Price and Volatility Spillovers between Chinese and Indian Stocks and their Time–Varying Market Linkages with Developed Equities

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Abstract

This paper studies price and volatility spillovers between Chinese and Indian stocks and their dynamic market linkages with major developed equities from 1998 to 2016. Tests reveal price and volatility spillovers from Chinese to Indian stocks before 2006, but the directions of shock transmissions became bi-lateral after 2006. Compared to Chinese equities, Indian stocks had been more open and susceptible to external shocks. Both indices were more vulnerable to price and volatility spillovers during the US Subprime Crisis and the European Debt Crisis, but were less so afterwards. There were significant asymmetric volatility spillovers between China–US and China–India equities which make them great diversification instruments within a global portfolio. The cross-border influence of Chinese and Indian stocks to other developed equities was limited after the Global Financial Crisis. Developed stock markets, especially the US market, had continually been major contributors of price and volatility spillovers world-wide.

Keywords: price and volatility spillovers, asymmetric shock transmission, GARCH, India, China, stock indices

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1. Introduction

India and China are the two largest and fastest growing emerging economies. China's GDP growth was 6.7 percent and India's 7.1 percent in 2016. By comparison, the United States, the European Union, and Japan only produced 1.5, 1.9 and 1 percent growth respectively (The World Bank, 2016). In order to support such stellar expansions, financial systems in China and India developed rapidly. Their stock markets have grown from being nonexistent or insignificant to top ranked in the world in less than forty years; now they are essential components of the global financial system.

After the Global Financial Crisis (GFC), the economies of these two emerging giants have continued to thrive, making what happens in China and India very important for the rest of the world. As an example, the volatile movements of the US stock market in the beginning of 2016 were primarily driven by bad economic news from China. While Chinese and Indian economies have becoming increasingly more important, one may ask whether their respective financial systems have also becoming more influential. Additional questions arise such as: Which country's equity influence the Chinese and Indian stocks the most? How do Chinese and Indian stocks respond to cross-border shocks and how do they transmit volatilities to other part of the world? And finally, how do Chinese and Indian stock markets, both developed so quickly yet each with unique characters, react to spillovers from each other?

This study utilizes modified Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family models to analyze price and volatility spillovers among the national and regional stock indices of India, China, US, Europe, and Japan. It focuses on shock transmissions between Indian and Chinese stocks and their changing market linkages with major developed equities over time.

Tests reveal that Indian stock markets were relatively more open than markets in China. Indian stocks were more sensitive to price and volatility spillovers from China. Chinese stocks only became responsive to shocks from India after 2006. Both equities were more prone to external shocks during the Global Financial Crisis and European Debt Crisis, but were less vulnerable after 2014. After the GFC, the influences of Chinese and Indian equities on developed stock markets remained insignificant even though their economic development became more important than ever. Short-term shock transmissions in global equity markets were mainly from developed to emerging and the US equity still was the main source of spillovers world-wide. There were significant asymmetric volatility spillovers between China–US and China–India indices. These findings have important applications for risk management, international portfolio diversification, and global financial policy coordination.

The study contributes to the literature in the following ways: It focuses on analyzing time-varying dynamics of price and volatility spillovers of Indian and Chinese stocks, with special emphases on studying their relationships with each other and with major developed equities; and it extends several GARCH family models to investigate symmetric and asymmetric price and volatility transmissions within and cross equity markets.

The remainder of this paper is organized as follows: Section 2 summarizes existing literature; Section 3 analyzes data and conducts structural break tests; Section 4 explains methodologies used; Section 5 presents test results; Section 6 concludes.

2. Literature Review

After the devastating effects of the Asian and Global Financial Crises, more literature focuses on studying volatility transmissions cross financial markets. With their increasing magnitudes, Indian and Chinese equity markets also attract much of research interest.

Since China and India are part of BRIC component, some research analyzed BRIC as a whole to represent the larger emerging market group. Kaur and Singh (2015) studied the leverage and volatility effect in the BRIC Countries' equities from July 2009 to June 2014. Junior et al. (2014) discovered that BRIC's markets showed less persistence but faster reactions to volatility shocks compared to those of developed markets.

China has a deep-rooted cultural influence on the Greater China region which includes Mainland China, Hong Kong, Macau, and Taiwan. Many articles attempted to investigate financial linkages of these economies. Johansson and Ljungwall (2009) found short-run return and volatility spillovers among the stock exchanges of Hong Kong, Taiwan, and China. The Mainland China market received direct and indirect shocks from markets in Hong Kong and Taiwan. Jin (2015) also confirmed that market integrations increased over time in the Greater China region. But Sheu and Cheng (2011)'s study concluded that, although there were considerable economic integrations, the Mainland China market was rather independent from other regional markets.

A number of articles focused on studying the Indian stock market and its relationship with developed markets. Sarkar (2012) used VAR, Granger Causality, and Variance Decomposition models to study volatility transmission from developed markets to India, and found that the US market was a major source of spillover. Turhan et al. (2012) also confirmed volatility transmission from the US to India. Padhi and Lagesh (2012) found shock spillover existed in the bilateral country pairs of India/Malaysia, India/Taiwan and India/Indonesia from 1994 to 2009. Singh and Singh (2016) discovered negative correlations between Indian and US markets. The relationship between India and US equity had remained strong even after the GFC, but had declined among India, Europe, Japan, and China stocks.

