Journal of Asian Economics 23 (2012) 344–352

Contents lists available at SciVerse ScienceDirect

Journal of Asian Economics

Dynamic linkages of stock prices between the BRICs and the United States: Effects of the 2008–09 financial crisis

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A R T I C L E   I N F O

Article history:
Received 26 June 2010
Received in revised form 14 April 2012
Accepted 19 April 2012
Available online 27 April 2012

JEL classification:
G01
G15
F44

Keywords:
Financial crisis
BRICs
Dynamic linkages of stock prices
Hong test

A B S T R A C T

In this paper, we investigate the dynamic linkages between the BRIC countries (Brazil, Russia, India, and China) and the United States in the mean and variance of stock prices for the period August 2, 2004, to April 30, 2010. In particular, we focus on the impact of the US financial crisis in September 2008 on the dynamic linkages between these stock prices. The sample period is divided into pre- and post-crisis periods in order to study the causal relationships in the mean and variance. The empirical results indicate that the international transmission of stock prices between the BRICs and the United States weakened in both the mean and variance on account of the 2008–09 US financial crisis.

1. Introduction

A number of empirical analyses have investigated the international linkage of stock prices by using a combination of unit root tests (Dickey & Fuller, 1979, 1981; Phillips & Perron, 1988; Said & Dickey, 1985), cointegration tests (Engle & Granger, 1987; Johansen, 1988; Johansen & Juselius, 1990), and the vector autoregression (VAR) approach.[1] Kasa (1992) reported a common stochastic trend in stock price indexes in the United States, Japan, the United Kingdom, Germany, and Canada. Tsutsui and Hirayama (2004) also explored the international linkage of stock prices among the United States, the United Kingdom, Germany, and Japan. Further, Hamori and Imamura (2000) empirically analyzed the causal relationship among stock prices in the G7 countries by employing the lag augmented vector autoregression (LA-VAR) method developed by Toda and Yamamoto (1995).

Moreover, a large number of empirical studies have focused on the impact of financial crises on the international transmission of stock prices. Malliaris and Urrutia (1992) analyzed lead–lag relationships for six major stock markets – the United States, Japan, the United Kingdom, Hong Kong, Singapore, and Australia – around the time of the US market crisis in October 1987. Masih and Masih (1997) also analyzed the dynamic linkages and propagation mechanisms of six important world stock markets – the United States, Japan, Canada, France, Germany, and the United Kingdom – around the same time.

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[1] See Sims (1980).

1049-0078/$ – see front matter
http://dx.doi.org/10.1016/j.asieco.2012.04.002

Further, Wang, Yang, and Bessler (2003) used the generalized impulse response analysis in order to examine the dynamic causal linkages and relationships among the five largest emerging African stock markets and the US market during the 1997–98 global emerging market crisis.[2]

This paper empirically analyzes the international transmission of stock prices between the BRIC countries (Brazil, Russia, India, and China) and the United States. It is well known that the BRICs currently account for more than a quarter of the world's land and about 42% of the world's population. Further, according to data released by the International Monetary Fund, GDP based on the purchasing power parity of the BRICs in 2010 was 18.6 trillion USD, which accounted for approximately 25% of the world's total GDP. Although the BRICs are developing rapidly, few previous studies have focused on the causal relationships among their stock markets and that of the United States, as is carried out in this paper.

Aktan, Mandaci, Kopurlu, and Ersener (2009) employed the VAR approach, Granger causality, and the impulse response tests in order to examine the linkages among the stock markets of the BRICs, Argentina, and the United States. Further, Cheung and Ng (1996) proposed a two-step cross-correlation function (CCF) approach[3] to test for causality in both the mean and variance. However, Cheung and Ng's test statistic may be subject to severe size distortion in the presence of causality in mean (Cheung & Ng, 1996; Pantelidis & Pittis, 2004).

In order to address this problem, Hong (2001) proposed a bivariate conditional mean that can be utilized to ensure that any causality in mean is filtered out when testing for causality in variance. Hong also suggested weighting the cross-correlation in order to obtain a more powerful test for causality. This paper uses the CCF approach incorporating the weighting cross-correlation.

