Cointegration relationship and time varying co-movements among Indian and Asian developed stock markets

Guidi, Francesco

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Francesco Guidi
Dipartimento di Economia
Università Politecnica delle Marche,
P.le Martelli, 8, Ancona, 60121, Italy
E-mail: francesco.guidi@univpm.it
Tel: +390712207110; Fax: +390712207102

Abstract

This paper aims to explore links between the Indian stock market and three developed Asian markets (i.e. Hong Kong, Japan and Singapore). The index prices are non-stationary so we used cointegration methodologies in order to explore interdependencies. Johansen methodologies reject the hypothesis of long-run relationships among all stock markets, while the Gregory-Hansen test rejects the hypothesis of no cointegration with structural breaks. Our results suggest that in the long-term the benefits for investing in India are limited. We further estimated the time-varying conditional correlation relationships among these markets We find that correlations rise dramatically during periods of crisis, while they return to their initial levels after those periods.

Keywords: Stock markets; cointegration; time-varying correlations.
JEL Classification: C32, G15.

1. Introduction

Increased financial integration among stock markets in the world leads international investors to look for new investment opportunities in order to reduce the potential risks of each investment. When stock market indices of different countries do not follow the same trend, then international investors can find good opportunities to diversify their portfolio investments among these countries. International investors are generally interested in emerging stock markets but the interdependence among these markets and developed markets may affect the scope for diversification possibilities (Pretorious, 2002). This last issue has been broadly investigated by the empirical literature seeking to detect relations among developed and emerging equity markets. For instance Huang et al. (2000) analysed short- and long-run relationships among two leading international stock markets (i.e. the USA and Japan) and several Asian emerging markets (China, Hong Kong and Taiwan) during the period 1992-1997. Although some evidence of short-run relationships has been detected among those markets, cointegration analysis does not find any long-term equilibrium among these markets.

Other authors have focused on the interdependence among developed equity markets and Eastern Europe emerging markets. For example Syriopoulos and Roumpis (2009) examined interdependences between several South Eastern Europe countries' equity markets and two mature equity markets like the US and Germany. Results show the existence of a long-run relationship although in the short term, investment opportunities may arise for investors interested in diversifying their portfolios in the South East Europe. Through the use of Dynamic Conditional Correlation models, it is shown that stock market returns of each group of countries seems to be highly correlated, while correlation among these groups is weaker.

Other authors have focused on the relationships among Asian stock markets. For instance Elyasiani et al. (1998) examined the relationships between Sri Lanka and Asian developed equity markets over the 1989-1994 period. Their study found that there was no interdependence between the Sri Lankan and the other stock markets. Qiao et al. (2008) examined the issue of integration among the

Chinese segmented stock markets and the Hong Kong stock market, finding bi-directional volatility spillover between the B-share Chinese and Hong Kong markets. Ratanapakorn and Sharma (2002) investigated how short- and long-run relationships changed across five regional stock markets for the pre- and post 1997 Asian crisis. Results show that no long-run relationships characterized their relationship before the Asian crisis, whereas some evidence of integration was observed after the crisis. The main conclusion is that the Asian crisis increased integration among these markets. Raj and Dhal (2008) investigated the degree of integration of India's stock markets with two Asian regional equity markets (i.e. Hong Kong and Singapore) and three leading international markets (i.e. Japan, UK, and US). Multivariate cointegration tests showed the existence of one cointegration relationship among these markets, whereas pair-wise cointegration tests between India and one of these markets rejected the hypothesis of cointegration. Also the work of Jang and Sul (2002) explored whether co-movements among a sample of Asian stock markets (i.e. Hong Kong Indonesia, Japan, Korea, Singapore, Taiwan and Thailand) changed as a consequence of the 1997 financial crisis. By using the Engle-Granger cointegration test, these authors found that cointegration characterized only a small number of countries, while after the crisis the number of cointegrated stock markets increased dramatically. However their work does not explain why the financial crisis should have increased integration among these markets. Interdependence among Latin American equity markets has been investigated only recently. Among these studies, Chen et al. (2002) investigated the interdependence among six Latin American stock markets during the period 1995-2000. Splitting the sample period in several sub-periods based on a number of global and regional financial crises (i.e. the 1997 Asian crisis and the 1998 Russian and Brazilian crises), these authors showed that Latin American stock markets shared a long-term relationship up until 1999. Bivariate and multivariate cointegration tests did not find evidence of a long-run equilibrium relationship after 1999. Other studies have considered both Asian and Pacific-Basin stock market relationships in order to analyse their degree of integration as well as the effect of 1997 financial crises on their equity markets. For instance Chelley-Steeley (2004) explored the speed of market integration among developed and emerging Asia-Pacific equity markets. Results show that integration among emerging Asia-Pacific countries tends to be faster than the integration between emerging and developed markets of that geographic area. In another study, Chi et al. (2006) examined whether the level of integration of several Asian emerging equity markets with both the Japanese and the US equity markets changed as a consequence of the 1997 financial crisis: results confirm that the integration increased immediately after the crisis.

All the above studies have broadly used cointegration methodologies to explore interaction among stock markets and detected relations among emerging and developed stock markets. The aim of this paper is to contribute to the empirical literature by analysing the existence of a long-run relationship between the Indian and several Asian developed markets, that is Hong Kong, Japan and Singapore mainly through cointegration methodologies. Studying the integration of India with major Asian stock markets is an interesting research topic for several reasons. Firstly foreign portfolio investments (FPI) into Indian stock markets increased dramatically in the last decade. The year 1999-2000 witnessed an inflow of 2.15 US $ billion dollars, by the end of 2008 India attracted more than 32 US $ billion (Reserve Bank of India, 2009), so it is worth investigating whether those flows of investment affected the integration of India's financial markets with the equity markets of other countries. Secondly, the Indian stock market has not been immune, like many other countries, from the recent international financial crisis. For instance the recent subprime mortgage crisis which triggered a global financial crisis also affected heavily the Bombay Stock Exchange, which lost 11.6% of its value on the 'Black Friday' of the October 24, 2008. As a result it seems to be appropriate to explore, for instance, the degree of correlation between India and other Asian markets in order to find out whether interdependence between Indian and Asian stock markets tends to strengthen during financial crisis periods. Overall our study tries to detect long-run interdependence among this market as well as Hong Kong, Japanese and Singapore stock markets from a prospective international investor from these countries seeking to diversify his/her portfolio in the closest emerging economy like India.

