861	4.861497	27.76618	66.67647	0.300216	0.395639
Variance decomposition of R_NIFTY						
1	1.639512	1.542746	10.99466	5.733818	80.28300	1.445779
2	1.708973	3.694782	14.22977	5.743807	74.68131	1.650328
3	1.716338	3.786098	14.24040	5.694966	74.49927	1.779269
4	1.717287	3.856656	14.22480	5.716743	74.42300	1.778797
5	1.719315	3.952233	14.19295	5.738880	74.34122	1.774717
Variance decomposition of R_SSE						
1	1.708560	0.048252	1.993854	1.121009	0.000000	96.83689
2	1.739545	1.324872	4.119215	1.122730	0.013500	93.41968
3	1.739729	1.325831	4.120777	1.122503	0.027225	93.40366
4	1.743612	1.324480	4.109331	1.119126	0.171978	93.27508
5	1.755216	1.410551	4.941777	1.237545	0.239832	92.17029
Ordering: Brazil, US, Russia, China, India.						
Source: Computed by the Authors; Table shows contribution of the respective market shocks in explaining forecasted error variations in another.						

Further, we employ [Diebold and Yilmaz's \(2011\)](#) total spillover index in order to capture gross return spillover effects across the US-BRIC equity markets. Under [Diebold and Yilmaz's \(2011\)](#) generalized framework, the VAR equations are modeled for each of the US-BRIC equity market returns to come out with a total spillover index ascertaining total contribution of the shocks on an asset arising from the contribution of all other markets using forecast error variance decompositions. Accordingly, we can construct a total return spillover index over all the markets sums to N:

$$S^g(H) = \frac{\sum_{i,j=1}^N \theta_{ij}^{-g}(H)}{N} \times 100 \quad (9)$$

where $\theta_{ij}^{-g}(H)$ represents H -step-ahead forecast error variance decompositions for $H=1,2$. [Fig. 10](#) is the graphical presentation of the spillover index across the years 2004-2014.

The index reflects time-varying⁵ gross spillover effects between the US-BRIC equity markets, highlighting varying market integration phenomenon in existence. During the Lehman Brother' episode, the spillover index witnessed a sudden spike, thereby reporting magnified spillover effects between the said markets; supporting earlier results. It also increased during the Euro-zone sovereign debt crisis in the year 2011. The index also reflects falling return spillover effects between the US-BRIC equity markets, ever since the Euro-zone financial crisis. This means that the markets are largely driven by their respective domestic events.

⁵ In order to incorporate time-varying aspect in total return spillover, rolling window estimation i.e., 200 days with 10 days ahead variances is done across the period 2004-2014.

