Correlation Dynamics in Equity Markets
Evidence from India

Executive Summary

Equity market integration has wider notion in finance literature. Markets are said to be highly integrated only if irrespective of the market, assets with similar risk have identical expected return. Albeit this, understanding the correlation structure and dynamics of the equity markets of the world is the first step in getting the bigger picture of market integration. Without a good correlation structure, other aspects of market integration are not theoretically reflective. Keeping that in mind this study aimed at analyzing the correlation structure of the Indian equity markets with that of world markets. This paper used daily data from 1st July 1997 to 18th August 2006 of the following 11 world indices: NASDAQ Composite (USA), S&P 500 (USA), FTSE 100 (UK) and DAX 30 (Germany) are classified as developed markets, whereas KLSE Composite (Malaysia), Jakarta Composite (Indonesia), Straits Times (Singapore), Seoul Composite (South Korea), Nikkei (Japan), Taiwan Weighted Index (Taiwan) and the S&P CNX Nifty (India) are considered as Asian markets.

The following three generic correlation measures are derived. *All markets* considered the entire 11 markets specified, *Asian markets* considered only the 7 markets classified, *developed markets* considered only the 4 markets classified. Further to get deeper insight on the individual correlation structure between S&P CNX Nifty with world markets two other measures are derived. *S&P CNX Nifty-Asian* considered S&P CNX Nifty with other 6 Asian markets and *S&P CNX Nifty-Developed* considered S&P CNX Nifty with the 4 developed markets. The following two methods are used to derive the correlation structure: i) unconditional correlation estimate and ii) dynamic time varying correlation estimate using a DCC-MVGARCH of Engle and Sheppard (2001). Both these estimates are exhibiting a poor correlation with an average correlation is below 30 percent. We used BSE 100 Index and estimated the unconditional correlation as a robustness check. The results found to be in similar pattern displayed by S&P CNX Nifty Index. The highest correlation is resulted for 4 developing countries specified with around 60 percent. The individual correlation structures between S&P CNX Nifty with other markets are fairly lower than other estimates.

In addition a Logistic Smooth Transition Regression (LSTR) model is implemented for the derived correlation series to identify potential regime shift in the correlation dynamics and to categorize the phase of integration across these markets. The LSTR results for the conditional time varying correlation of S*&P CNX Nifty-Asian* and *S&P CNX Nifty-Developed* shows that there is a significant regime shift in the year 2000 and there is a considerable increase in integration in the second regime. This indicates that the S&P CNX Nifty index is moving towards a better integration with other world markets but not at a very noteworthy phase. The high volatility in recent years faced by the Indian equity markets can be attributed to this low level of correlation and market integration with other world markets as it provides space for the global funds to diversify risk.

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1. Introduction

Equity market integration plays a very significant role in shaping the fortunes of any developing nation. The foreseeable benefits apply not only to the realm of financial markets but for economic growth and development itself: First, in a fully integrated capital market all risk factors trade at the same price. The law of one price will apply to all securities. This per se should have a positive effect on the functioning of financial markets and indirectly on the performance of investments. Second, greater integration would mean a free or relatively freer access to foreign financial markets. This better access would provide many firms a broader source for fund raising. Third, more internationally diversified stock and bond portfolios should as a consequence shift the frontier of efficient portfolios upwards and therefore for each given risk the average portfolio return should increase. It would create enormous opportunities for domestic and international investors to diversify their portfolios across the globe. Fourth, equity market integration is of considerable significance to issuers and investors as it plays a critical role in channeling funds. Stock markets tend to be very efficient in the allocation of capital to its highest-value users. Such integrated markets could also help to increase savings and investment, which are essential for economic development. An equity market, by allowing diversification across a variety of assets, helps reduce the risk the investors must bear, thus reducing the cost of capital, which in turn spurs investment and economic growth.