The contribution of this paper to the existing literature is twofold. First, it uses the CCF approach to test for causality in mean and causality in variance. Second, it analyzes the dynamic linkages between stock prices in the BRICs and the United States. To the best of our knowledge, no previous empirical analysis in financial literature has addressed the dynamic linkages between the stock markets of the BRICs and the United States during the 2008–09 US financial crisis. This crisis was triggered by the emergence of sub-prime loan losses in 2007, which affected other risky loans and over-inflated asset prices. With mounting loan losses and the collapse of Lehman Brothers on September 15, 2008, there was panic in the inter-bank loan market, and the US stock market index fell by over 6.9% on September 29, 2008.

In this paper, we divide the entire sample period into two sub-periods and use the CCF approach to examine the causal relationships in the mean and variance of stock prices. Further, we compare the results of the two sub-periods in order to study the impact of the 2008–09 US financial crisis on the dynamic linkages between the stock prices of the BRICs and the United States.

The remainder of the paper is organized as follows: Section 2 describes the data used in this study. Section 3 explains the weighting CCF approach. Section 4 presents and discusses the empirical results. Section 5 concludes the paper.

2. Data

In this study, we use the stock price indexes of the United States and the BRICs in order to identify the causal relationships among the stock prices of the five countries. The Dow Jones Industrial Average Index, BOVESPA Index, RTS Index, BSE SENSITIVE Index, and Shanghai Composite Index are used as the representative of US, Brazilian, Russian, Indian, and Chinese stock markets, respectively. We use the daily closing stock price indexes from August 2, 2004, to April 30, 2010, with 1194 observations for each country.[4] These stock price indexes were obtained from the Yahoo! Finance website (http://finance.yahoo.com/), and their first-differences are expressed as $y_t = \ln S_t - \ln S_{t-1}$, where S_t is the stock price index at time t. In order to compensate for missing values in the data for a particular country, corresponding observations were excluded for all countries.

Since the US stock market index fell by over 6.9% on September 29, 2008, the entire sample period was divided into two sub-periods: the pre-crisis period from August 2, 2004, to September 28, 2008 (876 observations), and the post-crisis period from September 29, 2008, to April 30, 2010 (318 observations). The statistical properties of the data are summarized in Tables 1 and 2, and the unconditional correlation matrixes are reported in Tables 3 and 4. The results of the Jarque–Bera test indicate that the null hypothesis of normal distribution is rejected for all cases. This result indirectly supports the characteristics of autoregressive conditional heteroskedasticity (ARCH) effects. Using these data, we analyze the differences in the causal relationships in these international stock markets before and after the crisis.

3. Empirical techniques

By incorporating the weighting cross-correlation into the CCF approach proposed by Cheung and Ng (1996) and Hong (2001), we considered the following two-step procedure in order to test for causality in mean and causality in variance. In the first step, we estimated a set of univariate time-series models that permit time variation in both the conditional mean and

[2] See Pesaran and Shin (1998).

[3] For the application of the CCF approach, refer to, for example, Hamori (2003), Bhar and Hamori (2005), Bhar and Hamori (2008), Tamakoshi (2011), Toyoshima and Hamori (2012), and Nakajima and Hamori (2012).

[4] The data of Yahoo! Finance for BRICs stock prices starts from August 2, 2004.

Table 1
Descriptive statistics for the pre-crisis period.

	USA	CHINA	BRAZIL	INDIA	RUSSIA
Mean	0.000103	0.000586	0.001056	0.000933	0.000979
Std. Dev.	0.009827	0.021932	0.018037	0.018716	0.021073
Skewness	−0.423892	−0.226725	−0.556528	−0.331750	−0.479202
Kurtosis	5.740814	7.160907	8.690504	4.595515	20.13352
Jarque–Bera	300.0812	638.7051	1225.756	108.8610	10736.11
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

Note: These are calculated using the first-differences in logarithmic stock prices.
Source: Yahoo! Finance database (http://finance.yahoo.com/).

Table 2
Statistical properties for the post-crisis period.

	USA	CHINA	BRAZIL	INDIA	RUSSIA
Mean	−0.000038	0.000705	0.000921	0.000896	0.000634
Std. Dev.	0.020159	0.021250	0.024960	0.027208	0.044277
Skewness	−0.655406	−0.249026	0.221985	−1.304743	−2.219080
Kurtosis	8.673216	4.207140	10.03014	12.04629	23.50108
Jarque–Bera	449.2228	22.59447	657.4642	1174.544	5829.889
Probability	0.000000	0.000012	0.000000	0.000000	0.000000

Note: These are calculated using the first-differences in logarithmic stock prices.
Source: Yahoo! Finance database (http://finance.yahoo.com/).