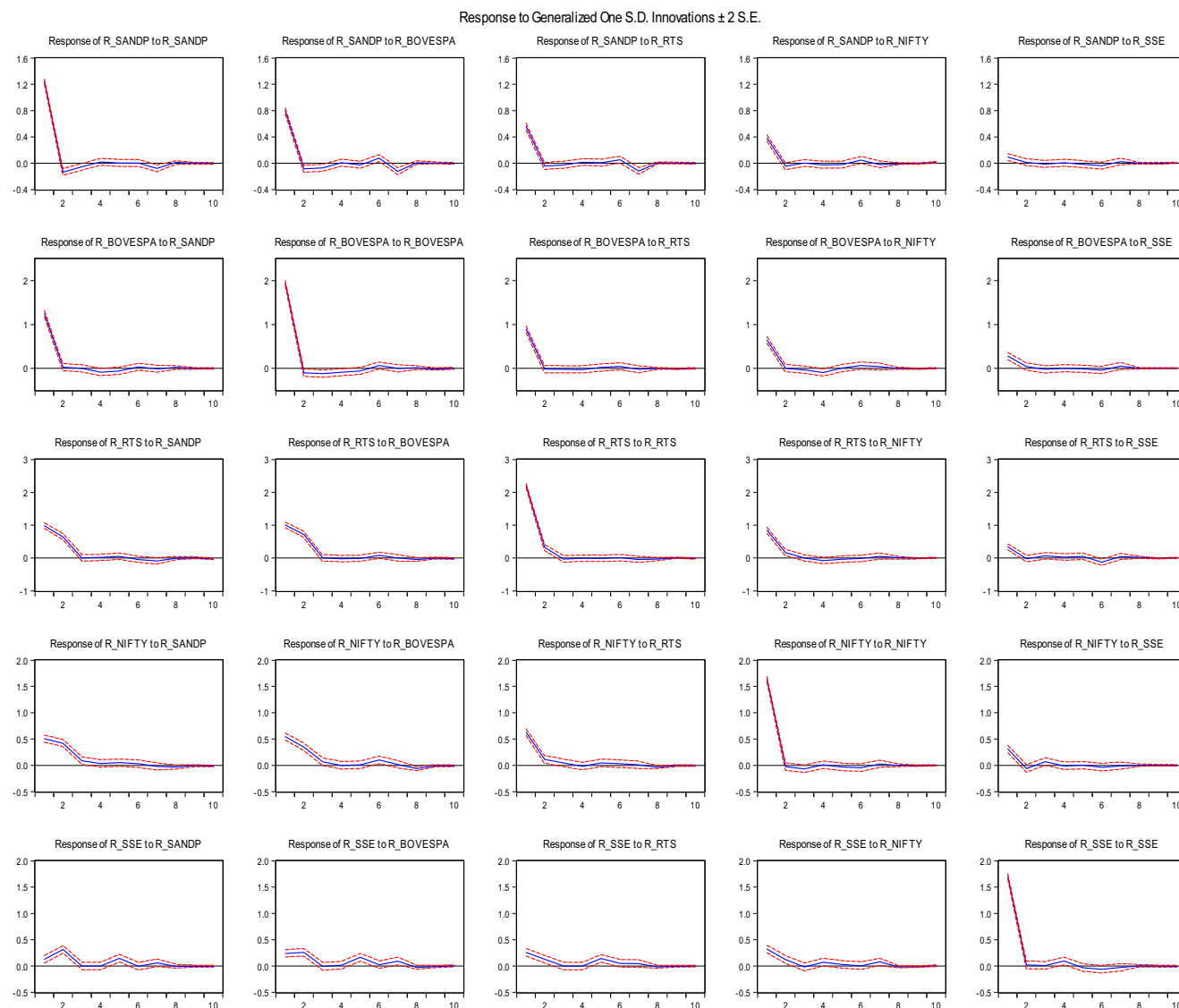


Fig. 9 – Generalized impulse responses (Full Sample Period).
Source: Computed by the Authors.

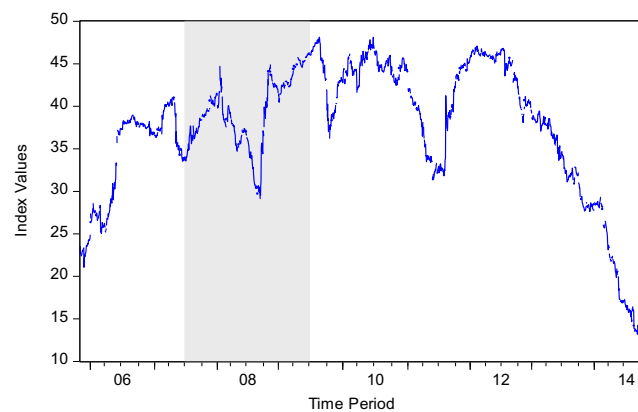


Fig. 10 – Total return spillover index.