A high degree of integration is not without its limitations. One constant argument however is that these limitations of integration do not begin to have an impact until very high rates of integration is achieved. Issues such as vulnerability to foreign price fluctuations, drain of domestic funds and the argument that excessive integration could be self-defeating are valid only when the degree of correlation between markets is very high. Consequently the obvious advantages are what most emerging economies focus on in their drive towards greater integration.

In literature measuring market integration has been done broadly through three ways. First, testing the segmentation of the equity markets via the international CAPM. It typically assumes that all the world's capital markets are perfectly integrated and therefore the asset risk can be related purely with the covariance of the local returns with the world market portfolio. Second, a significant number of studies have examined the integration through increasing correlations and cointegration in their returns over time. Third, time varying estimates rectifies the weakness in the above-mentioned methods that misses the important element of time variation in equity risk premia.

Market integration is something more than the correlation structure across the markets. Understanding the correlation structure is the first step towards understanding the wider notion of market integration. Without a good correlation structure, other aspects of market integration are not theoretically reflective. This study is an attempt to analyze the correlation structure and to test the equity market integration between the Indian equity market with some of the major World markets including the Asian markets.

The main contribution of this study over some of the previous studies is in two fold. First, this study uses DCC-MVGARCH model to estimate the dynamic correlation among the equity market of a developing country (India) with the World and Asian markets along with simple unconditional correlation. Second, a Logistic Smooth Transition Regression (LSTR) method is used to estimate not only the extent of correlation between returns but the also the pace of integration. The advantage of logistic trend models is that they can indicate the speed at which markets are getting integrated, information that cannot be attained through conventional correlation analysis. This paper is organized as follows. Section 2 gives a brief overview of the literature on equity market integration. Section 3 narrates the methodology to estimate the unconditional correlation, conditional correlation through DCC-MVGARCH model and explains the logistic smooth transition regression. Section 4 discusses the results and the final section concludes with a summary.

2. Literature

A rigorous test for equity market integration has had an interesting past, with varied conclusion being made on the back of a wide range of studies. One of the most striking features of financial integration is the extent of literature that exists in the topic. The body of literature can be classified based on the approach adopted by the author both in terms of econometric method as well as theoretical underpinning of the transmission mechanism. Since the seminal work of Grubel (1968), which expounded the benefits of international portfolio diversification, the relationship among national stock markets has been analyzed in a series of studies such as Granger and Morgenstern (1970), Ripley (1973), Lessard (1974,1976) and Panton, Lessig and Joy (1976) among others.

Other work in the field includes Eun and Shim (1989) VAR models to measure transmission of stock movements, providing evidence of co-movements between the US market and other world equity markets, Koutmos and Booth (1995) studied the asymmetric volatility transmissions in international stock markets using an Exponential GARCH model. In recent times Chelley-Steeley (2005) used a bivariate model along with logistic smooth transition regression to establish how rapidly the countries of Eastern Europe are moving away from market segmentation. Kearney and Poti (2006) examined the correlation dynamics for European equity markets using an asymmetric DCC-MVGARCH specification and found evidence in favor of structural break at the beginning of the process of monetary integration in Euro-zone.

A small body of literature exists in the Indian context, which predominantly depends on the bivariate and multivariate cointegration analysis. The study by Kumar and Mukhopadhyay (2002) uses a two-stage GARCH model and an ARMA-GARCH model to captures the mechanism by which NASDAQ daytime returns impacts not only the mean but also conditional volatility of Nifty overnight returns. Ignatius (1992) compared returns on the BSE Sensex with those on the NYSE S&P 500 Index and found no evidence of integration. Agarwal (2000) concluded that there is a lot of scope for the Indian stock market to integrate with the world market after having found a correlation coefficient of 0.01 between India and developed markets. By using Granger causality relationship and the pair wise, multiple and fractional cointegration, Wong, Agarwal and Du (2005) have found that the Indian stock market is integrated with the matured markets of the World. Nath and Verma (2003) tested for cointegration between the Nifty, STI and Taiex and found no evidence in favor of cointegration.