Table 3
Unconditional correlation matrix for the pre-crisis period.

	USA	CHINA	INDIA	BRAZIL	RUSSIA
USA	1.000000				
CHINA	−0.021287	1.000000			
INDIA	0.163115	0.208409	1.000000		
BRAZIL	0.606073	0.130022	0.240850	1.000000	
RUSSIA	0.222706	0.188612	0.420009	0.417335	1.000000

Note: These are calculated using the first-differences in logarithmic stock prices.
Source: Yahoo! Finance database (http://finance.yahoo.com/).

Table 4
Unconditional correlation matrix for the post-crisis period.

	USA	CHINA	INDIA	BRAZIL	RUSSIA
USA	1.000000				
CHINA	0.083397	1.000000			
INDIA	0.402033	0.294157	1.000000		
BRAZIL	0.781107	0.248452	0.481350	1.000000	
RUSSIA	0.503937	0.244176	0.582818	0.641779	1.000000

Note: These are calculated using the first-differences in logarithmic stock prices.
Source: Yahoo! Finance database (http://finance.yahoo.com/).

the conditional variance. An autoregressive (AR) model was used for the conditional mean and the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model[5] was used for the conditional variance in this step. The AR(k)–EGARCH(p,q) specification is expressed as follows:

$$x_t = a_0 + \sum_{i=1}^{k} a_i x_{t-i} + \varepsilon_t, \quad E_{t-1}(\varepsilon_t) = 0, \quad E_{t-1}(\varepsilon_t^2) = \sigma_t^2 \tag{1}$$

and

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{i=1}^{q} \beta_i \ln(\sigma_{t-i}^2), \tag{2}$$

[5] See Nelson (1991).

where $E_{t-1}(\ )$ is the conditional information operator based on the information at time $t-1$. Eq. (1) is the AR(k) model and indicates that the movement of a variable x_t is explained by its past movement ($x_{t-1}, x_{t-2}, \ldots$). Eq. (2) is the EGARCH(p,q) model and indicates that the sign of past shocks (good news or bad news) has different effects on volatility.

We assumed that the error term has a generalized error distribution (GED). The maximum likelihood method was used to estimate each model. The Schwarz Bayesian information criterion (SBIC)[6] was used to specify the AR model, and the smallest values of SBIC were preferred. The Ljung–Box Q test[7] was used to check the residuals of the AR model. The values of k, p, and q were chosen from $k = 1,2,\ldots,10$; $p = 1,2$; and $q = 1,2$, respectively, using the SBIC and residual diagnostics.

In the second step, we used the Cheung–Ng test (1996) in order to analyze causality in mean and causality in variance based on the empirical results obtained in the first step. In the second step, we standardized the residuals by the conditional mean and the squared residuals by the conditional variance. While the CCF of the standardized residuals was used to test the null hypothesis of no causality in mean, the CCF of the standardized squared residuals was used to test the null hypothesis of no causality in variance.

Following Cheung and Ng (1996), we began by summarizing the two-step procedure for testing causality. It was assumed that there were two stationary time series, X_i and Y_i, and three information sets, $I_{1t} = (X_{t-j}\,; j \geq 0)$, $I_{2t} = (Y_{t-j}\,; j \geq 0)$, and $I_t = (X_{t-j}, Y_{t-j}\,; j \geq 0)$. Y_t is said to cause X_t in mean if

$$E[X_t|I_{1t-1}] \neq E[X_t|I_{t-1}]. \tag{3}$$

Similarly, X_t is said to cause Y_t in mean if

$$E[Y_t|I_{2t-1}] \neq E[Y_t|I_{t-1}]. \tag{4}$$

We encounter feedback in mean if Y_t causes X_t in mean or vice versa. On the other hand, Y_t causes X_t in variance if

$$E[(X_t - \mu_{x,t})^2|I_{1t-1}] \neq E[(X_t - \mu_{x,t})^2|I_{t-1}], \tag{5}$$

where $\mu_{x,t}$ is the mean of X_t conditioned on I_{1t-1}. Similarly, X_t causes Y_t in variance if

$$E[(Y_t - \mu_{y,t})^2|I_{2t-1}] \neq E[(Y_t - \mu_{y,t})^2|I_{t-1}], \tag{6}$$

where $\mu_{y,t}$ is the mean of Y_t conditioned on T_{2t-1}. We encounter feedback in variance if X_t causes Y_t in variance or vice versa. The causality in variance is interesting, given that it has a directional relationship with volatility spillover across different assets or markets.