6. Concluding remarks

The US and BRIC economies are sharing increasing trade as well as financial linkages since the last decade. According to the IMF data, the Brazilian market is becoming an important export destination for the US economy, whereas, on the other hand, India's share in the United State's overall imports is substantially increasing since the last 15 years (2000–2014). The percentage contribution of the US-BRIC economies to overall cross border trade numbers is increasing over the years. The US market is becoming an important export destination for the respective BRIC markets. The contribution of the Chinese economy is quite high and significant in comparison to others. Considering these strong and ever increasing trade linkages, the present study attempts to capture dynamic interactions between the US and BRIC equity markets during different time frames. According to unconditional correlation coefficients, the Indian equity market is found to be a segmented or independent market ever since the crisis period, amongst the BRIC economies. This finding is partially consistent with [Singh and Singh \(2016\)](#), whereby the authors also reported reaffirmation of decoupling hypothesis with respect to Indian market since the financial crisis.

Generally, the dynamic interactions can be demarcated into two different categories depending on their time horizons, i.e. short run and long run. The long run interactions are captured through Johansen cointegration and vector error correction model (VECM) models; whereas on the other hand, the short run interactions are generated out of long run interactions among the underlying markets. The vector autoregression (VAR) model is employed to account for short run interactions among the said markets. Overall, the results report that all the markets are generally driven by their own market innovations. There is long run co-movement and causality relationship between the US and BRIC equity markets during the pre-crisis and post-crisis periods only. The results relating to the pre-crisis period are compatible with the findings of [Chittedi \(2009\)](#), whereby the author also reported existence of cointegrating vectors among the said markets considering the time period up till 2008. There is no significant evidence of the existence of common stochastic trends among the US-BRIC markets during the crisis and full sample periods. This further supports long run investment benefits for the international investors.

During the pre-crisis period, the Brazilian and Russian markets were following an independent dominant trend in the long run, whereby the US equity market was acting as a restoring agent toward long run equilibrium path in the event of any short run deviation. Around 4 percent of the disequilibrium adjustments used to take place in one day and rest in the coming days. However, during the post crisis period, only the US and Brazilian equity markets are found to be affected by the other equity markets in the long run. Around 2 percent of the adjustments take place in one day in the event of any disequilibrium, whereby the US and Brazilian are the only markets acting as restoring agents during this period. A possible reason for this long run co-movement after the financial crisis could be increasing equity investments in emerging markets in the wake of interest rate differentials and risk premiums. This phenomenon further requires the existence of positive risk and return relationship in the respective US-BRIC equity markets thereby justifying the investments made by the investors in the long run.

The results relating to the short run dynamics report that there is only uni-directional causality running from one market to another during pre-crisis, crisis and post-crisis periods. However, for the full sample period, bi-directional causality elements are also observed between the US-Brazilian and US-Russian markets. The market responses are largely transitory in nature, decaying after a few days during the crisis and full sample periods in the context of non-cointegrated variables. During the pre-crisis and post-crisis periods, the stimulated impulse responses generally highlight a substantial shift in the long run equilibrium relationship in the event of any market shock. Expectedly, there is uni-directional causality running from the US to BRIC equity markets during the crisis period. However, the Chinese equity market is found to be independent, driven by its own market shocks. These findings are critically important for the portfolio managers in their attempt of analyzing predictive power of one market in explaining movements in another. Overall, the results report changing market dynamics and partial integration across the years 2004–2014. So, there are short run portfolio diversification benefits available to the international investors. The impact of the US market on other BRIC equity markets is quite obvious during the crisis period, however, ever since the financial crisis, both the US and Brazilian markets are exerting stronger dynamic influence on other BRIC equity markets. It may be due to a greater degree of co-movement recorded between the US and Brazilian equity markets per se ([Aloui, Ben Aissa, & Nguyen, 2011](#)).

[Wang and Wang \(2010\)](#) asserted that the extent of influence of the developed market is associated with the degree of openness of the domestic economies. So, the results relating to the Chinese equity market are due to its relative closed economic system. Increasing foreign financial flows primarily act as transmitting agents, channelizing financial shocks from one economy to another; so, studies relating to long run and short run dynamic interactions among the integrated economies hold an important place for the portfolio managers as well as policy makers. Typically, there are two types of market participants: traders and investors, whereby traders are most of the time interested in understanding short run dynamic interactions between the different market segmentations as well as across different nations in order to enjoy arbitrage opportunities. Whereas, investors are usually interested in comprehending long run portfolio related advantages while accounting for common stochastic linkages. In this regard, the existing lead-lag relationships may clearly channelize the expected moves in the domestic economies thereby supporting overall financial system.