Previous research uncovered strong evidence of volatility spillovers from the US to other stock markets, both developed and emerging. The effect of spillover from the US to India is widely revealed, but the evidence is conflicted about China. Wang and Wang (2010) found that spillover effects from the US and Japan to China increased when the degree of emerging market openness increased. But Sheu and Cheng (2011) found that the Chinese market had been independent from the US from 1996 to 2009. Li's (2007) research also didn't find evidence to support direct spillover between China and the US during 2000 to 2005. Hence, more analyses are needed to further investigate changing market linkages of China with US and China with other developed markets after the GFC. Furthermore, existing literature puts more emphasis on analyzing shock transmissions from developed to emerging equities. With their increasing economic importance, there is a need to focus more on studying the relationship between Chinese and Indian markets, their influence to major developed equities, and their evolving importance in the global financial system. This research attempts to fulfill these agendas.

3. Data and Structural Breaks

This study uses five national and regional equity indices to represent five stock markets in the world. They are: Nikkei 225 of Japan (NIK), Shanghai Composite Index of China (SHCI), S&P BSE Sensex Index of India (Sensex), STOXX Europe 600 Index of European region (SXXP), and the S&P 500 Index of the U.S (S&P). Data samples span from 9/17/1998 to 7/8/2016.

An initial data inspection finds common and individual trends in the price series. To avoid spurious regression results, logarithmic returns are calculated using daily closing prices of each index. These logarithmic return series have features of volatility clustering, leptokurtosis, excess skewness, and non-normal distribution (Table 1).

Chinese and Indian stocks have low correlations with other indices and with each other. Pairwise correlations for China/ Europe and China/US are -0.009 and 0.002, and for India/US and India/China are 0.049 and 0.039 respectively. A simple Granger Causality test shows that, in general, European and American stocks granger cause changes of other stocks. Stock indices in China and the US granger cause each other. Such bilateral causality relationships also exist between stock pairs of Japan/US and Europe/US.

Table 1. Summary Statistics of Logarithmic Returns

	China	India	US	Europe	Japan
Mean	1.000016	1.000039	0.999998	0.999963	0.999978
Std. Dev.	0.002080	0.001873	0.001770	0.002289	0.001606
Skewness	-0.153602	-0.324164	-0.435437	-0.264289	-0.646647
Kurtosis	7.454389	11.52852	10.49280	7.403163	8.413551
Jarque-Bera	2800.171	10275.38	7992.155	2762.428	4351.280
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

Indian and Chinese stocks both experienced substantial rises and falls during 1998 to 2016. Therefore, characteristics of the whole sample period (1998-2016) may not capture attributes of a specific sub-period. In order to study changing dynamics of these equities, this paper uses three methods to test structural breaks of Chinese and Indian indices. These methods are: Sequential Testing Procedures (Bai, 1997), Global L Breaks Vs. None (Bai and Perron, 1998), and Information Criteria (Yao, 1988). Breakpoints derived from each method are compared and common break points identified by all three methods are used to determine sub-sample periods.

Sub-sample periods for China are determined as follows: 9/21/1998-12/18/2006; 12/19/2006-11/16/2010; 11/17/2010-8/26/2013; and 8/27/2013-7/8/2016. Sub-sample periods for India are: 9/21/1998-3/1/2006; 3/2/2006-7/31/2009; 8/1/2009-3/6/2014; and 3/7/2014-7/8/2016. Major global events and specific country developments contributed to these structural breaks.

This research also attempts to study diffences of cross-border spillovers before, during and after the GFC for Chinese and Indian stocks. Even though the Subprime Mortgage crisis of the US was in full swing by March of 2007, the turmoil didn't disturb the finanical markets until October. In order to test effects of global shock transmissions, the paper sets 10/31/2007 to 3/6/2009 as the GFC period since major world equity indices experienced significant and persistant downfalls during this time.

4. Methodology

Descriptive data analyses show that testing indices have typical characteristics of high frequency financial data such as volatility clustering, kurtosis, and excess skewness. The GARCH (p, q) process developed by Bollerslev (1986) can be used to address these issues. Previous research indicated that a GARCH (1, 1) is capable of capturing volatility dynamics of equity markets (Hansen and Lunde, 2005) and is used for this study.

To begin the analysis, this paper uses a GARCH-in-Mean model developed by Engle et al. (1987) as a base model. The base model is defined as follows:

$$R_t = \eta + \lambda h_t + \varepsilon_t \quad (1)$$
$$\mathrm{h_t} = \theta + \alpha\varepsilon_{t-1}^2 + \beta \mathrm{h_{t-1}} \quad (2)$$

With the following conditions: $\theta \geq 0, \alpha \geq 0, \beta \geq 0, \alpha + \beta < 1$

Equation 1 is the mean equation where R_t, the return of a stock index, is a function of $\boldsymbol{h}_t$, its conditional variance. Engle et al. (1987) argued that expected returns of a stock tend to increase when risk increases, so they added a conditional variance (or standard deviation) term as a risk variable to the mean equation.

Equation 2 is the variance equation where conditional variance $\boldsymbol{h}_t$ is modeled on its previous period's variance and squared errors. If coefficients $\alpha\ and\ \beta$ are positive and significant, the variance of error terms is time varying. The magnitudes of $\alpha\ and\ \beta$ reveal the speed of ARCH decay process. Their sum must be smaller than 1 to ensure the stability of the model.