Since the concept defined in Eqs. (1)–(4) is too general for empirical testing, an additional structure is required to make the general causality concept practically applicable.

X_t and Y_t were therefore assumed to be as follows:

$$X_t = \mu_{x,t} + \sqrt{h_{x,t}\varepsilon_t} \tag{7}$$

and

$$Y_t = \mu_{y,t} + \sqrt{h_{y,t}\varsigma_t}, \tag{8}$$

where ε_t and ζ_t are two independent white noise processes with zero mean and unit variance.

For the causality in mean test, the following standardized innovations were used:

$$\varepsilon_t = \frac{X_t - \mu_{x,t}}{\sqrt{h_{x,t}}} \tag{9}$$

and

$$\varsigma_t = \frac{Y_t - \mu_{y,t}}{\sqrt{h_{y,t}}} \tag{10}$$

Since both ε_t and ζ_t are unobservable, their estimates – $\hat{\varepsilon}_t$ and $\hat{\zeta}_t$ – were used to test the hypothesis of no causality in mean.

Subsequently, we computed the sample cross-correlation coefficient at lag k, $\hat{r}_{\varepsilon\varsigma}(k)$, from the consistent estimates of the conditional mean and variance of X_t and Y_t. This computation yields

$$r_{\varepsilon\varsigma}(k) = \frac{c_{\varepsilon\varsigma}(k)}{\sqrt{c_{\varepsilon\varepsilon}(0)c_{\varsigma\varsigma}(0)}}, \tag{11}$$

[6] See Schwarz (1978).
[7] See Ljung and Box (1978).

where $c_{\varepsilon\varsigma}(k)$ is the kth lag sample cross-covariance and is given by

$$c_{\varepsilon\varsigma}(k) = \begin{cases} \dfrac{1}{T}\sum_{t=1}^{T-k}(\hat{\varepsilon}_t - \bar{\varepsilon})(\hat{\varsigma}_{t+k} - \bar{\varsigma}) & \text{for } k = 0, 1, 2, \cdots \\ \dfrac{1}{T}\sum_{t=1}^{T+k}(\hat{\varepsilon}_{t-k} - \bar{\varepsilon})(\hat{\varsigma}_t - \bar{\varsigma}) & \text{for } k = 0, -1, -2, \cdots \end{cases}, \tag{12}$$

where $c_{\varepsilon\varepsilon}(0)$ and $c_{\varsigma\varsigma}(0)$ are defined as the sample variances of ε_t and ς_t, respectively.

Causality in the means of X_t and Y_t can be tested by examining $\hat{r}_{\varepsilon\varsigma}(k)$, the univariate standardized residual CCF. Under the condition of regularity, the following condition holds:

$$S_1 = T\sum_{i=j}^{k}\hat{r}^2_{\varepsilon\varsigma}(i) \xrightarrow{L} \chi^2_{k-j+1}, \quad i = 1, 2, \ldots, m, \tag{13}$$

where $\xrightarrow{L}$ indicates the convergence in distribution and χ^2_{k-j+1} indicates a chi-squared distribution with $k - j + 1$ degrees of freedom. Cheung and Ng (1996) suggest that this test statistic can be used to test the null hypothesis of no causality in mean from lag j to lag k.

For the causality in variance test, let u_t and ν_t be the squares of the standardized innovations that are given by

$$u_t = \frac{(X_t - \mu_{x,t})^2}{h_{x,t}} = \varepsilon_t^2 \tag{14}$$

and

$$\nu_t = \frac{(Y_t - \mu_{y,t})^2}{h_{y,t}} = \varsigma_t^2. \tag{15}$$

Since both u_t and ν_t are unobservable, their estimates – $\hat{u}_t$ and $\hat{\nu}_t$ – were used to test the hypothesis of no causality in variance.