Another important aspect is the existence of country or industry based effects at the time of asset allocations across international boundaries. Voluminous literature supports the existence of industry based effects at the time of portfolio constructions owing to augmenting integrated market structures. For instance, European Union (EU), Association of Southeast Asian Nations (ASEAN), etc., are greatly adding up to the concept of market integration. However, BRIC is a geopolitical economic bloc, wherein all the nations are still heterogeneous due to their diverse economic fundamentals. Consequently, country based

effects, like monetary and fiscal stances, political ideologies, growth rates, etc., matter a lot at the time of asset allocation decisions and short-long causal linkages thereon. Moreover, different monetary policy initiatives are also undertaken considering the co-movement and dynamic interactions among the underlying markets due to international transmission of the shocks through equity markets and confidence levels (Berben & Jansen, 2005).

These linkages further highlight the role of domestic investors and fiscal policies against adverse cross market dynamics. So, an understanding of long run as well as short run causal relationships is of paramount interest. As a future scope of study, integration and market linkages among BRIC and other developed equity markets like, the UK, Japan, EU nations or emerging markets can be undertaken. Additionally, South African equity market should also be included in the future studies; possibly a limitation of the present study.

Conflict of interest

There are no conflict of interests to declare.

REFERENCES

- Abbes, M. B., & Trichilli, Y. (2015). Islamic stock markets and potential diversification benefits. *Borsa Istanbul Review*, 15(2), 93–105.
- Abid, I., Kaabia, O., & Guesmi, K. (2014). Stock market integration and risk premium: Empirical evidence for emerging economies of South Asia. *Economic Modelling*, 37, 408–416.
- Adler, M., & Qi, R. (2003). Mexico's integration into the North American capital market. *Emerging Economic Review*, 4, 91–120.
- Ahmad, W., Sehgal, S., & Bhanumurthy, N. R. (2013). Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling*, 33, 209–225.
- Aloui, R., Ben Aissa, M. S., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking and Finance*, 35(1), 130–141.
- Aragó, V., & Salvador, E. (2011). Sudden changes in variance and time varying hedge ratios. *European Journal of Operational Research*, 215(2), 393–403.
- Arshanapalli, B., Doukas, J., & Lang, L. H. P. (1995). Pre and post-October 1987 stock market linkages between U.S. and Asian markets. *Pacific Basin Finance Journal*, 3, 57–73.
- Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2011). *Global crises and equity market contagion. working paper [1381]*. European Central Bank.
- Bekaert, G., & Harvey, C. (1995). Time-varying world market integration. *Journal of Finance*, 50(2), 403–444.
- Berben, R., & Jansen, W. J. (2005). Comovement in international equity markets: A sectoral view. *Journal of International Money and Finance*, 24(5), 832–857.