The rest of the paper is organized as follows. Sections 2 and 3 introduce methodologies and data used in this study. Section 4 discusses empirical results. Section 5 concludes.

2. Methodology

This study uses different techniques to analyze the relationships among the Indian and developed Asian markets. The first one we used was the Engle and Granger (1987) methodology which is based on analyzing stationarity of error term series obtained from the equation derived with level values of time series that are not stationary on the level but become stationary when their difference is taken. If the error term series is stationary, this means that there is a cointegration relationship between the mentioned two time series. In the first step of this procedure we estimated the following equation:

$$y_t = \beta_0 + \beta_1 x_t + e_t \tag{1}$$

where y_t and x_t are two different stock market indices. The estimated residuals $\hat{e}_t$ from the above equation are considered to be temporary deviation from the long-run equilibrium, then they were investigated by using the following ADF unit root test:

$$\Delta\hat{e}_t = \alpha_1 \hat{e}_{t-1} + \sum_{i=2}^{n} \alpha_i \Delta\hat{e}_{t-i} + \varepsilon_t \tag{2}$$

where α are the estimated parameters and ε_t is the error term. The cointegration test is conducted by a hypothesis test on the coefficient α_1. If the *t-statistic* of the coefficient exceeds a critical value, then the residuals from equation (1) are stationary, and thus the two stock markets y_t and x_t are cointegrated.

The next technique used was the Johansen's methodology (Johansen, 1988, 1991) which takes its starting point in the vector autoregression (VAR) of order *p* given by:

$$z_t = c + A_1 z_{t-1} + \ldots + A_p z_{t-p} + \mu_t \tag{3}$$

where z_t is an $n \times 1$ vector of variables that are integrated of order one – commonly denoted I(1) – and μ_t is a zero mean white noise vector process. This VAR can be re-written as:

$$\Delta z_t = c + \Pi z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta z_{t-i} + \mu_t \tag{4}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$. If the coefficient matrix Π has reduced rank $r < n$, then there exist $n \times r$ matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' z_t$ is stationary. r is the number of cointegration relationships, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector. It can be shown that for a given r, the maximum likelihood estimator of β defines the combination of z_{t-1} that yields the r largest canonical correlations of Δz_t with z_{t-1} after correcting for lagged differences and deterministic variables when present. Johansen proposed two different likelihood ratio tests of the significance of these canonical correlations and thereby the reduced rank of the Π matrix, that is the trace test and maximum eigenvalue test, which are given by the following equations:

$$\lambda_{trace} = -T \sum_{j=r+1}^{k} \ln(1 - \hat{\lambda}_j) \tag{5}$$

$$\lambda_{\max} = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{6}$$

where T is the sample size and $\hat{\lambda}_j$ are the estimated values of the characteristic roots obtained from the Π matrix. The trace test (λ_{trace}) tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors, while the maximum eigenvalue $(\lambda_{\max})$ tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ cointegrating vectors.

Gregory et al. (1996) through a series of simulation tests showed that the power of the Engle and Granger (1987) cointegration test is dramatically reduced if a break in the cointegration relationship occurs. In order to overcome this drawback, Gregory and Hansen (1996) proposed a new test which allowed for breaks in the cointegration relationship. In particular the Gregory-Hansen test tests the null hypothesis of no cointegration against the alternative of cointegration with a single structural break of unknown timing. The timing of a structural break changes under the alternative hypothesis if it is estimated endogenously. Gregory and Hansen suggest three alternative models accommodating changes in parameters of the cointegration vector under the alternative. The first one (equation 7) is the so-called level shift model (or C model) that allows for the change in the intercept only. The second model (equation 8) accommodating a trend in data also restricts a shift only to the change in level with a trend (C/T model). The last model (equation 9) allows for changes both in the intercept and slope of the cointegration vector (or R/S model).

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha' y_{2t} + e_t \tag{7}$$

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \beta t + \alpha' y_{2t} + e_t \tag{8}$$

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha' y_{2t} + \alpha_2' y_{2t} \varphi_{t\tau} + e_t \tag{9}$$

The dummy variable which captures the structural change is represented as:

$$\varphi_{t\tau} = \begin{cases} 0, \text{ } if \ \ t \le n\tau \\ 1, if \ \ t > n\tau \end{cases} \tag{10}$$

where $\tau \in (0,1)$ is a relative timing of the change point. Equations (7), (8), and (9) are estimated sequentially with the break point changing. Non-stationarity of the obtained residuals, is checked by the ADF test. Setting the test statistics to the smallest value of the ADF statistics in the sequence, we selected the value that constitutes the strongest evidence against the null hypothesis of no cointegration.

We also conducted the causality test based on Granger's (1969) approach in order to see any influence between stock markets here considered. In order to test for Granger causality, we considered two stock market indices x_t and y_t, then we estimated the following equations:

$$\Delta x_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta x_{t-1} + \sum_{i=1}^{m} \beta_{2i} \Delta y_{t-1} + \varepsilon_{1t} \tag{11}$$

$$\Delta y_t = \delta_0 + \sum_{i=1}^{n} \delta_{1i} \Delta y_{t-1} + \sum_{i=1}^{m} \beta_{2i} \Delta x_{t-1} + \varepsilon_{1t} \tag{12}$$

One has to be careful about the lags in the above equations with daily data. Due to different closing times (and to time differences) some markets close earlier than others. For example in the Bombay Stock Exchange (BSE hereafter), trading session opens at 9.55 am an closes at 15.30 pm. In the Tokyo Stock Exchange the normal trading sessions are from 09.00am to 11.00am and from 12.30pm to 03.00 pm. The Stock Exchange in Singapore has normal trading sessions from 09.00am to 05.00pm, while trading sessions in the Hong Kong Stock Exchange are from 10.00am to 12.30am and from 14.30pm to 16.00 pm. By the time BSE closes, the closing values for Hong Kong, Singapore and Tokyo are already known. We may note further the time difference among these countries, for instance Tokio time is 3.30 hours ahead the Mumbai (that is the Indian city where is located the BSE) time, while both Singapore and Hong Kong are 2.30 hours ahead Mumbai time. Tsutsui and Hirayama (2004) examining the relationship among four major stock markets (Germany, Japan, UK and USA) point out that the specification of a lag structure of a VAR model must take into account both different closing prices and time differences among these countries in order to obtain better estimates of the integration among these markets. In order to check the robustness of our results, we also follow the study of Tsutsui and Hirayama (2004), assuming that the impact of time differences and closing prices is relevant also in our work. Schotman and Zalevzka (2006) point out that a way of dealing with this problem is to choose between daily data with potential time-matching problem and low frequency data (weekly or monthly)[1]: the main drawback by using these last data is the loss of information. On the other side they argue that controlling for time differences in stock markets can improves estimates of market integration. I decided to follow this last alternative by taking into account time differences. So that in those Granger causality regression equations explaining BSE stock market, we include the same day's value of Tokyo, Hong Kong, or Singapore as been described above about the timing of closing values. By doing so, the significance of each of the other three stock prices might increase