Utilizing the base model described above, this paper extends Moon and Yu (2010)'s framework to several GARCH family models to study price and volatility spillovers cross different equity markets. The study places special emphasis on investigating asymmetric shock transmissions within and cross markets. It utilizes an EGARCH model to study asymmetric volatility spillover within a domestic market; a modified GARCH-in-Mean model to analyze both symmetric and asymmetric price and volatility spillovers from foreign markets; and a modified GJR-GARCH model to further investigate cross-border volatility transmission asymmetry.

4.1. EGARCH model

An EGARCH model tests the presence of both volatility clustering and asymmetry of past returns on volatility. Proposed by Nelson (1991), an EGARCH model is defined as follows:

$$R_t = \eta + \lambda \log(h_t) + \varepsilon_t \quad (3)$$
$$\log(\mathrm{h_t}) = \theta + \varphi\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \chi\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\log(\mathrm{h_{t-1}}) \quad (4)$$

Similar to that of a GARCH-in-Mean model, φ and β coefficients in the variance equation examine the presence of volatility clusters. The $\boldsymbol{\chi}$ term reveals asymmetric volatility spillover, also called the "leverage effect." A negative and significant $\boldsymbol{\chi}$ coefficient indicates that large volatility is associated with negative shock; in other words, negative shocks have more impact on volatility than positive shocks with equal magnitude within a domestic market.

4.2. Modified GARCH-in-Mean model

In addition to study dynamics of volatility spillover within a domestic stock market, this study also tests price and volatility spillovers cross different stock markets. A modified GARCH-in-Mean model in equation 5 and 6 serve these purposes.

$$R_{i,t} = \eta_i + \lambda_i h_{i,t} + \sum_{i=1}^{p} \psi_i \mathrm{R_{i,t-1}} + \sum_{j=1}^{q} \omega_j R_{j,t-1} + \varepsilon_{i,t} \quad (5)$$

$$\mathrm{h_{i,t}} = \theta_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \, \mathrm{h_{i,t-1}} + \sum_{j=1}^{q} \gamma_j \, C_{j,t-1} \tag{6}$$

With the following conditions: $p \geq 1, q \geq 1$

$$\theta_i \geq 0, \alpha_i \geq 0, \beta_i \geq 0$$
$$\alpha_i + \beta_i < 1$$

In mean equation 5, $R_{i,t}$ is regressed on its own lagged daily return $\mathrm{R_{i,t-1}}$, its own conditional variance $h_{i,t}$, and the lagged returns of foreign indices $R_{j,t-1}$. The coefficients of $R_{j,t-1}$ capture price spillovers from foreign equity js to a domestic index. Foreign indices js are also placed in the variance equation 6 as exogenous variables to investigate cross-border volatility spillovers. $C_{j,t-1}$ are lagged residuals derived from equation 1 of the base model for foreign indices js. Coefficients of $c_{j,t-1}$ capture volatility spillovers from foreign indices to a domestic index i. Such spillover can be symmetric or asymmetric depending on the sign of coefficient γ_j.

4.3. Modified GJR-GARCH Model

In order to further investigate volatility spillover asymmetries, the study adopts the dummy variable approach used in the Glosten-Jagannathan-Runkle GARCH model (Glosten et al., 1993). The original GJR-GARCH Model tests volatility asymmetry within a domestic market. This study includes dummy thresholds to test asymmetric volatility spillovers from foreign markets.

$$R_{i,t} = \eta_i + \lambda_i h_{i,t} + \sum_{i=1}^{p} \psi_i \mathrm{R_{i,t-1}} + \sum_{j=1}^{q} \omega_j \, R_{j,t-1} + \varepsilon_{i,t} \tag{5}$$

$$\mathrm{h_{i,t}} = \theta_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \, \mathrm{h_{i,t-1}} + \sum_{j=1}^{q} \gamma_j \, C_{j,t-1} + \sum_{j=1}^{q} \delta_j \, D_{j,t-1} C_{j,t-1} \tag{7}$$

The mean equation 5 is the same one used in the modified GARCH-in-Mean model. However, equation 7 adds dummy variables $D_{j,t-1}$ in the variance equation as thresholds to identify negative volatility from foreign markets. The dummy is 1 if lagged residual derived from equation 1 is negative, and is 0 if positive. If δ_j is negative and significant, it indicates that negative volatility from a foreign index j reduces volatility of a domestic index i. This will further verify the asymmetric volatility spillover from j to i identified by the γ_j coefficient.

Since risk and return relationship may or may not hold true for some emerging equities due to different degrees of market efficiency, some tested models may not have significant conditional variances in their mean equations. In such cases, only modified GARCH models are estimated. Final model selections are based on comparisons of the Logarithm Maximum Likelihood and Akaike and Schwartz Information Criterion. Several residual diagnostic tests such as autocorrelations and ARCH effect are also conducted to ensure the goodness-of-fit of models.