Subsequently, we computed the sample cross-correlation coefficient at lag k, $\hat{r}_{uv}(k)$, from the consistent estimates of the conditional mean and variance of X_t and Y_t. This yields

$$\hat{r}_{uv}(k) = \frac{C_{uv}(k)}{\sqrt{C_{uu}(0)C_{\nu\nu}(0)}}, \tag{16}$$

where $C_{uv}(k)$ is the kth lag sample cross-covariance given by

$$c_{uv}(k) = \begin{cases} \dfrac{1}{T}\sum_{t=1}^{T-k}(\hat{u}_t - \bar{u})(\hat{\nu}_{t+k} - \bar{\nu}) & \text{for } k = 0, 1, 2, \cdots \\ \dfrac{1}{T}\sum_{t=1}^{T+k}(\hat{u}_{t-k} - \bar{u})(\hat{\nu}_t - \bar{\nu}) & \text{for } k = 0, -1, -2, \cdots \end{cases}, \tag{17}$$

where $C_{uu}(0)$ and $C_{\nu\nu}(0)$ are defined as the sample variances of $\hat{u}_t$ and ν_t, respectively.

Causality in the variance of X_t and Y_i can be tested by examining the squared standardized residual CCF, $\hat{r}_{uv}(k)$. Under the condition of regularity, the following equation holds:

$$S_2 = T\sum_{i=j}^{k}\hat{r}^2_{uv}(i) \xrightarrow{L} \chi^2_{k-j+1} \quad \text{for } 1, 2, \ldots, m. \tag{18}$$

This test statistic can be used to test the null hypothesis of no causality in variance from lag j to lag k.

However, since the test statistic of Cheung and Ng (1996) (say, S_1 and S_2) may be subject to severe size distortion in the presence of causality in mean, we incorporated the weighting cross-correlation suggested by Hong (2001) into the CCF approach. Then, the test statistics for the causality in mean and causality in variance are given as follows:

$$M_1 = \frac{S_1 - k}{\sqrt{2k}} \xrightarrow{L} N(0, 1) \tag{19}$$

and

$$M_2 = \frac{S_2 - k}{\sqrt{2k}} \xrightarrow{L} N(0, 1). \tag{20}$$

M_1 and M_2 are one-sided tests; upper-tailed $N(0,1)$ critical values must be used.[8] For example, the asymptotic critical value at the 1% level is 2.326. If the test statistic is larger than the critical value of the normal distribution, the null hypothesis is

[8] We set k equal to 5 for the empirical analysis.

rejected. In the subsequent section, we use M_1 and M_2 to test causality in mean and causality in variance between the BRICs and the United States for both the pre- and post-crisis periods.

4. Empirical results

4.1. The pre-crisis period

In the pre-crisis period, the AR(1)–EGARCH(1,1) model was selected for the United States, Brazil, Russia, and India, whereas the AR(3)–EGARCH(1,1) model was selected for China.

Table 5 presents the empirical results of the AR–EGARCH models for the pre-crises period. As indicated in this table, the coefficient of the GARCH term (β) is estimated to be 0.9725 for the United States, 0.9368 for Brazil, 0.8856 for Russia, 0.9232 for India, and 0.9722 for China; all coefficient values are statistically significant at the 1% level. The coefficients of the asymmetric effect (γ) are estimated to be −0.1486 for the United States, −0.1262 for Brazil, −0.1650 for Russia, −0.2097 for India, and −0.0426 for China; all coefficients are statistically significant at the 1% level. Further, the GED parameter is estimated to be 1.3238 for the United States, 1.4429 for Brazil, 1.0481 for Russia, 1.3952 for India, and 0.9409 for China; all parameters are statistically significant at the 1% level. Since each of these estimates is below 2.0, the tails of the error terms are heavier than that of the normal distribution. This suggests the existence of ARCH effects.

Table 5 also indicates the diagnostics of the empirical results of the AR–EGARCH models—the $Q(s)$ statistic and the $Q^2(s)$ statistic. The Q statistic at lag s, $Q(s)$, is a test statistic for the null hypothesis that there is no autocorrelation up to order s for standardized residuals; it is asymptotically distributed as χ^2, with the degrees of freedom equal to the number of autocorrelation less the number of parameters. The Q^2 statistic at lag s, $Q^2(s)$, is a test statistic for the null hypothesis that there is no autocorrelation up to order s for standardized squared residuals. As indicated in Table 5, the null hypothesis of no autocorrelation up to order 20 for standardized residuals and standardized squared residuals is accepted for all countries, which supports the specification of each model.

Tables 6 and 8 indicate the sample cross-correlations of the standardized residuals and standardized squared residuals. If the cross-correlation of the (squares of the) standardized residuals are statistically significant, there is evidence of causality in mean (variance). The column labeled "M_1 (causality-in-mean)" provides the cross-correlation based on the standardized residuals themselves, and these are used to test the causality in mean. Similarly, the column labeled "M_2 (causality-in-variance)" provides the cross-correlation based on the squares of standardized residuals, and these are used to test the causality in variance.