[1] Analysing equity spillovers among several worldwide stock indices, Ng (2000) argues that using weekly data is a way to avoid the problem to deal with nonsynchronous trading effects due to time differences among countries.

substantially. After estimating the Granger-causality we run an F-test for joint insignificance of the coefficients. Assuming the null hypothesis that x_t does not Granger cause y_t and vice versa, a rejection of the null hypothesis show a presence of Granger causality. The Granger causality tests are performed for each pair of stock indices.

In this work we also focus on the volatility of stock markets. The main reason is that volatility is a measure of the risk of the expected returns. In order to explore the issue we used the Dynamic Conditional Correlation specification of the Multivariate GARCH model developed by Engle (2002). In particular we considered the following DCC-GARCH model for a 2-dimensional vector process for two stock markets stock returns which is given by the following conditional mean equation:

$$y_t = E(y_t / I_{t-1}) + r_t \tag{13}$$

where I_{t-1} is the information set at time t-1. Each univariate error process has the specification $r_{i,t} = h_{i,t}^{1/2}\varepsilon_{i,t}$, and the conditional variance $E(r_{i,t}^2 / I_{t-1}) = h_{i,t}$ follows a univariate GARCH(1,1) process, that is:

$$h_{i,t} = \alpha_{i0} + \alpha_{i1} r_{i,t-1}^2 + \beta_{i1} h_{i,t-1} \tag{14}$$

with the non-negativity and stationarity restrictions imposed. The conditional correlations are allowed to be time-varying by following the GARCH(1,1) model given by:

$$q_{i,j,t} = \bar{\rho}_{i,j}(1-\alpha-\beta) + \alpha\varepsilon_{i,t-1} + \beta q_{i,j,t-1} \tag{15}$$

where $q_{i,j,t}$ is the time-varying covariance of ε_t, $\bar{\rho}_{i,j}$ is the unconditional variance of ε_t, while α and β are nonnegative scalar parameters.

3. Data

The sample consists of daily closing stock index prices of India (BSE 30), Hong Kong (Hang Seng), Japan (Nikkei 225), and Singapore (STI) from January 4, 1999 to June 17, 2009 with the exception of the STI index whereas, due to data availability, time series start on August 31, 1999. All indices have been obtained from *Thomson Financial Datastream* and they are in domestic currency in order to avoid problems associated with transformation due to fluctuations in exchange rates[2]. Table 1 shows that during the sample period, the BSE index had the highest average rate of returns followed by the Hang Seng index. The standard deviation of returns on BSE are higher than the standard deviation of returns on Hang Seng, Nikkei or STI. All returns have negative skewness implying that the distribution has a long right tail, while the kurtosis values are high in all cases implying that the distribution are peaked relative to normal. The Jarque-Bera test indicates that none of the stock market returns is normally distributed.

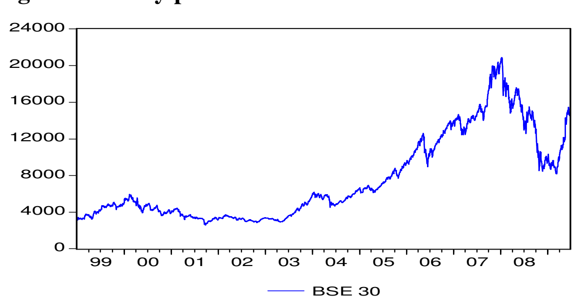
Table 1 – Summary statistics of daily returns

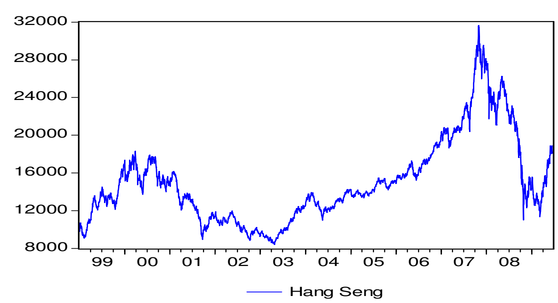
	BSE 30	Hang Seng	Nikkei 225	STI
N. obs	2727	2727	2727	2556
Mean	0.0005	0.0002	-0.0001	1.51e-05
Maximum	0.159	0.134	0.132	0.07
Minimum	-0.118	-0.135	-0.121	-0.08
Std. Dev.	0.017	0.016	0.015	0.013
Skewness	-0.087	-0.009	-0.304	-0.232
Kurtosis	8.899	10.703	9.868	7.385
Jarque-Bera Test	3957.98	6743.54	5403.12	2070.95
Probability	0.00	0.00	0.00	0.00

Notes: All daily returns were calculated as log differences using daily closing prices.

Figure 1 plots the index values for India, Hong Kong, Japan and Singapore. The Nikkei index observed a steep fall during the period 2000-2003. From 2003 to 2007 an upward trend is common across all markets. From the second half of 2007 we observe a dramatic decline of stock prices across all markets, whereas some increases seem to characterize the second quarter of 2009.

Figure 1 – Daily prices





[2] It must be pointed out that *Thomson Financial Datastream* database treats public holidays as missing data, replacing them by figures calculated by linear interpolation.