Table 2. Test Results from EGARCH Models

The model: Variance Equation only $\log(\mathrm{h_t}) = \theta + \varphi \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \chi \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta \log(\mathrm{h_{t-1}})$ (4)

a. Whole Sample Period Results of All Country Indices (1998-2016)

	SHCI		Sensex		S&P		NIK		SXXP	
	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
θ	-0.450***	-5.952	-0.557***	-12.593	-0.476***	-11.306	-0.731***	-10.003	-0.388***	-14.381
φ	0.199***	9.299	0.181***	17.208	0.142***	12.257	0.203***	14.318	0.137***	17.596
χ	-0.034***	-2.896	-0.111***	-16.969	-0.145***	-15.402	-0.084***	-11.991	-0.096***	-20.715
β	0.975***	176.882	0.967***	312.818	0.972***	342.484	0.956***	183.361	0.977***	499.166

b. Test Results of the Chinese Index (Sub-Sample Periods)

	9/21/1998-12/18/2006		12/19/2006-11/16/2010		11/17/2010-8/26/2013		8/27/2013-7/8/2016	
	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
θ	-1.010***	-4.351	-0.477***	-2.346	-2.433*	-1.688	-0.601***	-3.397
φ	0.280***	6.912	0.140***	3.131	-0.043	-0.614	0.291***	4.607
χ	-0.100***	-4.028	-0.053**	-2.082	-0.131**	-2.124	0.020	0.590
β	0.935***	54.199	0.969***	61.386	0.811***	7.287	0.969***	76.076

c. Test Results of the Indian Index (Sub-Sample Periods)

	9/21/1998-3/1/2006		3/2/2006-7/31/2009		8/1/2009-3/6/2014		3/7/2014-7/8/2016	
	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
θ	-1.270***	-4.792	-0.587***	-3.775	-0.475***	-3.638	-19.218*	-1.745
φ	0.240***	6.079	0.215***	3.992	0.056*	1.906	-0.110	-0.857
χ	-0.122***	-4.797	-0.143***	-3.925	-0.132***	-5.814	0.011	0.134
β	0.914***	45.627	0.966***	85.319	0.968***	105.902	-0.412	-0.513

*, **, *** denote statistically significant at the 10%, 5%, and 1% level, respectively

5. Test Results

5.1. EGARCH model

This study uses a simple EGARCH model to test volatility spillover within a domestic stock market. Test results in Table 2a show that $\varphi, \chi, and\ \beta$ coefficients for all indices are statistically significant during the entire sample period, suggesting that both volatility clustering and asymmetry phenomena existed for all five indices from 1998 to 2016.

However, results from sub-sample analyses reveal that Chinese and Indian indices may not have these characteristics for certain time periods. Volatility clustering, an occurrence when large price changes followed by large price changes, is a typical phenomenon for equities. Table 2c shows that $\varphi\ and\ \beta$ coefficients for India are insignificant from 2014 to 2016, indicating no volatility clustering. Asymmetric spillover is another common theme for equities when negative shocks cause more volatility than positive shocks with the same magnitude. In such instances, the χ coefficients should be negative and significant; yet Table 2b and 2c show that χ coefficients are insignificant for China during 2013-2016 and for India during 2014-2016, indicating no asymmetric spillover within their domestic markets.

5.2.Modified GARCH-in-Mean Model

The study further employs a modified GARCH-in-Mean model to study price and volatility spillovers cross different equity markets. Table 3a-c present results.

5.2.1. Whole Sample Period Results

Test results suggest that the Chinese stock market was relatively isolated during 1998-2016 (Table 3a). The only significant coefficient in the mean equation is 0.062, indicating a positive price spillover from US to China. There is no significant price or volatility transmission from other markets. This is not a surprise given that the Chinese government imposed capital controls limiting foreign capital access to financial markets in China. The Chinese stock market had been dominated by domestic individual investors; thus the return and volatility characteristics of Chinese stocks were unique and largely driven by local factors. This is confirmed by the significant ARCH (α) and GARCH (β) coefficients in variance equations and their nearly close to one sum; suggesting that past fluctuations of Chinese equities had a positive and long term effect on their own future volatilities, and that such effect had been dissipating very slowly.

By comparison, the Indian index was more susceptible to external shocks with most testing coefficients being statistically significant (Table 3a). Different from that in China, India's domestic equity participation was very low. Indian households invested only five percent of their savings in stocks in 2014-2015 and three percent in 2013-2014. Foreign Institutional Investors (FII) dominated market activities in India. In 2015, FII held 10.45 percent of shares listed for Indian companies. This was more than the combined shares held by Indian mutual funds (2.68 percent) and financial institutions (5.32 percent) (ISMR, 2015). With a strong presence of FII, it is reasonable to assume that Indian equities could be more responsive to external shocks. Test results confirm that there were positive price and volatility spillovers from the US and Japan to India. The surprise outcome was the negative price and volatility spread from China to India during 1998-2016. One possible explanation for this negative effect is that global investors treated Indian and Chinese equities as sustitutes and chose to invest in India when there were bad returns and increased volatility in China. Since the Chinese market had been relatively closed to foreign investors, one does not observe significant spillover effect from India to China.

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Table 3. Test Results from Modified GARCH-in-Mean Models

The model: Mean Equation $R_{i,t} = \eta_i + \lambda_i h_{i,t} + \sum_{i=1}^{p} \psi_i \mathrm{R}_{\mathrm{i,t-1}} + \sum_{j=1}^{q} \omega_j R_{j,t-1} + \varepsilon_{i,t}$ (5)

Variance Equation $\mathrm{h}_{\mathrm{i,t}} = \theta_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \mathrm{h}_{\mathrm{i,t-1}} + \sum_{j=1}^{q} \gamma_j C_{\boldsymbol{j,t-1}}$ (6)

a. Test Results of the Chinese and Indian Indices (Whole Sample Period, 1998-2016)