Though research on India has evolved constantly both in terms of econometric techniques and the focus of study, nevertheless, a gap still exists in terms of literature on India. The existing literature though provides valuable insights into the extent of integration; none of the studies have really focused on the underlying dynamics of the process of integration over time. The liberalization effort has often been assumed to be instantaneous process rather than a gradual one. This study, in contrast, attempts to measure the pace of integration, which at its core works on the premise that integration follows a traceable path over time. This potentially serves as a critical indicator of the strength of the integration process, and provides an insight into the longevity of the same.

3. Methodology

3.1 Unconditional Correlation Estimates

The unconditional correlations are derived from the conventional second moments on asset returns. This method is widely used in the literature because of its simplicity. The estimates are computed from the cross products of the standardized daily log-return R_{it} deviations from their monthly sample means and sum them to obtain monthly non-overlapping correlation estimates for each pair of indices i and j.

$$c_{i,j,t} = \frac{\sum_0^n (R_{i,t-n} - \overline{R}_{i,t})(R_{j,t-n} - \overline{R}_{j,t})}{\sqrt{\sum_0^n (R_{i,t-n} - \overline{R}_{i,t})^2 \sum_0^n (R_{j,t-n} - \overline{R}_{j,t})^2}} \tag{1}$$

From the above pair wise correlation we can get the equally weighted average correlation across the market indices as follows

$$UCCORR_t = \sum_{i-1}^{n} \frac{1}{n} \sum_{j=1}^{n} \frac{1}{n} c_{i,j,t} \tag{2}$$

Where n is the number of market indices.

3.2 Conditional Correlation Estimates

The main shortcomings of the above mentioned unconditional correlation estimates are two fold. First, the average of squares and cross products are consistent estimators of the second moments of the return distributions, albeit its consistency ad hoc representation of the volatility and correlation process, it might be biased in small samples. Second, aggregating the daily data to get monthly estimates of correlation will result in potential small sample problem. To overcome these deficiencies in the unconditional correlation estimates we apply the recently developed DCC-MVGARCH model of Engle (2002) and Engle and Sheppard (2001).

This class of MVGARCH models differs from other specification as it was designed to allow for two-stage estimation. In the first stage the univariate GARCH model is estimated for each series in examination and the residual series are obtained and in the second stage these residual along with the standard deviation obtained from the first stage are used to estimate the dynamic correlation. In this study we followed Engle and Sheppard (2001) methodology to estimate the dynamic correlation among the market indices. The returns from n indices are conditionally multivariate normal with zero expected value and covariance matrix H_t.

$$R_t \big| \Im_{t-1} \sim N(0, H_t) \text{ and } H_t \equiv D_t C_t D_t \tag{3}$$

where D_t is nxn diagonal matrix of time varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the i^{th} diagonal, and C_t is the time varying correlation matrix. The elements of D_t are described as h_{it} that takes the form

$$h_{it} = \omega_i + \sum_{p=1}^{P} \alpha_{ip} R_{it-p}^2 + \sum_{q=1}^{Q} \beta_{iq} h_{it-q} \tag{4}$$

For i = 1, 2 … with usual GARCH restrictions for non-negativity and stationarity being imposed. The subscripts p and q are the lag length of the each series, with this Engle and Sheppard (2001) derived the dynamic correlation structure as follows:

$$Q_t = (1-\alpha-\beta)\,\overline{Q} + \alpha(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + \beta Q_{t-1}$$

$$C_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where $\overline{Q}$ is the unconditional covariance of the standardized residuals resulting from the first stage estimation and Q_t^* is the diagonal matrix consists of square root of diagonal elements of the Q_t. So C_t will be the correlation matrix that takes the form $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$.