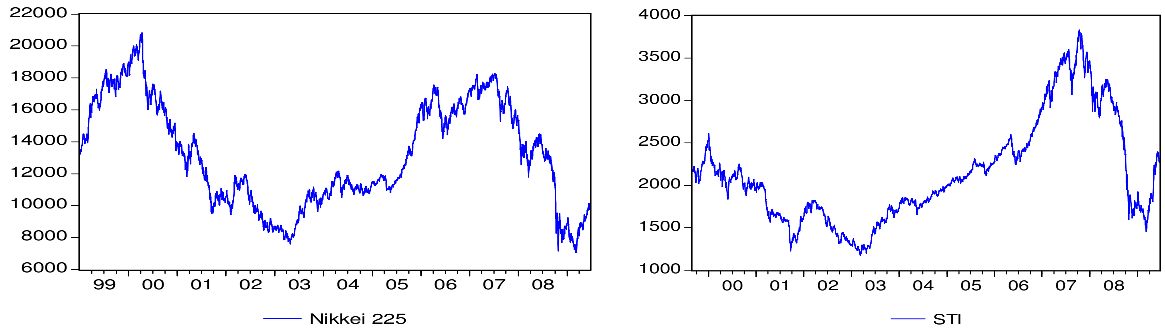


Figure 2 plots the stock market index returns of each of the countries here considered. We note that there is evidence of volatility clustering, that is small (large) returns tend to be followed by small (large) returns. The phenomenon suggests that volatility changes over time.

Figure 2 – Daily returns

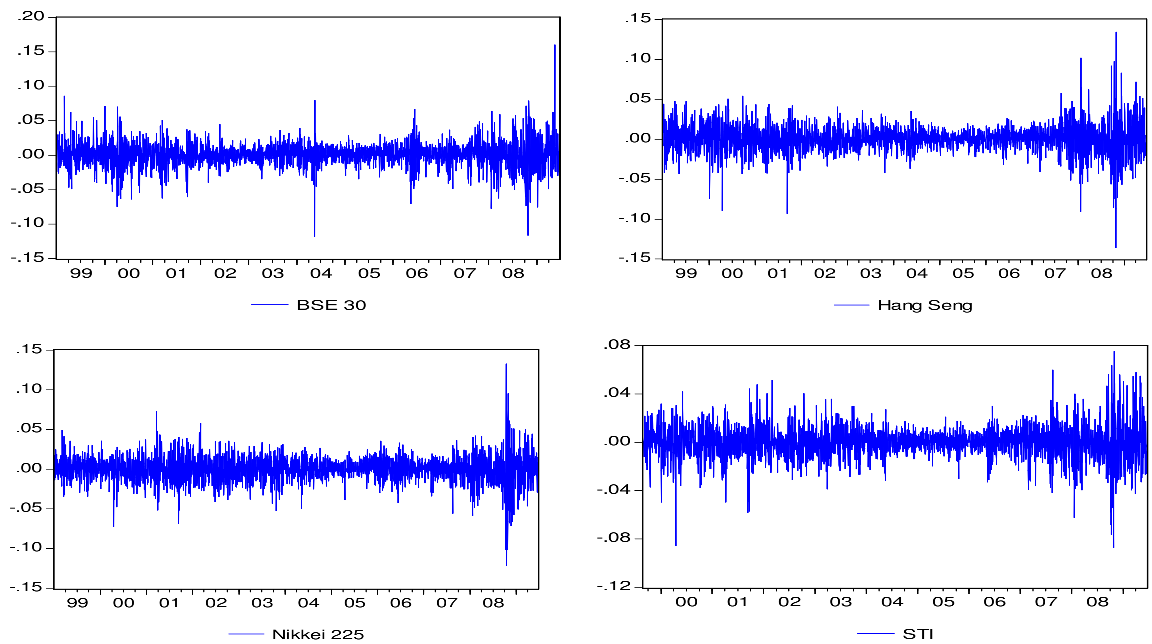


Table 2 reports the unconditional correlation of the returns of the four Asian markets. We can observe that the highest correlation is between the STI and Nikkei (over 68%) while the lowest is between BSE and Nikkei (about 30%)[3].

[3] Roll (1992) argues that the low correlations among international stock markets may be due to reasons like indices construction, differences in the industrial structure as well as in the conduct of national monetary policies.

Table 2 – Correlations of stock index returns January 4, 1999 through June 17, 2009

	BSE 30	Hang Seng	Nikkei 225	STI
BSE 30	1			
Hang Seng	0.429	1		
Nikkei 225	0.306	0.567	1	
STI	0.465	0.688	0.520	1

Notes: The stock returns are in nominal terms in domestic currency.

3. Empirical results

A necessary condition to perform a cointegration test is that the order of integration of variables have to be the same. In order to detect the order of integration we employed both the Augmented Dickey-Fuller (1979) and Phillips-Perron (1988) unit root tests, whose results are shown in Table 3. The null hypothesis of a unit root is not rejected for all indices in log level, whereas it is rejected when they are taken in their log first differences. Having shown that these variables are stationary in the first difference, that is I(1), then we can say that they satisfy the necessary conditions for cointegration.

Table 3 – Results of the unit root tests

	Lag length p	ADF	P-value [a]	Bandwidth	PP	P-value [a]
Variables in log level						
BSE 30	0	-0.612	0.865	10	-0.639	0.859
Hang Seng	0	-1.771	0.395	8	-1.734	0.413
Nikkei 225	0	-1.455	0.556	7	-1.341	0.612
STI	0	-1.235	0.660	5	-1.292	0.635
Variables in First log difference						
BSE 30	0	-49.676	0.001	13	-49.650	0.00
Hang Seng	0	-53.034	0.00	7	-53.064	0.00
Nikkei 225	0	-53.077	0.00	7	-53.206	0.00
STI	0	-49.178	0.00	3	-49.183	0.00

Notes: The critical value for both the ADF and PP t-statistics are -3.43, -2.86, and -2.56 at 1%, 5% and 10% levels of significance respectively. For both tests, a constant term was included. For the ADF test the optimal lag lengths is determined by using the AIC. For the PP test the spectral estimation method is the Bartlett kernel, while the Bandwidth is the Newey-West. The p-values are the MacKinnon (1996) one-sided p-values.