Table 6 presents the empirical results of the causality between the stock markets of the United States and the BRICs for the pre-crisis period. As is evident from Table 6, there is no evidence of either causality in mean or causality in variance between the US and the Brazilian stock markets.

As is also evident from Table 6, there is a close relationship in mean between the United States and the BRICs, except for Brazil. For example, there is one-way causality in mean from the United States to Russia and India. Moreover, there is feedback in mean between the United States and China. Table 6 further indicates that there is only one causality in variance,

Table 5
Empirical results of the AR–EGARCH models for the pre-crisis period.

Model	USA AR(1)–EGARCH(1,1)	CHINA AR(3)–EGARCH(1,1)	INDIA AR(1)–EGARCH(1,1)	BRAZIL AR(1)–EGARCH(1,1)	RUSSIA AR(1)–EGARCH(1,1)
Mean equation					
a_0	0.0004 (0.0002)	0.0002 (0.0004)	0.0017 (0.0004)**	0.0014 (0.0006)*	0.0024 (0.0004)**
a_1	−0.0646 (0.0336)	−0.0199 (0.0243)	0.0468 (0.0359)	−0.0049 (0.0350)	0.0211 (0.0294)
a_2		0.0194 (0.0242)			
a_3		0.0724 (0.0239)**			
Variance equation					
ω	−0.3326 (0.0803)**	−0.3323 (0.1213)**	−0.8165 (0.1527)**	−0.5799 (0.2132)**	−1.1146 (0.2536)**
α_1	0.0891 (0.0394)*	0.1722 (0.0448)**	0.2223 (0.0483)**	0.0893 (0.0411)*	0.2534 (0.0543)**
γ_1	−0.1486 (0.0310)**	−0.0426 (0.0243)**	−0.2097 (0.0350)**	−0.1262 (0.0311)**	−0.1650 (0.0399)**
β_1	0.9725 (0.0077)**	0.9722 (0.0134)**	0.9232 (0.0165)**	0.9368 (0.0241)**	0.8856 (0.0284)**
GED parameter	1.3238 (0.0825)**	0.9409 (0.0526)**	1.3952 (0.0894)**	1.4429 (0.0905)**	1.0481 (0.0606)**
Diagnostic					
$Q(20)$	16.410 [0.691]	19.123 [0.514]	10.255 [0.963]	24.355 [0.227]	19.172 [0.511]
$Q^2(20)$	14.714 [0.793]	10.271 [0.963]	17.704 [0.607]	8.5945 [0.987]	25.048 [0.200]

Notes: The numbers given in parentheses are standard errors. The numbers given in square brackets are the p-values. $Q(20)$ is the Ljung–Box Q statistic for the null hypothesis that there is no autocorrelation up to order 20 for standardized residuals. $Q^2(20)$ is the Ljung–Box Q statistic for the null hypothesis that there is no autocorrelation up to order 20 for standardized squared residuals.
Source: Authors' calculations using Eviews based on Yahoo! Finance database (http://finance.yahoo.com/).
* Statistical significance at the 5% level.
** Statistical significance at the 1% level.

Table 6
Test statistics for causality-in-mean and causality-in-variance for the pre-crisis period: the United States and the BRICs.

M_1 (causality-in-mean)		M_2 (causality-in-variance)	
BRA → USA 1.4153	USA → BRA −0.7244	BRA → USA −0.1528	USA → BRA −0.4894
RUS → USA 0.9239	USA → RUS 11.0706**	RUS → USA −1.3711	USA → RUS 0.0700
IND → USA 0.9239	USA → IND 27.2616**	IND → USA −0.1202	USA → IND 6.4824**
CHI → USA 3.9272**	USA → CHI 5.1985**	CHI → USA 2.0797	USA → CHI −0.9322

Notes: USA, United States; BRA, Brazil; RUS, Russia; IND, India; CHI, China. X → Y indicates that X causes Y.
Source: Authors' calculations using Eviews based on Yahoo! Finance database (http://finance.yahoo.com/).
** Significance at the 1% level.

that is, from the United States to India. Thus, there is a dynamic linkage between the United States and the BRICs, particularly in mean before the US financial crisis.

