Study of Common Stochastic Trend and Co-Integration in the Emerging Markets
A Case Study of India, Singapore and Taiwan

Golaka C Nath & Sunil Verma

Abstract

The relationship between the stock markets of the developed countries has been examined extensively in the literature. This study examines the interdependence of the three major stock markets in South Asia. Using daily stock market data from January 1994 to November 2002, we examine the stock market indices of India (NSE NIFTY), Singapore (STI) and Taiwan (Taiex). The index level series are non-stationary and so we employ bi-variate and multivariate cointegration analysis to model the linkages among these stock markets. We found no cointegration between the stock market indices for the entire period and hence no long run equilibrium. We found mild causality for some years in the study though most of the time these markets have not been interlinked. The study has used. It should be borne in mind that the tests carried out only tests for presence or absence of linear relationships.

June 2003

Introduction

Financial literature has presented a strong emphasis on the interaction amongst international financial markets. Since the October 1987 stock market crash a large empirical literature has emerged testing interdependence among national equity markets. Portfolio diversification models (Markowitz, 1952; Sharpe, 1964; Lintner, 1965) have been developed on the premise of strong interdependence of various markets. If stock markets move together then investing in various markets would not generate any long-term gain to portfolio diversification. Therefore, it is important for both investors and academicians to know whether stock markets are interlinked. The issue is also important for policy makers for the following reason; if stock markets are found to be closely linked then there is a danger that shocks in one market may spill over to other markets. The interest on study of interlinkages of various markets has increased considerably following the abolition of foreign exchange controls in both mature and emerging markets during last 15 years, the technological developments in communications and trading systems and attaining such technology at cheaper costs, and the introduction of innovative financial products in markets giving market participants opportunity to hedge their risk, increasing cross-border movement of funds, issuers raising funds through American Depository Receipts and Global Depository Receipts, which have created more opportunities for global international investments. The gradual dismantling of regulatory barriers and the introduction of more advanced technology, have called for new market structures and practices, keeping in mind the move to reach a global standardization. In particular, the new attractive emerging equity markets have attracted the attention of international fund managers as an opportunity for portfolio diversification and have also intensified the curiosity of academics in exploring international market linkages.

Over the past fifteen years, financial markets have become increasingly global. In the globalised financial markets, the main challenge for both investors and policy makers is to take advantage of and promote efficiency enhancing aspects of market interaction, while containing and controlling the undesirable destabilising effects. The early literature, however, merely showed whether or not there were benefits from international portfolio diversification, ignoring the issue of how the degree of capital market integration may actually affect these diversification benefits.

Emerging equity markets have continued to grow and have seen the relaxation of foreign investment restrictions, especially during the last 15 years, primarily through country deregulation. India, one of the major emerging markets in Asia initiated the financial sector reforms by way of adopting international practices in its financial market. Indian compamies have raised funds from abroad through issuance of American Depository Receipts (ADR's) or General Depository Receipts (GDR's) that allow trade of foreign securities on the NYSE, NASDAQ or on non-American exchanges.

International economic integration is, in general, a trend that is well worth promoting. The case for capital mobility requires a few more nuances than does the case for trade in goods and services. Some believe that there are possible market failures in financial markets - arising, for example, from the presence of speculative overshooting and from the absence of an international debtors' bankruptcy court -- and that these have contributed to difficulties in emerging markets. But overall, the advantages of open financial markets dominate. Equities are a particularly attractive mode for international cross border capital flows. In the event of adverse economic outcomes, equity prices automatically fall, eliminating the need for lengthy and costly negotiations between borrower and creditor countries.

Regional integration of equity markets has two distinct facets. First, issuers and investors expand their activities more widely across the region. Here the point is that the abolition of barriers to cross-border equity holdings allows borrowers to raise capital more cheaply and allows investors to earn better returns. Such integration of capital markets also helps promote integration along other lines as well, such as integration of money markets and of markets in goods and services. Second, equities are increasingly traded on exchanges outside the home country. Trading in equities is a financial service. Much like other goods and services, comparative advantage may dictate that it is more efficient to undertake the trading in a foreign financial center than domestic.

We intend to explicitly characterize the dynamic interactions among these emerging markets in Asia to study their level of integration. The objective of the paper is to understand the dynamic inter-linkages between three important emerging equity markets in Asia viz. India, Taiwan and Singapore and to understand whether the stock markets in these Asian are interlinked. If these markets are independent then investors in these countries can invest in different markets of the region to diversify their portfolio and the authorities in the region need not worry about any contagious effects if one market experiences any turmoil. The present study will help in understanding portfolio diversification strategy of international investors who operates in these markets.

The plan of this paper is as follows, in Section 2 we deal with the existing literature survey, section 3 deals with theory and methodological issues behind this paper followed by the Section 4 deals in stationarity of data used in the study while Section 5 deals with the data and section 6 deals with the results followed by Section 7 where we conclude.