China			India		
Mean Equation					
Variable	Coefficient	z-Statistic	Variable	Coefficient	z-Statistic
λ	0.143***	2.732	λ	0.140***	2.682
CN(-1)	0	0.011	ID(-1)	0.014***	4.271
ID(-1)	-0.004	-0.249	CN(-1)	-0.034***	-3.956
US(-1)	0.062***	3.361	US(-1)	0.210***	13.875
EU(-1)	0.015	1.151	EU(-1)	-0.003	-0.255
JP(-1)	-0.008	-0.453	JP(-1)	0.024*	1.891
Variance Equation					
α	0.086***	7.103	α	0.295***	5.902
β	0.902***	75.103	β	0.582***	13.861
ID(-1)	0.002	0.623	CN(-1)	-0.015***	-6.329
US(-1)	-0.003	-0.629	US(-1)	0.028	1.44
EU(-1)	0.001	0.65	EU(-1)	-0.007	-1.319
JP(-1)	-0.003	-0.574	JP(-1)	0.084***	2.756
	Log likelihood	16535.45		Log likelihood	17027.15

b. Test Results of the Chinese Index (Sub-Sample Periods)

	9/21/1998-12/18/2006		12/19/2006-11/16/2010		11/17/2010-8/26/2013		8/27/2013-7/8/2016	
Mean Equation								
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
λ	0.498***	3.667	0.328	1.584	5.720***	6.512	0.159	1.433
CN(-1)	-0.002	-0.123	-0.022	-0.72	-0.041	-0.764	0.046	1.068
ID(-1)	0	0.011	-0.029	-0.633	-0.039***	-2.882	0.073	1.353
US(-1)	-0.03	-1.381	0.200***	4.843	0.101*	1.68	0.148**	2.456
EU(-1)	0.013	1.124	0.042**	1.985	0.087***	2.816	-0.034	-1.054
JP(-1)	0.050**	2.386	-0.091*	-1.849	-0.051	-0.638	-0.079	-1.641
Variance Equation								
α	0.225***	3.775	0.109**	2.296	0.035***	2.822	0.143***	3.293
β	0.495***	6.103	0.63***	5.006	0.633***	11.162	0.839***	24.05
ID(-1)	-0.004	-0.639	0.110*	1.917	0.227***	3.935	-0.013	-0.514
US(-1)	-0.020*	-1.783	0.04	0.911	-0.009	-0.927	0.03	0.603
EU(-1)	-0.008**	-2.003	-0.006	-0.33	0.026**	2.205	0.002	0.337
JP(-1)	0.011	0.365	-0.087*	-1.717	-0.027***	-4.11	-0.013	-0.547
	Log likelihood	8037.409	Log likelihood	3423.709	Log likelihood	20133.06	Log likelihood	2491.501

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c. Test Results of the Indian Index (Sub-Sample Periods)

	9/21/1998-3/1/2006		3/2/2006-7/31/2009		8/1/2009-3/6/2014		3/7/2014-7/8/2016	
Mean Equation								
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
λ	-0.107	-1.096	-0.156*	-1.77	0.498**	2.247	2.323	1.308
ID(-1)	0.058***	2.068	-0.041	-0.945	0.031	0.771	0.03	0.529
CN(-1)	-0.019	-0.911	-0.021	-0.809	0.008	0.333	-0.03	-1.43
US(-1)	0.146***	4.972	0.352***	6.984	0.249***	7.2	0.198***	4.575
EU(-1)	0.032	1.601	-0.009	-0.229	-0.087***	-3.337	0.021	0.844
JP(-1)	0.013	0.447	0.023	0.444	-0.013	-0.491	0.011	0.284
Variance Equation								
α	0.124***	4.683	0.088**	2.412	0.054**	2.51	0.038	1.169
β	0.803***	22.801	0.798***	15.936	0.888***	24.322	0.533**	2.323
CN(-1)	-0.006*	-1.657	0.015	1.54	0.002	0.475	-0.001	-0.299
US(-1)	0.019	1.011	0.013	0.329	0.008	1.322	-0.004	-0.254
EU(-1)	-0.003	-0.554	0.049*	1.957	0	0.122	0.002	0.55
JP(-1)	0.039	1.627	0.037	0.721	0.004	0.866	0.005	0.508
	Log likelihood	7148.321	Log likelihood	3143.385	Log likelihood	4609.729	Log likelihood	8665.156

The λ coefficients are 0.140 for India and 0.143 for China and are both significant at one percent level, signaling that Indian and Chinese stocks tend to reward investors with higher returns for taking more risk in the long term.

5.2.2. Sub-Sample Periods Results

Whole sample period analyses may not capture unique characteristics of Chinese and Indian equities during different time frames. Table 3b-c present sub-sample results for further analyses.

China: Although the whole sample results indicate that the Chinese index was relatively insensitive to external shocks, sub-sample analyses suggest that market linkages between Chinese and other indices were quite different during 2006-2013.

Mean equation results in Table 3b show that from 1998 to 2006, SHCI only responded to a price shock from Japan; but from 2006 to 2013, SHCI also became sensitive to price effect from the US and Europe. To demonstrate, price spillover from the US to China was at its strongest, reached 0.2 when the Subprime Crisis spread worldwide; from Europe to China increased to 0.087 when the European Sovereign Debt Crisis deepened. The price shock from India to China also became significant from 2010 to 2013, but the coefficient is surprisingly negative. During this time period, the performance of Chinese equity was weak due to top leadership transitions and a slowing down economy, but Indian's Sensex broke its historical record of 21,000 points with the help of double digit economic growths. For this reason, the negative return spillover from India to China can be interpreted as a result of global portfolio rebalancing.