4.2. The post-crisis period

As described above, we examined the causality of stock prices using the AR–EGARCH models and cross-correlation analysis for the post-crisis period. The AR(1)–EGARCH(1,1) model was used for the United States, Russia, India, and China; the AR(8)–EGARCH(1,2) model was used for Brazil.

Table 7 presents the empirical results of the AR–EGARCH models for the post-crises period. The coefficient of the GARCH term (β) is estimated to be 0.9797 for the United States, 0.0746 and 0.8570 for Brazil, 0.9829 for Russia, 0.9953 for India, and 0.9669 for China. The coefficients of the asymmetric effect (γ) are estimated to be −0.1240 for the United States, −0.1206 for Brazil, 0.0806 for Russia, 0.0426 for India, and −0.0283 for China. It must be noted that this asymmetric parameter is not statistically significant for Brazil and China. The GED parameter is estimated to be 1.4290 for the United States, 1.3975 for Brazil, 1.5907 for Russia, 1.2680 for India, and 1.2564 for China. Each parameter is statistically significant at the 1% level. Since each of these estimates is below 2.0, the tail of the error terms is heavier than that of a normal distribution. This suggests the existence of ARCH effects.

Table 7
Empirical results of the AR–EGARCH models for the post-crisis period.

	USA	CHINA	INDIA	BRAZIL	RUSSIA
Model	AR(1)–EGARCH(1,1)	AR(1)–EGARCH(1,1)	AR(1)–EGARCH(1,1)	AR(8)–EGARCH(1,2)	AR(1)–EGARCH(1,1)
Mean equation					
a_0	0.00141 (0.0007)*	0.0019 (0.0010)*	0.0019 (0.0003)**	0.0016 (0.0010)	0.0039 (0.0015)*
a_1	−0.1219 (0.0581)*	0.0232 (0.0550)	0.0207 (0.0445)	−0.0160 (0.0581)	0.0901 (0.0580)
a_2				−0.0357 (0.0476)	
a_3				0.0311 (0.0486)	
a_4				−0.0770 (0.0495)	
a_5				−0.0345 (0.0486)	
a_6				−0.0059 (0.0481)	
a_7				0.0118 (0.0472)	
a_8				−0.1262 (0.0491)*	
Variance equation					
ω	−0.2504 (0.0692)**	−0.3590 (0.2203)	−0.0191 (1.09E−07)**	−0.8250 (0.2324)**	−0.1350 (0.0256)**
α_1	0.0781 (0.0423)	0.1270 (0.0697)	−0.0390 (2.81E−06)**	0.3568 (0.1170)**	0.0066 (0.0348)
γ_1	−0.1240 (0.0458)**	−0.0283 (0.0403)	0.0426 (0.0136)**	−0.1206 (0.0624)	0.0806 (0.0312)**
β_1	0.9797 (0.0064)**	0.9669 (0.0250)**	0.9953 (2.61E−05)**	0.0746 (0.0461)	0.9829 (0.0036)**
β_2				0.8570 (0.0443)**	
GED parameter	1.4290 (0.1895)**	1.2564 (0.1531)**	1.2680 (0.1006)**	1.3975 (0.1786)**	1.5907 (0.1820)**
Diagnostic					
$Q(20)$	19.802 [0.470]	17.295 [0.634]	16.104 [0.710]	16.934 [0.657]	15.184 [0.766]
$Q^2(20)$	20.639 [0.419]	17.302 [0.633]	6.2370 [0.999]	20.949 [0.400]	20.912 [0.402]

Notes: The numbers given in parentheses are standard errors. The numbers given in square brackets are the *p*-values. $Q(20)$ is the Ljung–Box Q statistic for the null hypothesis that there is no autocorrelation up to order 20 for standardized residuals. $Q^2(20)$ is the Ljung–Box Q statistic for the null hypothesis that there is no autocorrelation up to order 20 for standardized squared residuals.
Source: Authors' calculations using Eviews based on Yahoo! Finance database (http://finance.yahoo.com/).
* Statistical significance at the 5% level.
** Statistical significance at the 1% level.

Table 8
Test statistics for causality-in-mean and causality-in-variance for the post-crisis period: the United States and the BRICs.