- Bhar, R., & Nikolova, B. (2009). Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate EGARCH framework. *Global Finance Journal*, 19(3), 203–218.
- Bianconi, M., Yoshino, J. A., & Machado de Sousa, M. O. (2013). BRIC and the U.S. financial crisis: An empirical investigation of stock and bond markets. *Emerging Markets Review*, 14, 76–109.
- Booth, G. G., So, W. R., & Tse, Y. (1999). Price discovery in the German equity index derivatives markets. *Journal of Futures Markets*, 9(6), 619–643.
- Carrieri, F., Errunza, V., & Hogan, K. (2007). Characterizing world market integration through time. *Journal of Financial and Quantitative Analysis*, 42, 915–940.
- Chen, G., Firth, M., & Rui, O. M. (2002). Stock market linkages: Evidence from Latin America. *Journal of Banking & Finance*, 26, 1113–1141.
- Cheng, H. (2000). *Cointegration test for equity market integration: The case of the Great China Economic Area (Mainland China, Hong Kong, and Taiwan)*. Japan/United States: George Washington University.
- Cheng, H., & Glascock, J. L. (2006). Stock market linkages before and after the Asian financial crisis: Evidence from Three Greater China Economic Area Stock Markets and the US. *Review of Pacific Basin Financial Markets and Policies*, 9(2), 297–315.
- Cheung, Y., & Mak, S. (1992). The international transmission of stock market fluctuations between developed markets and the Asian-Pacific markets. *Applied Financial Economics*, 2, 43–47.
- Chittedi, K. R. (2009). Global stock market development and integration: With special reference to BRIC countries. *International Review of Applied Financial Issues and Economics*, 2(1), 3–21.
- Dekker, A., Sen, K., & Young, M. (2001). Equity market in the Asia Pacific region: A comparison of the orthogonalized and generalized VAR approaches. *Global Finance Journal*, 12, 1–33.
- Diamandis, P. F. (2009). International stock market linkages: Evidence from Latin America. *Global Finance Journal*, 20, 13–30.
- Diebold, F. X., & Yilmaz, K. (2011). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.
- Dimpfl, T., & Jung, R. C. (2012). Financial market spillovers around the globe. *Applied Financial Economics*, 22(1), 45–57.
- Enders, W. (2014). *Applied econometric time series*. Hoboken, New Jersey: John Wiley & Sons, Inc..
- Ewing, B. T., & Wunnava, P. V. (2004). Union-nonunion wage differentials and macroeconomic activity. In P. V. Wunnava (Ed.), *The changing role of unions: New forms of representation* (pp. 156–157). USA: M.E. Sharpe.
- Gregory, A. W., & Hansen, B. E. (1996). Residual-based tests for cointegration in models with regime shifts. *Journal of Econometrics*, 70, 99–126.
- Harvey, C. R. (1995). Predictable risk and returns in emerging markets. *Review of Financial Studies*, 8(3), 773–816.
- Hyde, S. J., Bredin, D. P., & Nguyen, N. (2007). Correlation dynamics between Asia-Pacific, EU and US stock returns. In S. Kim, & M. D. McKenzie (Eds.), *Asia-Pacific financial markets: Integration, innovation and challenges (International Finance Review, Volume 8)* (pp. 39–61). Emerald Group Publishing Limited.

- Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59, 1551-1580.
- Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford: Oxford University Press.
- Karolyi, A., & Stulz, R. (2002). Are financial assets priced locally or globally? In G.M. Constantinides, M. Harris, & R.M. Stulz (Eds.), *Handbook of the economics of finance*: (1. pp. 975-1020). Amsterdam: Elsevier.
- Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions & Money*, 21, 92-106.
- Kenourgios, D., & Samitas, A. (2011). Equity market integration in emerging Balkan markets. *Research in International Business and Finance*, 25 (3), 296-307.
- Lagoarde-Segot, T., & Lucey, B. M. (2007). Capital market integration in the Middle East and North Africa emerging markets. *Emerging Markets Finance & Trade*, 43(3), 34-57.
- Lamba, A. S. (2005). An analysis of the dynamic relationships between South Asian and developed equity markets. *International Journal of Business*, 10(4), 393-402.
- Lane, P. R. (2014). Cross-border financial linkages: Identifying and measuring vulnerabilities. *CEPR Policy Insight* 77.
- Lehkonen, H., & Heimonen, K. (2014). Timescale-dependent stock market comovement: BRICs vs. developed markets. *Journal of Empirical Finance*, 28, 90-103.
- Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7, 77-91.
- Masih, R., & Masih, A. M. M. (2001). Long and short term dynamic causal transmission amongst international stock markets. *Journal of International Money and Finance*, 20, 563-587.
- Menon, N. R., Subha, M. V., & Sagar, S. (2009). Cointegration of Indian stock markets with other leading stock markets. *Studies in Economics and Finance*, 26, 87-94.
- Naranjo, A., & Aris, P. (1997). Financial market integration tests: An investigation using US equity markets. *Journal of International Financial Markets, Institutions and Money*, 7, 93-135.
- Palamalai, S., Kalaivani, M., & Devakumar, C. (2013). Stock market linkages in emerging Asia-Pacific markets. *SAGE Open*, 3(4). <http://dx.doi.org/10.1177/2158244013514060>.
- Pati, P. C., & Rajib, P. (2011). Intraday return dynamics and volatility spillovers between NSE S&P CNX nifty stock index and stock index futures. *Applied Economics Letters*, 18(6), 567-574.
- Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17-29.
- Rejeb, A. B., & Boughrara, A. (2015). Financial integration in emerging market economies: Effects on volatility transmission and contagion. *Borsa Istanbul Review*, 15(3), 161-179.
- Royfaizal, R. C., Lee, C., & Azali, M. (2007). *Asean-5+3 and US stock markets interdependence before, during and after Asian financial crisis*. MPRA Paper 10263. Germany: University Library of Munich.
- Samarakoon, L. P. (2011). Stock market interdependence, contagion, and the U.S. financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions & Money*, 21, 724-742.
- Sehgal, S., Ahmad, W., & Deisting, F. (2015). An investigation of price discovery and volatility spillovers in India's foreign exchange market. *Journal of Economic Studies*, 42(2), 261-284.
- Shachmurove, Y. (2006). Dynamic linkages among the stock exchanges of the emerging tigers of the twenty first century. *International Journal of Business*, 11(3), 319-344.
- Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48(1), 1-48.
- Singh, A., & Singh, M. (2016). Cross country co-movement in equity markets after the US financial crisis: India and major economic giants. *Journal of Indian Business Research*, 8(2), 98-121.
- Singh, A., & Kaur, P. (2015). Stock market linkages: Evidence from the US, China and India during the subprime crisis. *Timisoara Journal of Economics and Business*, 8(1), 137-162.
- Singh, A., & Kaur, P. (2016). Do BRIC equity markets co-move in long run? *Theoretical Economics Letters*, 6(2), 119-130.
- Singh, A. (2016). On the linkages between INDIA VIX and US Financial Stress Index. *Theoretical Economics Letters*, 6(1), 68-74.
- Stulz, R. M. (1981). A model of international assets pricing. *Journal of Financial Economics*, 9, 383-406.
- Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. *International Review of Financial Analysis*, 39, 7-18.
- Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1-2), 225-250.
- Valadkhani, A., & Chancharat, S. (2008). Dynamic linkages between Thai and international stock markets. *Journal of Economic Studies*, 35(5), 425-441.
- Wang, Y., & Liu, L. (2016). Spillover effect in Asian financial markets: A VAR-structural GARCH analysis. *China Finance Review International*, 6 (2), 150-176.
- Wang, M., & Ye, J. (2016). The relationship between covariance risk and size effects in emerging equity markets. *Managerial Finance*, 42(3), 174-190.
- Wang, P., & Wang, P. (2010). Price and volatility spillovers between the Greater China markets and the developed markets of US and Japan. *Global Finance Journal*, 21, 304-317.
- Wuthisatian, R. (2014). Cointegration of stock markets: The case of Thailand. *Review of Market Integration*, 6(3), 297-320.
- Xu, H., & Hamori, S. (2012). Dynamic linkages of stock prices between the BRICs and the United States: Effects of the 2008-09 financial crisis. *Journal of Asian Economics*, 23, 344-352.
- Zouhair, M., Lanouar, C., & Ajmi, A. N. (2014). Contagion versus interdependence: The case of the BRIC Countries during the subprime crises. In M. Arouri, S. Boubaker, & D. Nguyen (Eds.), *Emerging markets and the global economy* (pp. 555-582). San Diego: Academic Press.