3.3 Logistic Smooth Transition Regression

The logistic smooth transition function has a long tradition in the statistical modeling of changing regimes, being introduced by Bacon and Watts (1971) and extended to time series regression and autoregressive models by Lin and Teräsvirta (1994) and Granger and Teräsvirta (1993). The LSTR model identifies any fundamental change as a single structural break that leads to a smooth transition between two regimes as opposed to an instantaneous shift in the underlying relationship. In this paper, we employ a variation of the simple, nonlinear, smooth transition logistic trend model suggested by Granger and Teräsvirta (1993). The smooth transition model is applied to the equity market correlations generated from the unconditional and condition correlation estimates. The Logistic Smooth Transition Regressive model is generally defined as follows,

$$\rho_{ij,t} = \alpha + \beta S_t(\gamma,\tau) + \nu_t \tag{5}$$

$$S_t(\gamma,\tau) = (1+\exp(-\gamma(t-\tau T)))^{-1},\ \gamma > 0 \tag{6}$$

where $\rho_{ij,t}$ is the correlation between the NSE index (i) and one of the market index in examination (j) at time t with S_t playing the role of a smooth transition continuous function bounded between 0 and 1. The α and β are coefficients. The parameter τ determines the timing of the transition midpoint and γ measures the speed of adjustment.

For $\gamma > 0$ we have $S_{-\infty}(\gamma,\tau) = 0$, $S_{+\infty}(\gamma,\tau) = 1$ and $S_t(\gamma,\tau) = 0.5$. In the limiting case when $\gamma = 0$, $S_t(\gamma,\tau) = 0$ for all t and no integration takes place. The trend component has been removed from the model, as there is no reason to expect equity market correlations to exhibit a trend increase. If $\gamma < 0$ the initial and final states of the model are reversed, however the interpretations of the various parameters still remain the same. Further, the model assumes $\rho_{ij,t}$ to be stationary around a mean that changes from an initial value of 'α' (prior to integration) to '$\alpha+\beta$'. Thus, 'α' is a measure of market integration in the first regime and 'β' is the increase (if b is positive) or decrease (if b is negative) in market integration in the second regime.

4. Results

This paper considered the following 11 indices. As a representative of developed markets, NASDAQ Composite (USA), S&P 500 (USA), FTSE 100 (UK) and DAX 30 (Germany) are taken. Asian markets include S&P CNX Nifty (India), KLSE Composite (Malaysia), Jakarta Composite (Indonesia), Straits Times (Singapore), Seoul Composite (South Korea), Nikkei (Japan) and Taiwan Weighted Index (Taiwan). Daily data from 1st July 1997 to 18th August 2006 are taken from NSE India website (www.nseindia.com) for S&P CNX Nifty index and Yahoo Finance (finance.yahoo.com) for all other indices.

The study period we have selected is dictated by two facts. First, we use S&P CNX Nifty as benchmark index for India, so we have data only from July1997. Second, we get consistent data for all other markets in question for the specified time period only.

4.1 Unconditional Correlation Estimates

A set of unconditional correlation estimates have been derived. It includes correlation for all the markets taken, correlation for Asian markets and correlation for developed markets. As explained in Section 3, estimation of unconditional correlation involves three steps. First calculating monthly mean returns of each index for 110 months from July 1997 to August 2006. Second calculating non overlapping pair wise correlation for the returns of each two indices using Equation1 and finally the average of these pair wise correlations will give us the unconditional correlation estimates across all these markets, while the stand alone average of Asian markets and the developed markets will give us the unconditional correlation of those particular markets.

Table 1 list the average pair wise correlation structure between the markets and Table 2 provides the average unconditional correlation estimates for all the three market classification i.e. all markets, Asian markets and developed markets.