Given that all variables are non-stationary integrated of order 1, we proceed to test whether those I(1) variables are cointegrated. We employed the Engle-Granger test to carry out the cointegration analysis in a bivariate setting taking the log form (Ln) of each stock market index. The first step of the Engle and Granger method requires the estimation of the long-run equation through OLS, so we obtained:

$$LnBSE_t = \underset{(0.187)}{-8.66} + \underset{(0.019)}{1.818}\ LnHangSeng_t \qquad (16)$$

$$R^2 = 0.760, \ DW = 0.009, \ \text{F-statistic} = 8665{,}765$$

$$LnBSE_t = 1.467 + 0.770 \ LnNikkei_t \tag{17}$$
$$\quad (0.389) \quad (0.041)$$
$$R^2 = 0.113, \ DW = 0.001 \ \text{F- statistic} = 350{,}21$$

$$LnBSE_t = -5.447 + 1.865 \ LnSTI_t \tag{18}$$
$$\quad (0.159) \quad (0.021)$$
$$R^2 = 0.756, \ DW = 0.006 \ \text{F- statistic} = 7948{,}92$$

If LnBSE and LnHangSeng on the one hand, and LnBSE and LnNikkei on the other hand have a cointegration relationship, the residual error series of each of the above equations should have stationarity. Following the second step of the Engle and Granger procedure we checked whether residuals of the above equations satisfied these last requirements. Results (table 4) show that there is no long run relationship between BSE and other Asian equity markets by using the specification of the ADF without trend, while there is weak evidence of a cointegration relationship between BSE and Hang Seng as well as between BSE and STI when the ADF test with trend and intercept is used. Because the visual inspection of the residuals of equation (16) does not show evidence of trend we may consider the results of ADF test without trend more reliable, on the other hand residuals of equations (17) and (18) show some trend, so we consider the ADF test results more consistent with trend an intercept[4]. From these last considerations we may infer that there is no long-run relationship between BSE and Hang Seng stock markets, while a weak relationship exists among BSE and the STI stock markets.

Table 4 – ADF test results on Engle-Granger cointegration test residuals

	ADF Test statistic without trend	ADF Test statistic with trend and intercept
LnBSE and LnHangSeng	-1.889	-3.330*
LnBSE and LnNikkei	-0.032	-2.775
LnBSE and LnSTI	-1.618	-3.210*

Notes: In the ADF test, critical values are -3.432, -2.862, and -2.567 on models without trend, and -3.961,-3.411, and -3.1247 on models with trend for 1%, 5%, 10% levels. Three/two/one stars rejections of the null hypothesis of a unit root at the 1%, 5%, and 10% levels.

In order to check the robustness of the above cointegration results, we also employed the Johansen cointegration test. Johansen's procedure requires estimating a VAR(p). A fundamental element in

[4] Residuals of the estimated equations are available upon request.

the specification of the VAR models is the determination of the lag length p. There are several criteria for estimating the appropriate model which takes into account several elements like smaller residuals and loss of degrees of freedom due to the number of estimated parameters. In order to estimate the optimal number of lag p of the VAR we used both the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC): by using both we chose the model that minimized the information criteria value. Results are shown in table 5. When we estimated the VAR with BSE and Nikkei in log form, the AIC selects a VAR model with 7 lags, while the SC selects a model with 2 lags[5]. We estimated the VAR(2) model selected by the SC given that it is the more parsimonious in terms of coefficients to estimate: anyway checking for the serial correlation of the residual series through the autocorrelation LM test, we rejected the null hypothesis of no serial correlation. In order to eliminate serial correlation, we decided to estimate a VAR(4): checking for the serial correlation we were not able to reject the null hypothesis of no serial correlation of the residual series. Employing the same methodology, we found that BSE and Hang Seng indices seem to be best represented by a VAR of order 5. Further a VAR with 2 lag lengths was estimated for BSE and STI equity market indices. Finally, following AIC results we estimated a VAR(5) for BSE, Hang Seng, Nikkei and STI indices: given the SC results, we estimated initially a VAR(2), but this model shown serial correlations in the residual series so we shifted to a VAR(5) where the null hypothesis of no correlation in the residual series was not rejected by the autocorrelation LM test.

After estimating the above VAR models we were able to conduct the Johansen cointegration test at both bivariate and multivariate level. The empirical findings (Panel A of Table 5) do not support the presence of the cointegrating vector in the BSE and Nikkei stock markets. The null hypothesis the BSE and Nikkei market are not cointegrated $(r = 0)$ against the alternative of one cointegrating vector $(r \leq 1)$ is not rejected, since both the λ_{trace} and λ_{max} statistics do not exceed the critical values the 5% level of significance. We came to the same conclusion relatively to the BSE and Hang Seng

[5] There is a theoretical reason for such a different result in terms of lags to apply. As emphasized by Lütkepohl (1991, p. 151), the reason is the different weight attached to the penalty term for the number of parameters.

as well as between the BSE and STI equity markets. Although we found no evidence of cointegration on a bivariate basis between the Indian and Asian developed markets, we want to detect if these markets, as group, could be cointegrated. Therefore, a multivariate Johansen test was carried out. The results (Panel b of Table 5) indicate that there is no long-term relationship among the four stock markets.

Table 5 – Tests for the number of Cointegrating vectors

	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
Panel A: Bivariate Johansen cointegration results				
BSE 30 and Nikkei 225 market indices				
r = 0	1.934	15.494	1.934	14.264
r ≤ 1	1.74E-05	3.841	1.74E-05	3.841
BSE 30 and Hang Seng market indices	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r = 0	7.042	15.494	6.852	14.264
r ≤ 1	0.189	3.841	0.189	3.841
BSE 30 and STI market indices	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r = 0	4.4	15.494	4.354	14.264
r ≤ 1	0.046	3.841	0.046	3.841
Panel B: Multivariate Johansen cointegration results				
BSE 30, Hang Seng, Nikkei 225, and STI	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r = 0	35.872	47.856	16.903	27.584
r ≤ 1	18.968	29.797	14.517	21.131
r ≤ 2	4.451	15.494	4.449	14.264
r ≤ 3	0.002	3.841	0.002	3.841

Notes: The 5% critical values provided by MacKinnon et al. (1999) indicate no cointegration.

Then we applied the methodology of Gregory and Hansen (1996) to detect structural changes which may affect the results of the cointegration test. The Gregory-Hansen test results (table 6) show that the Indian market has a long run relationship with the Hong Kong market that is not detected by previous cointegration tests: the timing of the breaks (breaks date: August 15, 2000; November 11, 2002 and May 20, 2003) seem to be quite heterogeneous. Results of the Gregory-Hansen test reveal also links between the Indian stock market and that of Japan: 2 out of 3 break dates converge on May 6, 2003. From the Gregory and Hansen results we may conclude that there is a long-run relationship among India and developed Asian markets, this also means that although these markets may have a different path from each other in the short run, they will stay close to each other in the long run. Is it possible to have opposite results by applying both the Johansen and the Hansen-Gregory cointegration test? From our empirical results we can say that the answer seems to be positive, anyway also other empirical studies find evidence of similar results. For instance Fernandez-Serrano and Sosvilla-Rivero (2001) studying the long run relationship between Japan and several emerging Asian stock markets, found that the Johansen test found no cointegration vector while the Gregory and Hansen test showed evidence of long run relationship between Japanese and Taiwanese as well as Japanese and Korean equity markets. So our results seem to be supported by that last work.