Literature Survey:

The most of the existing literature on the study of inter linkages among markets have followed the approach that involves testing the interdependence directly using cointegration (or VAR) techniques and these studies have been done concerning markets of developed and emerging countries. According to this approach if stock prices indices of two or more countries are found to be cointegrated then this implies that stock markets of these countries are interdependent. Our study has also been designed on the basis of this approach and we have reviewed the literature pertaining to the same.

Taylor and Tonks (1989) studies the market integration concerning markets of U.S., Germany, Netherlands and Japan using monthly data on stock price indices for the sub-periods, April1973 – September 1979 and October 1979 – June 1986 and employed is a bivariate cointegration technique (Engle and Granger, 1987). They found stock price index of the U.K. was cointegrated with the stock price index of the U.S., Germany, Netherlands and that of Japan for the later period but not for the former period. Based on these results they suggested that there is no long-term gain from diversification for the U.K investors after the abolition of exchange control. Kasa (1992) also explored common stochastic trends in the stock markets of the U.S., the U.K., Japan, Germany and Canada using monthly and quarterly data from 1974 to 1990 and found that a single common stochastic trend driving these countries stock markets. Byers and Peel (1993) examined the interdependence between stock price indices of the U.S., the U.K., Japan, Germany and the Netherlands using bivariate and multivariate cointegration (Johansen, 1988) techniques for the period October 1979 – October 1989 but unlike Taylor and Tonks they did not find any cointegration either for the group as a whole or for the pairs of markets. Kanas (1998) explored the linkages between the U.S. and European stock markets using the daily data and found that the U.S. stock market was not pairwise cointegrated with any of the six European stock markets. Roca (1999) investigated the price linkages between the equity markets of Australia and that of the U.S., U.K., Japan, Hong Kong, Singapore, Taiwan and Korea using weekly stock market and found that no cointegration between Australia and other markets. But he found that the Granger causality tests revealed that Australia is significantly linked with the U.S. and the U.K.

The literature review shows that there is conflicting evidence on the issue of international stock market linkages and hence the issue needs further investigation. In this paper we examine the linkages among the three emerging Asian markets which have introduced substantial reforms during last one decade and these markets have some common trading time zone which can help investors to move from one market to another if the need arises unlike a market like US which has a no common time zone when these markets are open.

Methodological Issues

The dynamic linkage may simply be examined using the concept of Granger's (1969, 1988) causality. Formally, a time series X_t Granger-causes another time series Y_t if series Y_t can be predicted with better accuracy by using past values of X_t rather than by not doing so, other information being identical. In other words, variable X_t fails to Granger-cause Y_t if

$$\Pr(Y_{t+m} \mid \Psi_t) = \Pr(\mathrm{Y}_{\mathrm{t+m}} \mid \Omega_t) \qquad (1)$$

where $\Pr(\bullet)$ denotes conditional probability, ψ_t is the set of all information available at time t and Ω_t is the information set obtained by excluding all information on X_t from ψ_t. .

Testing causal relations between two stationary series X_t and Y_t (in bivariate case) can be based on the following two equations

$$Y_t = a_0 + \sum_{k=1}^{p} a_k Y_{t-k} + \sum_{k=1}^{p} b_k X_{t-k} + u_t \qquad (2)$$

$$X_t = j_0 + \sum_{k=1}^{p} j_k Y_{t-k} + \sum_{k=1}^{p} \Phi_k X_{t-k} + v_t \qquad (3)$$

where p is a suitably chosen positive integer; a_k ṡ and ß$_k$ ṡ, k = 0,1, … ..,p are constants; and u_t and v_t usual disturbance terms with zero means and finite variances. The null hypothesis that X_t does not Granger-cause Y_t is not accepted if the ß$_k$ ṡ, k>0 in equation (2) are jointly significantly different from zero using a standard joint test (e.g., an F test). Similarly, Y_t Granger-causes X_t if the f_k ṡ, k>0 coefficients in equation (3) are jointly different from zero.

It may be mentioned that the above test is applicable to stationary series. In reality, however, underlying series may be non-stationary. In such cases, one has to transform the original series into stationary series and causality tests would be performed based on transformed-stationary series. A special class of non-stationary process is the I(1) process (i.e. the process possessing a unit root). An I(1) process may be transformed to a stationary one by taking first order differencing. Thus, while dealing with two I(1) process for causality, equations (2) and (3) must be expressed in terms of differenced-series. However, if underlying I(1) processes are cointegrated, the specifications so obtained must be modified by inserting the lagged-value of the cointegration relation (i.e. error-correction term) as an additional explanatory variable (Engle and Granger, 1987). In other words, equations (2) and (3) should be modified as

$$\Delta Y_t = a_0 + \sum_{k=1}^{p} a_k \Delta Y_{t-k} + \sum_{k=1}^{p} b_k \Delta X_{t-k} + d \; \mathrm{ECT}_{t-1} + u_t \qquad (4)$$

$$\Delta X_t = f_0 + \sum_{k=1}^{p} f_k \Delta Y_{t-k} + \sum_{k=1}^{p} \Phi_k \Delta X_{t-k} + h \; ECT_{t-1} + v_t \qquad (5)$$

where Δ is the difference operator and ECT_{t-1} represents an error correction term derived from the long-run cointegrating relationship between the I(1) processes X_t and Y_t. This term can be estimated by using the residual from a cointegrating regression. Clearly, if X_t and Y_t are I(1) but not cointegrated, the term ECT_{t-1} would be absent from equations (4) and (5).