Table 1: Average Pair wise Correlation Structure

Markets	**S&P CNX Nifty**	**NASDAQ**	**S&P 500**	**FTSE 100**	**DAX 30**	**KLSE**	**JTSE**	**Strait Times**	**Seoul**	**NIKKEI**	**Taiwan**
S&P CNX Nifty	1.000										
NASDAQ	0.118	1.000									
S&P 500	0.103	0.882	1.000								
FTSE 100	0.206	0.447	0.480	1.000							
DAX 30	0.191	0.524	0.533	0.749	1.000						
KLSE	0.126	0.120	0.094	0.134	0.136	1.000					
JTSE	0.232	0.046	0.037	0.120	0.121	0.238	1.000				
Strait Times	0.241	0.230	0.202	0.349	0.339	0.373	0.298	1.000			
Seoul	0.291	0.231	0.214	0.298	0.321	0.257	0.243	0.454	1.000		
NIKKEI	0.244	0.267	0.228	0.347	0.346	0.293	0.207	0.455	0.488	1.000	
Taiwan	0.183	0.217	0.171	0.213	0.230	0.230	0.210	0.414	0.423	0.390	1.000

Table 2: Average Unconditional Correlation Estimate with S&P CNX Nifty

Market	**Average Unconditional Correlation Estimate**
All Markets	0.2824
Asian Markets	0.2994
Developed Markets	0.6026

The average unconditional correlation estimates clearly shows that the developed markets are highly integrated with higher correlation estimate whereas the Asian markets are integrated very lower with low correlation estimate. This also pulls down the average all market correlation to further lower level.

To understand the correlation between S&P CNX Nifty index with the Asian markets and other developed markets, we calculate non overlapping pair wise correlation for the returns of S&P CNX Nifty index with other indices using Equation1 and average it to get unconditional correlation estimates. The average unconditional correlation estimate of S&P CNX Nifty index with Asian markets is 0.2193 where as with the developed markets it is very lower with 0.1545.

The results clearly exhibits the week equity market integration across the Asian markets and in particular Indian equity market integration with both Asian and developed markets. As a robustness check we used BSE 100 index instead of S&P CNX Nifty index as a representative of Indian equity market. The results are in the similar pattern with slightly lower correlation than the S&P CNX Nifty index. Table 3 presents the results.

Table 3: Average Unconditional Correlation Estimate with BSE 100

Market	Average Unconditional Correlation Estimate
All Markets	0.2815
Asian Markets	0.2989
Developed Markets	0.6026
BSE-Asian Markets	0.2176
BSE-Developed Markets	0.1453

4.2 Conditional Correlation Estimates

The advantage of conditional correlation estimates is that it gives a dynamic time varying estimates. So there is no need to find the deviation of daily return from the monthly mean to calculate the correlation for each month. This removes the disadvantages associated with averaging. The DCC-MVGARCH model is used on the daily returns of the above mentioned indices to derive the time varying conditional correlation estimates[1]. Table 4 presents with the parameter estimates of the model in two segments. First the estimates of univariate GARCH (1, 1) models of the individual indices, followed by the DCC-MVGARCH (1, 1) estimates. Engle and Sheppard's (2001) test for constant correlation

[1] The model is estimated in MATLAB using GARCH Tool Box

among the returns rejected the null of constant correlation in favor of a time varying correlation matrix.

Table 4: Estimates of the DCC-MVGARCH model

		Coefficient
Univariate GARCH (1, 1)		
S&P CNX Nifty	ω	0.0025** (0.0000)
	α_1	0.1044** (0.0017)
	β_1	0.8264** (0.0071)
NASDAQ	ω	0.0002** (0.0000)
	α_1	0.0751** (0.0005)
	β_1	0.9249** (0.0004)
S&P 500	ω	0.0002** (0.0000)
	α_1	0.0897** (0.0007)
	β_1	0.9015** (0.0008)
FTSE 100	ω	0.0002** (0.0000)
	α_1	0.0962** (0.0003)
	β_1	0.8945** (0.0003)
DAX 30	ω	0.0006** (0.0000)
	α_1	0.0979** (0.0007)
	β_1	0.8911** (0.0006)
KLSE	ω	0.0001** (0.0000)
	α_1	0.0556** (0.0012)
	β_1	0.9444** (0.0011)
JTSE	ω	0.7778 (0.5319)
	α_1	0.0957 **(0.0036)
	β_1	0.0001 (0.0001)
Strait Times	ω	0.0003** (0.0000)
	α_1	0.1118** (0.0014)
	β_1	0.8882** (0.0011)
Seoul	ω	0.0003** (0.0000)
	α_1	0.0739** (0.0009)
	β_1	0.9257** (0.0008)
NIKKEI	ω	0.0007** (0.0000)
	α_1	0.0824** (0.0004)
	β_1	0.8949** (0.0006)
Taiwan	ω	0.0004** (0.0000)
	α_1	0.0704** (0.0007)
	β_1	0.9229** (0.0007)
DCC-MVGARCH (1, 1)		
α		0.0123** (0.0000)
β		0.9620** (0.0002)