Variance equation results in Table 3b disclose information of volatility spillover. The Chinese index was responsive to volatility spillovers from the US and Europe before 2006, from India and Japan during 2006-2013 and also from Europe during 2010-2013. SHCI became only sensitive to its own past volatilities after 2013. There is evidence of asymmetric volatility spillovers to China since coefficients of Europe, the US, and Japan were negative for some periods, indicating that increased volatilities from these markets reduced volatilities of Chinese stocks periodically.

India: The US index had a strong and consistent positive price effect on Indian stocks throughout all four sub-sample periods (Table 3c). The price impact from the US was at its strongest (0.352) during 2006-2009, but spillover from Europe was negative during 2009-2014, implying that turmoil in Europe boosted returns of the Indian index.

In the volatility channel, China contributed negative volatility spillover to India before 2006. There was also a volatility spillover from Europe to India during 2006-2009. But after 3/7/2014, the Sensex was relatively immune to either price or volatility spillover from all foreign indices except the S&P in the US. The insignificant α coefficient during this time period indicates that Indian stocks did not have volatility clustering. The λ coefficient also became insignificant, suggesting that risk and return may not be positively correlated for Indian stocks. These results are similar to the ones derived from the previous EGARCH analyses.

5.3.Modified GJR-GARCH Model with Dummies

Test results from the modified GARCH-in-Mean model reveal two results worthy of further investigation. First, both Chinese and Indian indices were more susceptible to external shocks from 2006 to 2014, during which time two major financial crises occurred. Second, there were occurrences of cross-border asymmetric volatility spillovers, indicating that increasing volatility in a foreign index reduces volatility in a domestic index.

In order to further analyze these phenomena, the study utilizes a modified GJR-GARCH model that incorporates dummy variables to identify negative foreign market volatilities. The

Table 4. Test Results from Modified GJR-GARCH Models with Dummies

The model: Mean Equation $R_{i,t} = \eta_i + \lambda_i h_{i,t} + \sum_{i=1}^{p} \psi_i \mathrm{R}_{\mathrm{i,t-1}} + \sum_{j=1}^{q} \omega_j R_{j,t-1} + \varepsilon_{i,t}$ (5)

Variance Equation $\mathrm{h}_{\mathrm{i,t}} = \theta_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \mathrm{h}_{\mathrm{i,t-1}} + \sum_{j=1}^{q} \gamma_j \boldsymbol{C_{j,t-1}} + \sum_{j=1}^{q} \delta_j D_{j,t-1} \boldsymbol{C_{j,t-1}}$ (7)

a. Test Results of the Chinese Index (Before, during, and after the GFC)

	9/17/1998 -10/30/2007		10/31/2007- 3/6/2009		3/7/2009 - 7/8/2016	
	Mean Equation					
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
CN(-1)	0.032**	1.879	-0.009	-0.28	0.021	0.72
ID(-1)	-0.008	-0.512	-0.031	-0.624	-0.011	-0.348
US(-1)	-0.01	-0.531	0.180***	3.273	0.105***	5.943
EU(-1)	0.022	1.445	0.085	1.529	0.026	1.172
JP(-1)	0.027	1.339	-0.152**	-2.099	-0.04	-1.611
	Variance Equation					
A	0.040***	2.615	0.215*	1.914	0.063***	2.67
β	0.890***	53.102	0.176	1.332	0.882***	36.566
ID(-1)	0.001	0.325	0.085	1.31	-0.015***	-4.36
US(-1)	-0.011**	-2.037	0.054	0.993	0.015	1.163
EU(-1)	0.003	1.284	-0.042**	-2.278	0.006	1.077
JP(-1)	0.018**	2.375	-0.019	-0.372	-0.002	-0.377
DID(-1)	3.6E-08	0.333	-3.2E-06*	-1.767	-3.2E-08	-0.271
DUS(-1)	-2.5E-07**	-2.091	5.8E-06***	2.863	1.9E-07	1.292
DEU(-1)	3.4E-0***7	3.105	-4.7E-06***	-2.937	-1.7E-07	-1.195
DJP(-1)	-1.1E-07	-0.998	5.6E-06***	3.474	-1.1E-07	-0.851
	Log likelihood	8796.216	Log likelihood	1084.333	Log likelihood	6727.796

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b. Test Results of the Indian Index (Before, during, and after the GFC)

	9/17/1998 -10/30/2007		10/31/2007- 3/6/2009		3/7/2009 - 7/8/2016	
Mean Equation						
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
ID(-1)	0.033	1.436	-0.088***	-2.753	0.024	0.872
CN(-1)	-0.023	-1.591	-0.071	-1.6	-0.007	-0.442
US(-1)	0.219***	66.931	0.221***	38.491	0.215***	8.851
EU(-1)	0.016	0.956	-0.018	-0.582	-0.02	-1.242
JP(-1)	0.013	0.532	0.076	1.15	0.008	0.418
Variance Equation						
α	0.054***	1.415	-0.083**	-2.142	-0.005	-0.553
β	0.520***	8.586	0.981***	28.896	0.935***	63.977
CN(-1)	-0.015**	-2.493	-0.005	-0.399	-0.001	-0.793
US(-1)	0.009	0.24	0.038**	2.526	0.006*	1.771
EU(-1)	0.005	0.399	-0.007	-0.538	-0.001	-0.685
JP(-1)	0.090*	1.964	-0.043	-1.457	-0.002	-0.562
DCN(-1)	-4.8E-07**	-2.341	-1.6E-07	-0.367	4.7E-08	1.405
DUS(-1)	5.5E-08	0.22	-1.4E-06**	-2.056	-4.8E-08	-0.975
DEU(-1)	-1.4E-07	-0.557	2.4E-06***	2.965	3.3E-08	0.829
DJP(-1)	-2.6E-07	-1.263	-1.2E-06	-1.447	1.3E-08	0.261
	Log likelihood	8799.469	Log likelihood	1135.6	Log likelihood	7236.922

c. Test Results of the US, European, and Japanese Indices (after the GFC)