Table 6 - Test for structural breaks – Gregory and Hansen (1996) cointegration test

Model specification	Breakpoint	GH Test statistic	5% Critical Value	Ho: No cointegration
BSE 30 and Hang Seng stock markets returns				
Fullbreak (C/S)	2000:08:15	-21.826	-5.50	Reject
Trend (C/T)	2003:5:20	-21.612	-5.29	Reject
Constant (C)	2002:11:05	-21.557	-4.92	Reject
BSE 30 and Nikkei 225 stock markets returns				
Fullbreak (C/S)	2003:05:06	-23.258	-5.50	Reject
Trend (C/T)	2007:11:12	-23.325	-5.29	Reject
Constant (C)	2003:05:06	-23.255	-4.92	Reject
BSE 30 and STI stock markets returns				
Fullbreak (C/S)	2001:09:06	-21.378	-5.50	Reject
Trend (C/T)	2007:12:31	-21.350	-5.29	Reject
Constant (C)	2002:11:04	-21.295	-4.92	Reject

Notes: The critical values for the Gregory-Hansen tests are drawn from Gregory and Hansen (1996).

As pointed out by Égert and Kočenda (2007), given that the indices are difference stationary and because the cointegration results do not show clear evidence of robust cointegration between them, the Granger causality test seems to be an appropriate tool in order to detect further the relationship among these markets. Results (table 7) show that there is bilateral or feedback causality between BSE and Hang Seng stock market. We note also that the direction of causality is from BSE and Nikkei, however, there is no reverse causation from Nikkei to the BSE stock index. Finally we found that the STI causes the BSE market returns and vice versa.

As pointed out previously, the trading hours of Japan, Hong Kong and Singapore are several hours ahead of those of the Indian stock markets: this means that Indian BSE stock market closes several hours after the closure of the other three markets due to time difference. This implies that STI, Hang

Seng and Nikkei closing prices are already known by the time BSE closes. This consideration lead us to conclude that in a regression equation with the BSE as dependent variable we have to include the same day's value of Tokyo, Hong Kong or Singapore as been described above about the time of closing prices in the BSE on the same day (along with past prices) as regressors. Taking into account that, we explore whether results are different due to time differences[6]. After taking the effect of the same day's closing prices in regression equation to explain BSE including the same day's values of Tokyo, Hong Kong and Singapore, we find that the significance of each of the other three stock prices increases substantially (table 7).

Table 7 – Granger-causality test for returns

	F-statistic	Probability
BSE 30 does not cause Hang Seng market	10.990	1.8E-05
Hang Seng does not cause BSE 30 market	2.645	0.071
Hang Seng does not cause BSE 30 market [taking the effect of the same day's value of the Hang Seng on the BSE 30]	306.03	1.E-120
BSE30 does not cause Nikkei 225 market	37.906	5.8E-17
Nikkei 225 does not cause BSE 30 market	1.2	0.301
Nikkei 225 does not cause BSE 30 market [taking the effect of the same day's value of Nikkei 225 on the BSE 30]	138.45	5.5e-58
BSE 30 does not cause STI market	4.179	0.015
STI does not cause BSE 30 market	6.273	0.001
STI does not cause BSE 30 market [taking the effect of the same day's value of STI on the BSE 30]	360.98	9.E-139

Recognizing that constant correlation coefficients are not able to show the dynamic market conditions in response to innovations[7], next we apply the DCC-GARCH models proposed by Engle (2002). The parameter estimates of the DCC-GARCH models are reported in Table 8: from that table we can see that the estimates of the mean equations and variance equations are statistically significant which are consistent with the time varying volatility hypothesis. In addition the sum of estimated coefficients in the volatility equations are close to unity, this means that volatility exhibits a highly persistent behaviour for each pair-wise correlation among stock markets. The estimated

[6] Also Sohel-Azad (2009) checked whether Granger-Causality results are robust when time differences across markets are take into account.

[7] Longin and Solnik (1995) indicate several reasons why correlations among stock markets are not constant over time. They are the presence of a time trend, as well as the presence of threshold and asymmetry. The first reason is associated to the progressive removal of impediments to international investments. The second is due to common factors that affect international markets at the same time.

coefficients on the persistence $\left(q_{i,j,t-1}\right)$ of the time varying correlation are quite similar in each of the bivariate DCC models estimated as well as the coefficients that show the effects of the most recent co-movements $\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1}\right)$.