Note: Standard errors in parentheses and ** denotes significance at 1% level

The results show a significant parameter estimates for DCC-MVGARCH (1, 1) model. Figure 1 plots the three conditional correlation estimates derived for returns of all the markets, Asian markets and the Developed markets. The graph clearly shows that none of these conditional correlation estimates are showing any significant trend. Over the past decade the correlation among these markets are flat, in other words we can say the market integration across these markets are naïve.

Figure 2 graphs the time varying conditional correlation estimates derived for S&P CNX Nifty index with developed markets and Asian markets. The graph shows a slight upward movement across S&P CNX Nifty and other Asian markets and the developed markets in the recent years. The average of this conditional correlation estimates are again gives a similar picture that of unconditional correlation estimates. Table 5 presents the results. While considering correlation on returns as an initial aspect of equity market integration, these results clearly shows that the Indian equity market is still in the infancy with respect to world market integration.

Figure 1: Conditional Correlation Estimates

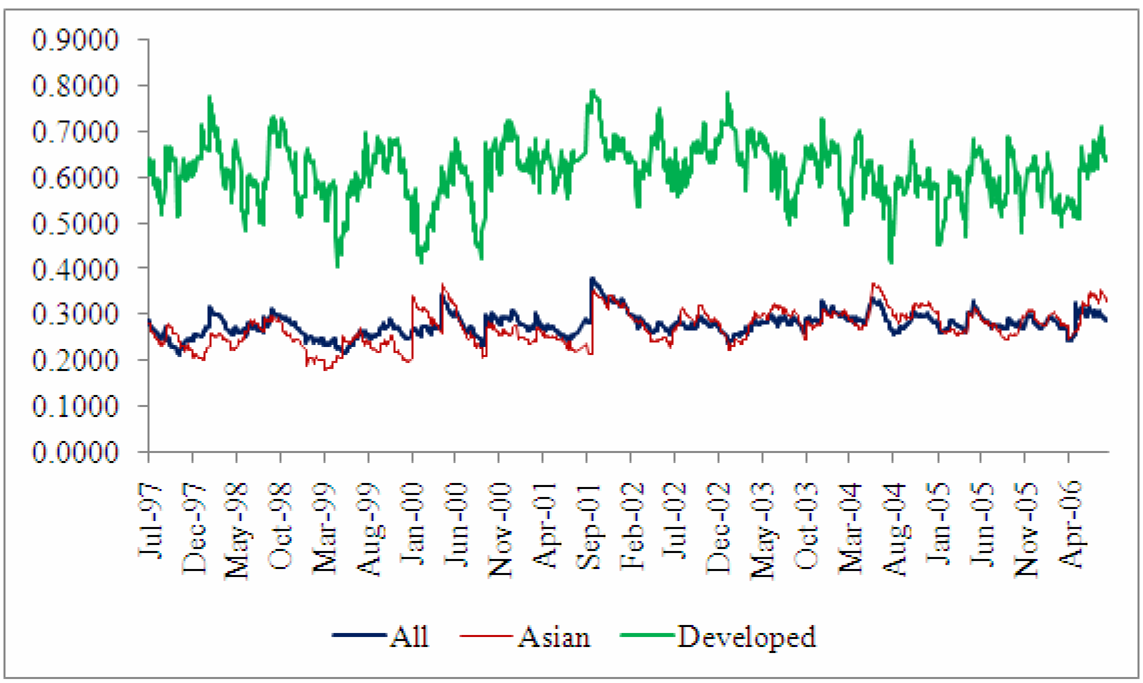

Figure 2: Conditional Correlation Estimates between S&P CNX Nifty and Asian & Developed Markets