S&P			SXXP			NIK		
Mean Equation								
	Coefficient	z-Statistic		Coefficient	z-Statistic		Coefficient	z-Statistic
US(-1)	0.106***	5.016	EU(-1)	-0.145***	-5.608	JP(-1)	-0.143***	-6.278
CN(-1)	0.016	0.984	CN(-1)	-0.024	-0.933	CN(-1)	-0.026	-1.599
EU(-1)	-0.005	-0.243	US(-1)	0.315***	31.919	EU(-1)	0.076***	54.021
ID(-1)	0.009	0.342	ID(-1)	0.030	0.867	ID(-1)	0.029	1.422
JP(-1)	0.010	0.505	JP(-1)	0.022	0.780	US(-1)	0.393***	18.960
Variance Equation								
α	-0.044**	-2.020	A	-0.038**	-2.287	α	0.103	1.095
β	0.826***	33.687	β	0.774***	22.046	β	0.478***	2.958
CN(-1)	0.003	1.017	CN(-1)	0.041**	2.203	CN(-1)	0.004	0.384
EU(-1)	0.013***	2.842	US(-1)	0.142***	2.129	EU(-1)	0.004	0.445
ID(-1)	0.003	0.278	ID(-1)	0.065	1.442	ID(-1)	-0.011	-0.692
JP(-1)	-0.001	-0.129	JP(-1)	-0.043	-0.843	US(-1)	0.000	-0.015
DCN(-1)	-8.1E-08	-1.590	DCN(-1)	-4.1E-08	-0.218	DCN(-1)	-2.1E-07	-0.828
DEU(-1)	1.4E-07**	2.221	DUS(-1)	8.2E-07***	3.680	DEU(-1)	-1.8E-07	-0.654
DID(-1)	1.6E-07***	3.179	DID(-1)	-7.4E-08	-0.447	DID(-1)	-2.3E-07	-0.896
DJP(-1)	-2.8E-08	-0.426	DJP(-1)	3.6E-07	1.611	DUS(-1)	-3.0E-07	-1.063
	Log likelihood	7095.906		Log likelihood	6477.154		Log likelihood	7116.711

modified GJR-GARCH model also focuses on studying how price and volatility spillovers differ before, during and after the GFC for Chinese and Indian stocks. Although time periods used are different, test results from the GJR-GARCH model are mostly consistent with those from the GARCH-in-Mean model. Table 4a-c present test results.

5.3.1. Before the Global Financial Crisis (9/7/1998-10/30/2007)

China: Similar to the results derived from the GARCH-in-Mean model, the Chinese index was relatively isolated with no price spillover from other indices in the mean equation. The GJR-GARCH model finds volatility spillovers from the US and Japan to China. The negative coefficient of the US index in the variance equation suggests that increased volatility of the S&P in the US reduced volatility of SHCI in China. The negative volatility dummy coefficient of the US is minuscule, but enough to confirm volatility spillover asymmetry. Considering the Chinese economy increased eleven fold in real terms from 1979 to 2006, it is possible that investors became more optimistic about investing in emerging China when there was turmoil in the US market. Thus, including both American and Chinese shares in a global portfolio would help reduce overall systematic risk. However, investment opportunities in China were limited for global investors before the GFC.

India: Test results again reveal significant price spillovers from the US to India and volatility spillovers from China to India. Since coefficients of China volatility and China dummy are both negative, there was asymmetric volatility spillover from China to India in the variance equation. If investors considered Indian and Chinese equities as competing alternatives, they may have treated bad news in China as a sign for holding on to their investments in India. Thus, increased negative volatility from the Chinese index decreased volatility of Indian stocks. It is worth noting that coefficients of cross-border dummies are all very small. Nonetheless, they provide further evidence of volatility asymmetry. Similar to that of the Chinese and American pair, Indian and Chinese stocks also provide diversification benefits within a global portfolio.

During the Global Financial Crisis (10/31/2007-3/6/2009)

China: Test results show that there were significant price spillovers from the US and Japan to China; however, the negative price shock from Japan was puzzling. There were more puzzling results during this time period. For example, dummy coefficients for India and Europe are negative but for US and Japan are positive. It is difficult to explain these conflicting results. Nevertheless, one can make a definitive conclusion that the Chinese stock market, although still relatively isolated, had become more sensitive to external shocks during the GFC.

India: The Sensex was influenced by strong price and volatility shocks from the US during the GFC. Instead of overreacting to shocks from all different channels as was the case in China, investors in India seemed to respond to shocks coming directly from the center of the crisis. The Indian stock market was dominated by FIIs who were able to process information more efficiently during the crisis.

5.3.2. After the Global Financial Crisis (3/7/2009-7/8/2016)

Shock transmissions from developed to emerging markets were strong during the crisis. The price spillovers from the US to China (0.180) and to India (0.221) both increased significantly in the midst of the crisis. After the GFC, the US still had both positive price and volatility spillovers to India, but only a positive price impact on China. The strength of price spillover reduced to 0.105 for China and to 0.215 for India. China also received a negative volatility spillover from India after the crisis, suggesting that increased volatility in Indian index decreased volatility in Chinese stocks. This asymmetric response once again points out the diversification effect by having both Chinese and Indian shares in a global portfolio.