Table 8 - Results of Bivariate DCC-GARCH (1,1) models on daily return indices

Panel A – BSE 30 and Hang Seng markets			
	BSE 30		**Hang Seng**
I. Returns equations $E\left(y_{i,t}/I_{t-1}\right)=y_{i,t}-r_{i,t}$			
Constant	0.001*** (2.24e-04)		6.77e-04*** (2.11e-04)
II. Volatility equations $E\left(r_{i,t}^2/I_{t-1}\right)=h_{i,t}$			
Constant	5.83E-06***(7.97e-04)		1.11***(2.970)
$r_{i,t-1}^2$	0.117***(0.007)		0.061***(0.005)
$h_{i,t-1}$	0.870***(0.007)		0.936***(0.005)
III. Correlation equation $E\left(\varepsilon_{i,t}\varepsilon_{j,t}/I_{t-1}\right)=q_{i,j,t}$			
$\varepsilon_{i,t-1}\varepsilon_{j,t-1}$		0.02***(0.004)	
$q_{i,j,t-1}$		0.961***(0.007)	
Panel B – BSE 30 and Nikkei 225 markets			
	BSE 30		**Nikkei 225**
I. Returns equations $E\left(y_{i,t}/I_{t-1}\right)=y_{i,t}-r_{i,t}$	0.001***(2.24e-04)		5.09e-04***(2.3E-04)
Constant			
II. Volatility equations $E\left(r_{i,t}^2/I_{t-1}\right)=h_{i,t}$	6.70e-06***(8.9e-07)		2.87e-06***(6.3e-07)
Constant			
$r_{i,t-1}^2$	0.127***(0.008)		0. 086***(0.007)
$h_{i,t-1}$	0.857***(0.008)		0.904***(0.008)
III. Correlation equation $E\left(\varepsilon_{i,t}\varepsilon_{j,t}/I_{t-1}\right)=q_{i,j,t}$			
$\varepsilon_{i,t-1}\varepsilon_{j,t-1}$		0.017***(0.005)	
$q_{i,j,t-1}$		0.968***(0.009)	
Panel C – BSE 30 and STI markets			
	BSE 30		**STI**
I. Returns equations $E\left(y_{i,t}/I_{t-1}\right)=y_{i,t}-r_{i,t}$			
Constant	0.001***(2.47E-04)		5.503E-04***(1.986)
II. Volatility equations $E\left(r_{i,t}^2/I_{t-1}\right)=h_{i,t}$			
Constant	6.507***(9.02E-07)		1.41E-06***(0.0031)
$r_{i,t-1}^2$	0.128***(0.008)		0.086***(0.0071)
$h_{i,t-1}$	0.857***(0.008)		0.910***(0.006)
III. Correlation equation $E\left(\varepsilon_{i,t}\varepsilon_{j,t}/I_{t-1}\right)=q_{i,j,t}$			
$\varepsilon_{i,t-1}\varepsilon_{j,t-1}$		0.023***(0.004)	
$q_{i,j,t-1}$		0.962***(0.008)	

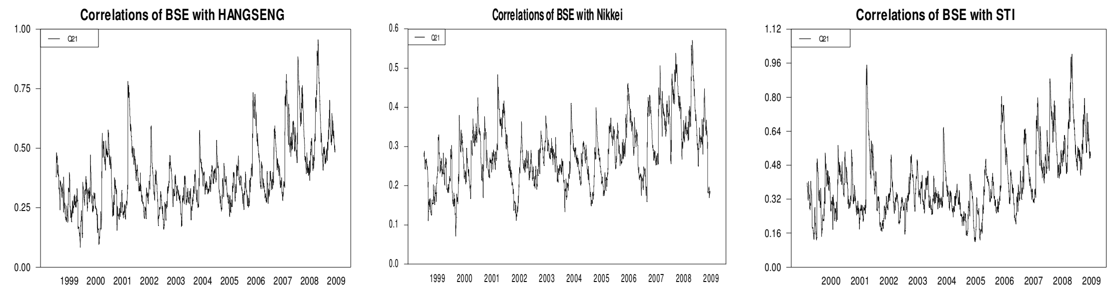
Notes: Standard error are in parenthesis. Three/Two/One stars indicate the significance level at 1%, 5% and 10%.

The dynamic time varying correlations obtained from the above DCC-GARCH models are plotted in Figure 3. All figures show evidence of varying patterns in the correlation dynamic path, which is the reason for using the DCC-GARCH modelling strategies. Considering the BSE and Hang Seng stock markets returns, the plotted DCC correlations range in a corridor with the lowest value of 0.083 in November 1999 and the highest of 0.955 in October 2009, while correlations among BSE and STI range between 0.119 and 1.00 In respect to the two other indices, BSE seems to be less time-varying correlated with the Nikkei market, where the DCC estimate varies between 0.071 and 0.570 (Fig. 3). In other words correlations between BSE and Nikkei returns has remained the lowest of the three set of correlations. From Figure 3, during the period of the Twin Tower attacks (September 11th, 2001), the correlation between BSE and Asian developed equity markets rose dramatically when most of the markets all over the world responded simultaneously to the attacks in the USA[8], this also means that the higher the correlation, the larger is the co-movement between market. After that period we can observe a sharp decline in the intensity of the co-movements. Another increase, in time-varying correlation is observed from 2006 to 2008, when the US sub-prime mortgage crisis triggered a global financial crisis; the highest level of correlation was on October 23rd and 24th, 2008 when all stock markets here considered reported heavy losses. On October the 24th, returns fell heavily by 11.6% in the BSE index, -10.5% in the Nikkei, -8.65% in both Hang Seng and STI stock markets in line with many of the world's stock exchanges with negative returns of around 10% in most indices. Thus the DCC analysis suggests that short-term interdependencies between the BSE and Asian developed markets rose dramatically through the crisis period but since then they returned to approximately initial levels. What can be inferred from this behaviour? As noted by Pretorious (2002) co-movements among stock markets might be attributed to three facts like the contagion effect, economic integration as well as stock market

[8] As pointed out by Charles and Darnè (2006), the Twin Tower attacks affected the world stock markets with the US stock markets that closed on the subsequent four days, and European stock markets as well as the Nikkei 225 which experienced negative shocks immediately in the days subsequent to the attacks.

characteristics[9]. Given that India is an emerging country while the other countries are among the most developed countries in Asia, we may guess strong differences between industrial similarity and market size which takes place among emerging and developed countries so high correlations might be mainly explained by the so called ‘contagion effect’.

Figure 3– Time varying correlations for pair wise stock markets returns



In order to check whether inclusion of the same day’s value for each preceding Asian market (that is Hong Kong, Japan and Singapore) may alter the result somewhat, we re-run all the previous DCC models with that specification. Results are given in table 9. Overall mean and volatility equations show behaviour quite similar to the benchmark models (that is DCC models estimated in table 8). Main differences come up in the values of coefficients of the past shocks parameter, that is $\varepsilon_{i,t-1}\varepsilon_{j,t-1}$, on current dynamic correlations: these values are not significant in 2 out of 3 cases. A further difference is evidenced through the plot of correlations among these markets (Figure 4). In all cases, there is no evidence of increasing or decreasing correlation among these markets during the whole period considered. Peaks in correlations seem to have a sporadically frequency: we may suppose that reasons are international events which affected almost all international stock markets. We observe several peaks in each graph of figure 3. Among them we note one in the second part of 2001 and another one in 2007: as pointed out above, these events were the Twin Tower attacks as well as the start of the sub-prime crisis in 2007. Kuper and Lestano (2007) argue that linkages

[9] Contagion occurs when co-movements of equity markets are not explained by economic fundamentals. Economic integration among countries is based on trade relationships, as well as economic indicators which can affect directly stock markets, like, interest rates and inflation, while stock market characteristics are based on the composition of whole economies as well as the size of equity markets (Pretorious, 2002).