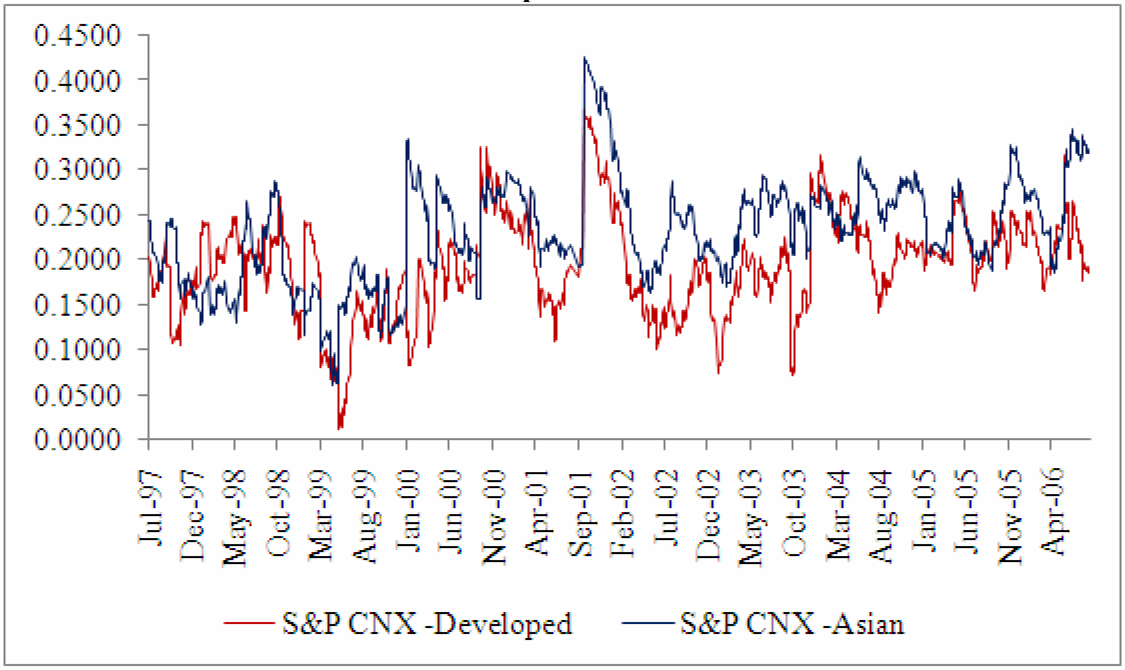

Table 5: Average Conditional Correlation Estimate with S&P CNX Nifty

Market	Average Conditional Correlation Estimate
All Markets	0.2777
Asian Markets	0.2747
Developed Markets	0.6145
S&P CNX -Asian Markets	0.2321
S&P CNX -Developed Markets	0.1924

In literature there are many studies that established the emerging markets have relatively low correlation with the developed markets. Low correlation provides a space for international diversification opportunities and in effect provides an explanation for flooding capital towards emerging markets. This capital flow is not only for risk diversification but also for the returns in emerging markets that are much higher than the developed markets. Goetzmann and Jorion (1999) found that the returns from a sample of emerging markets are three times higher than that from a sample of developed markets.

We used Logistic Smooth Transition Regression (LSTR) model to qualify this low correlation exhibited by S&P CNX Nifty index against the Asian and the developed markets towards the following objectives. Firstly to validate the low correlation as an indicator of low level of market integration and secondly to check for any possible movement it shows towards integration.