M_1 (causality-in-mean)		M_2 (causality-in-variance)	
BRA → USA −0.3520	USA → BRA −1.3321	BRA → USA −0.0993	USA → BRA 0.1948
RUS → USA −1.4135	USA → RUS 3.6479**	RUS → USA −0.8594	USA → RUS 0.0766
IND → USA −0.9159	USA → IND 7.4533**	IND → USA −0.6937	USA → IND 0.2123
CHI → USA −0.5175	USA → CHI 1.9277	CHI → USA −0.9630	USA → CHI −1.0459

Notes: USA, United States; BRA, Brazil; RUS, Russia; IND, India; CHI, China. X → Y indicates that X causes Y.
Source: Authors' calculations using Eviews based on Yahoo! Finance database (http://finance.yahoo.com/).
** Significance at the 1% level.

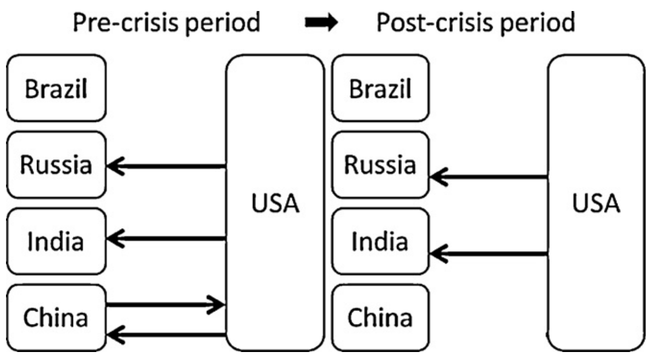

Fig. 1. Causality-in-mean between the BRICs and the United States.
Source: Compiled by the authors based on the results obtained in Tables 6 and 8.

Further, Table 7 presents the diagnostics of the empirical results of the AR–EGARCH models for the post-crises period. As indicated in the table, the null hypothesis of no autocorrelation up to order 20 for standardized residuals and standardized squared residuals is accepted for all countries, which supports the specification of each model.

Table 8 presents the empirical results of the cross-correlation analysis between the United States and the BRICs. Compared with the results shown in Table 6, we find a remarkable difference between the pre- and post-financial crisis periods. As indicated in Table 8, we find only one causality in mean (i.e., from the United States to India), but no causality in variance between the United States and the BRICs. Thus, it is likely that the US financial crisis may have significantly affected the dynamic linkage of stock prices between the United States and the BRICs. This might indicate a change in investor behavior after the US financial crisis, for example shifting their funds from stock markets to other markets such as commodities markets including gold and petroleum. Thus, a change in US stock prices might affect commodity prices but not stock prices in other countries. These results are summarized in Figs. 1 and 2.

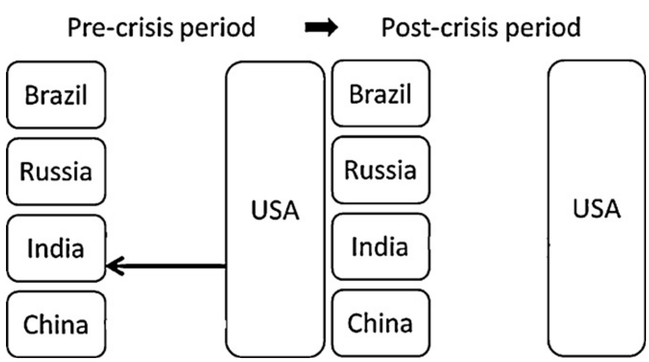

Fig. 2. Causality-in-variance between the BRICs and the United States.
Source: Compiled by the authors based on the results obtained in Tables 6 and 8.

5. Concluding remarks

In this paper, we used the test developed by Hong (2001) to investigate the causal relationships of stock prices in mean and variance between the BRICs and the United States. In particular, we focused on the impact of the US financial crisis of September 2008, which was triggered by the emergence of sub-prime loan losses in 2007, on the dynamic linkages between the stock prices of the BRICs and the United States. Our empirical results indicated that the international transmission of stock prices between the BRICs and the United States significantly weakened in both the mean and variance after the 2008–09 financial crisis period. This might reflect a change in investor behavior after the US financial crisis.[9]

Acknowledgements

We would like to thank Michael Plummer (the editor-in-chief), an anonymous referee, Kazuhiro Ohtani, and Hisashi Tanizaki for their helpful comments and suggestions.

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[9] There is another approach to analyzing causality in variance. For example, Engle and Kroner (1995) represented a bivariate GARCH(1,1)–BEKK (Baba, Engle, Kraft, and Kroner) model for a conditional covariance matrix. Further, Comete and Liberman (2000) tested the non-causality in variance in terms of the relevant zero restrictions on conditional variance parameters. This will be the basis for our further research.