Influence of Chinese and Indian Stocks to Developed Equities after the GFC

The study confirms that both Chinese and Indian equities were sensitive to strong price and volatility spillovers from developed markets during the GFC. Has the situation changed after the GFC? In 2014, China became the number one economy (measured by Purchase Power Parity) in the world with India following closely behind as the third. With their increased economic importance, it is reasonable to argue that Chinese and Indian financial markets should become more influential to the rest of the world as well.

However, test results presented in Table 4c show that the cross-border spillovers of Chinese and Indian equities had been limited from 2009 to 2016. After 2009, the S&P 500 in the US only received volatility spillovers from SXXP in Europe. There was no price or volatility transmission from China to US. The miniscule volatility dummy of India is also meaningless since the volatility coefficient from India to the US was insignificant. SXXP of Europe received strong price (0.315) and volatility shocks (0.142) from the S&P in the US and only weak volatility spillover from SHCI in China. Strong price spillovers to Japan also came from the US (0.393) and Europe (0.076).

Test results suggest that increased volatility in the US stock market in early 2016 was primarily caused by news of slowing down Chinese economy, not as a result of volatility spillover from the Chinese equity. This implies that equity performance in China had not been associated with its economic news; in other words, Chinese stocks had been decoupled from its economic fundamentals. According to Reuters, Chinese stock market was dominated by retail investors. There were approximately 200 million retail investors in China conducting nearly 85 percent of total trades by mid-2015(Shen and Goh, 2015). Since retail investors were more susceptible to market sentiment and behavioral biases, investment decisions in China have not been made based on economic fundamentals, but rather as speculative gambles for short term profits.

In sum, this study confirms that after the GFC, shock transmissions to global financial markets were not from emerging equities in China and India but rather from developed US and European markets as were before. The US stock market has continually been the main source of price and volatility spillovers. Even though their economic importance increased significantly, the influence of Chinese and Indian equities have remained limited after the GFC.

Several proposals may help explain why Chinese and Indian stocks had limited global impact regardless of their increased economic status. First, their equity performance has not been true portrayal of their economic achievement. Speculative retail investors in China and nervous FII in India have caused their stocks to deviate from fundamental values significantly. Second, emerging stock markets are still relatively small. Although China's Shanghai and India's Bombay Stock Exchanges were already ranked number 4 and 11 in the world in 2016, their market capitalizations were only 20.9 and 7.7 percent of that of the New York Stock Exchange (CaproAsia, 2017). Third, the equity markets in China and India have not yet played an important role in supporting economic growth. Their stock market capitalization ratios, ratios that measure the importance of equity market in an economy, averaged 60.1 and 69.9 percent for China and India during 2013-2016. These numbers were significantly below the world average of 94.4 percent and much lower than those of developed nations such as the OECD members (105.6 percent) and the US (145.7 percent) (The World Bank, 2016). Chinese companies relied on bank loans and retained earnings as primary sources of capital, equity capital accounted for less than five percent of total corporate funding (Cendrowski, 2015). In India, less than 1.5 percent of the population invested in securities (Nayyar, 2015). There is a huge potential for both countries to further develop their equity markets.

Lastly, policy restrictions and government interventions have caused inefficiencies in these emerging markets. For example, the Chinese government often times initial public offerings and the Indian government imposes Minimum Alternate Taxes on foreign investors. These interferences contributed to dramatic ups and downs in their stock performances and reduced both the credibility and influence of Chinese and Indian equities.

6. Conclusion

Utilizing several modified GARCH family models, this research studies price and volatility spillovers among national and regional stock indices of China, India, US, Europe, and Japan. The study focuses on Chinese and Indian stocks, their changing market linkages with each other and with major developed equities.

Test results suggest that the Indian index was relatively more open and susceptible to external shocks compared to the Chinese equity. The Chinese index had a negative price and volatility spillovers to Indian shares starting in 1998, but shock transmissions became bidirectional since 2006. After the GFC, Chinese and Indian economies have had notable impacts on global economic development and multinational corporations' performance. However, due to lacking of maturity, magnitude, and efficiency, the influence of their equities had been insignificant. Major developed markets continually to be strong sources of cross-border price and volatiltiy spillovers.

The study discovers consistent asymmetric volatility spillovers between China–US and China–India indices, suggesting that proper allocations of these equities help reduce systematic risk within a global portfolio. However, caution is warranted since risk may not be compensated when investing in emerging stocks during certain time periods. To achieve proper diversification, global investment decisions should be based on not only economic fundamentals of emerging nations but also their changing financial linkages with other markets.

This study confirms results from previous research that developed stock markets were the main channels of shock transmissions. The US stock market continually to be the dominant force in transmitting volatility worldwide. Spillovers from the US to emerging markets strengthened during the GFC and remained potent thereafter. The powerful and dominant role of the US market points to the importance of US monetary and financial policies. Policy directives in developed countries like the US have both strong domestic as well as global influences. For example, the global financial crisis, which originated from sub-prime lending in the US, was able to penetrate the relatively isolated equity market in China; and a Fed announcement of a potential interest rate hike caused a significant capital flight out of India in 2013. To achieve increased stability in the global financial system, international monetary and financial policy coordination and cooperation are essential today more than ever.

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