4.3 Logistic Smooth Transition Regression

Smooth transition analysis is basically an approach to model deterministic structural change in time series regression. Chelley-Steeley (2004) applied that for equity markets in Asia-Pacific region to analyze market integration. She argues that first step prior to the application of smooth transition is to check for stationarity of the correlations and consistent levels of comovement. Since a stationary correlation would indicate no breaking point and no change in the level of integration. We perform an augmented Dickey Fuller (ADF) test on all the correlation series we derived above. The results are shown Table 6 for unconditional correlation series and Table 7 for conditional time varying correlation series.

Table 6: Unit Root Test for Unconditional Correlation Series

Correlation Series	ADF Statistics
All Markets	-2.582**
Asian Markets	-3.100**
Developed Markets	-1.968*
S&P CNX -Asian Markets	-8.463**
S&P CNX -Developed Markets	-5.591**

** and * indicates significance at 1% and 5% levels respectively

Table 7: Unit Root Test for Conditional Time varying Correlation Series

Correlation Series	ADF Statistics
All Markets	-0.437
Asian Markets	-0.417
Developed Markets	-0.691
S&P CNX -Asian Markets	-1.327
S&P CNX -Developed Markets	-0.827

** and * indicates significance at 1% and 5% levels respectively

From the above tables, it clearly indicates that for the unconditional correlation series all the series are stationary whereas for the conditional time varying correlation series all the series are I(1). As pointed out above running a smooth transition regression for stationary series is meaningless. Also the idea of running a smooth transition regression is to figure out the level of market integration by S&P CNX Nifty index towards other Asian and developed markets. So we estimated the model depicted in equations 5 and 6 only for S&P CNX Nifty with Asian markets and the developed markets. Table 8 provides the results.

Table 8: Results from Smooth Transition Model

Parameters	S&P CNX-Asian	S&P CNX-Developed
α	0.1885 (0.002)**	0.1739 (0.002)**
β	0.0113 (0.003)**	0.0804 (0.002)**
γ	0.4433 (3.041)	0.5119 (0.452)
τ	0.3036 (0.010)**	0.2743 (0.001)**

** and * indicates significance at 1% and 5% levels respectively

A significant τ shows that the series have a regime shift in terms of market integration. By considering the values of τ we can find the transition midpoint for S&P CNX Nifty-Asian correlation series in mid of April 2000 and for S&P CNX Nifty-Developed correlation series it is in January 2000. For both Asian and developed markets β is positive, that means that there is an increase in market integration in the second regime. Insignificant γ in both the estimates reflects the fact that the pace of integration is not very rapid across these markets. The results clearly shows that after the year 2000, S&P CNX Nifty index is moving towards a better integration with Asian and other developed markets but not with significant level of speed.

5. Conclusion

This study analyzed the correlation dynamics between Indian equity market with Asian and other developed markets. For India we considered S&P CNX Nifty index as representative index and used BSE 100 index for robustness check. Daily data for the period from 1^{st} July 1997 to 18^{th} August 2006 are considered for the study with 10 other world indices. Two methods namely unconditional correlation and conditional time varying correlation with DCC-MVGARCH model are used to extract the correlation across these markets. Both the measures display a poor correlation across these markets particularly that of S&P CNX Nifty index with six Asian markets and S&P CNX Nifty index with four developed markets separately. The average correlation for these markets are below 30 percent with only the four developed markets show a high correlation between them with more than 60 percent. Further a smooth transition model is applied to understand regime shifts in the correlation series as well as the pace of market integration. The results support a significant regime shift in the year 2000 and after that the pace of integration across S&P CNX Nifty index with Asian markets and other developed markets has showed a positive movement but not at very rapid pace. This is in support of the argument that an emerging market gives space for diversification for global funds and the high volatility in recent years faced by the Indian equity markets can be attributed to this fact.

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