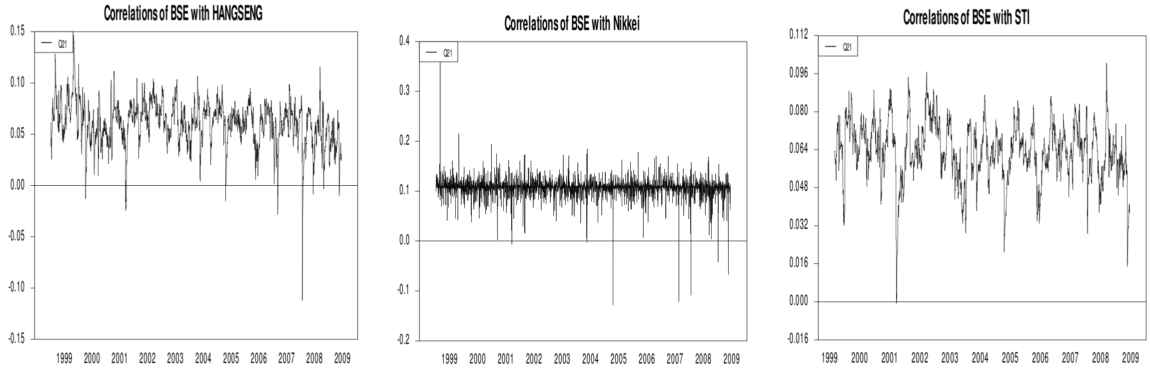
between financial markets can be affected by the crisis events: so we may affirm that the time varying correlation among the Indian and Asian developed stock markets seems to raises in correspondence of unexpected international crisis. Overall the correlations among these markets are generally positive, this implies a certain degree of interdependence during the period considered.

Table 9 - Results of Bivariate DCC-GARCH (1,1) models on daily return indices

Panel A – BSE 30 and Hang Seng markets	**BSE 30**	**Hang Seng**
I. Returns equations $E(y_{i,t} / I_{t-1}) = y_{i,t} - r_{i,t}$		
Constant	0.0014*** (0.0025)	5.589e-04** (2.247e-04)
II. Volatility equations $E(r_{i,t}^2 / I_{t-1}) = h_{i,t}$		
Constant	6.8e-06*** (1.5e-06)	9.952e-07*** (3.605e-07)
$r_{i,t-1}^2$	0.131***(0.0157)	0.06***(0.007)
$h_{i,t-1}$	0.853***(0.017)	0.937***(0.007)
III. Correlation equation $E(\varepsilon_{i,t}\varepsilon_{j,t} / I_{t-1}) = q_{i,j,t}$		
$\varepsilon_{i,t-1}\varepsilon_{j,t-1}$	0.041**(0.072)	
$q_{i,j,t-1}$	0.929***(0.038)	
Panel B – BSE 30 and Nikkei 225 markets	**BSE 30**	**Nikkei 225**
I. Returns equations $E(y_{i,t} / I_{t-1}) = y_{i,t} - r_{i,t}$		
Constant	0.0014*** (0.0002)	3.94e-04*(2.38E-04)
II. Volatility equations $E(r_{i,t}^2 / I_{t-1}) = h_{i,t}$		
Constant	6.77e-06***(1.57e-06)	2.94e-06***(8.051)
$r_{i,t-1}^2$	0.130***(0.0156)	0.086***(0.009)
$h_{i,t-1}$	0.857***(0.0167)	0.903***(0.01)
III. Correlation equation $E(\varepsilon_{i,t}\varepsilon_{j,t} / I_{t-1}) = q_{i,j,t}$		
$\varepsilon_{i,t-1}\varepsilon_{j,t-1}$	0.0002(0.0005)	
$q_{i,j,t-1}$	1.0001***(0.000839)	
Panel C – BSE 30 and STI markets	**BSE 30**	**STI**
I. Returns equations $E(y_{i,t} / I_{t-1}) = y_{i,t} - r_{i,t}$		
Constant	0.001***(0.00026)	4.898E-04**(1.93e-04)
II. Volatility equations $E(r_{i,t}^2 / I_{t-1}) = h_{i,t}$		
Constant	6.917E-06***(1.47E-06)	1.328E-06***(4.231E-07)
$r_{i,t-1}^2$	0.141***(0.015)	0.097***(0.01)
$h_{i,t-1}$	0.842***(0.0163)	0.9***(0.01)
III. Correlation equation $E(\varepsilon_{i,t}\varepsilon_{j,t} / I_{t-1}) = q_{i,j,t}$		
$\varepsilon_{i,t-1}\varepsilon_{j,t-1}$	-0.003(0.003)	
$q_{i,j,t-1}$	0.961***(0.022)	

Notes: Standard error are in parenthesis. Three/Two/One stars indicate the significance level at 1%, 5% and 10%.

Figure 4– Time varying correlations for pair wise stock markets returns with inclusion of the same day's value



Conclusions

In this paper, we have explored the relationship between Indian and Asian developed equity markets over the 1999-2009 period. By applying the unit root test we find that all stock prices are nonstationary, as a consequence they can be used in cointegration methodologies. Applying the Engle and Granger cointegration test we do not find evidence of cointegration among these markets at a 5% level, also using the most sophisticated Johansen cointegration test, no long-run relationship between India and every one of the Asian developed markets was discovered. Further examination using the Gregory-Hansen approach rejects the null hypothesis of no cointegration with structural breaks among these markets. From the last results we may infer that the presence of an equilibrium relationship does limit the potential benefits for portfolio diversification of international investors aiming to share their investments among India and one of the other stock markets considered here. We may also add that the presence of equilibrium relationships may be due to the strengthening of trade relations among India and the other countries considered in the present study.

We further estimated the conditional relationships between the Indian and Asian stock markets by estimating bivariate DCC-GARCH models. On the one hand results show that the assumption of constant conditional correlation does not hold given that we find evidence of time varying correlations between stock markets, further the DCC analysis suggests that the conditional correlations between India and these other markets rose dramatically through the periods of international crisis (i.e the September 11, 2001 attacks as well as the recent subprime mortgage financial crisis), although after those crises the conditional correlations returned to their initial levels.

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