However the deficiencies as brought forward by a number of researchers (Johansen, 1998 and Phillips and Durlauf, 1986) are:

- Finite sample problems of lack of power in unit roots and cointegration tests,
- Asymmetrical treatment of variables as endogenous and exogenous as there is simultaneous equation bias of bi-directional causality, and
- Lack of possibilities for running hypothesis tests on cointegrating relationship.

The first two problems are taken care of by the use of large sample size and all of them are overcome by Johansen's methodology, 1988. In particular, the Johansen methodology provides estimates of all the cointegrating vectors that exist within a vector of variables, fully captures the underlying time series properties of the data, and offers a test statistic for the number of cointegrating vectors with an exact limiting distribution. This test may therefore be viewed as more discerning in its ability to reject a false null hypothesis.

Johansen's Methodology (1988): Johansen's method can be illustrated by considering the following general autoregressive representation for the vector Y, which contains n variables, all of which are I(1),

$$Y_t = a_1 Y_{t-1} + a_2 Y_{t-2} + \ldots. + a_k Y_{t-k} + e_t \qquad (6)$$

where k is the maximum lag, e_t is assumed to be a (*n x1*) vector of Gaussian error terms, and a is a (*n x n*) matrix of coefficients.

In order to use Johansen's test, the above vector autoregressive process can be reparametarized and turned into a vector error correction model of the form as:

$$\Delta Yt = \Pi_1 Y_{t-k} + \Gamma_1 \Delta Y_{t-1} + \ldots. + \Gamma_{k-1} \Delta Y_{t-(k-1)} + e_t \qquad (7)$$

where

$$\Pi = (\sum_{j=1}^{k} b_i) - I_g \text{ and } \Gamma_i = (\sum_{j=1}^{i} b_j) - I_g$$

The issue of potential cointegration is investigated when we compare both sides of equation {7}. As $Y_t \sim I(1)$, $\Delta Y_t \sim I(0)$, so are ΔY_{t-i}. This gives the left-hand side of equation {7} stationarity. Since ΔY_{t-i} are all stationary, the right-hand side of equation {7} will also be stationary if ΠY_{t-k} is also stationary. The Johansen test centers around an examination of the Π matrix. The Π can be interpreted as a long run coefficient matrix, since in equilibrium, all the ΔY_{t-i} will be zero, and setting the error terms, e_t to their expected value of zero will leave $\Pi Y_{t-k} = 0$. The test for cointegration between the *Y*s is calculated by looking at the rank of the Π matrix via eigenvalues. The rank of a matrix is equal to the number of its characteristic roots (eigenvalues) that are different from zero. If the eigenvalues (l_i) are roots, they must be less than 1 in absolute values and positive. If the variables are not cointegrated, the rank of Π will not be significantly different from zero, so $(l_i) \approx 0 \forall i$. The test statistics actually incorporates ln(1- l_i), rather than the (l_i) themselves, but still when (l_i) = 0, ln(1- l_i) = 0

Suppose now that the rank (Π) = 1, then ln(1-λ_1) will be negative and ln(1-λ_i)= $0 \forall i > 1$. If the eigenvalue is non-zero, then ln(1-λ_i) < $0 \forall i > 1$. That is Π to have a rank of 1, the largest eigenvalue must be significantly non-zero, while others will not be significantly different from zero.

Testing for the existence of potential cointegrating relationships among the variables involves testing for statistically significant eigenvalues (λ_i). The eigenvector (ν_i) corresponding to the statistically significant eigenvalues (λ_i) are the coefficient of the variables in the cointegrating relationship. Johansen (1988) suggests the following two likelihood ratio tests, depending on the null and alternative hypotheses considered.

$$l_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1 - \hat{l}i)$$

and

$$l_{\max}(r, r+1) = -T \ln(1 - \hat{l}_{r+1})$$

where r is the number of cointegrating vectors under the null hypothesis and $\hat{l}i$ is the estimated value for the *i*th ordered eigenvalue from the Π matrix. The l_{trace} is a joint test where the null is that the number of cointegrating vectors is less than or equal to *r* against an unspecified or general alternative that there are more than *r*. The l_{max} conducts separate tests on each eigenvalue, and has as its null hypothesis that the number of cointegrating vectors is *r* against an alternative of *r+1*.

Between Johansen's two likelihood ratio tests for cointegration, the trace test shows more robustness to both skewness and kurtosis (i.e., normality) in residuals than the maximum eigenvalue test (see Cheung and Lai 1993, for details): therefore we employ the trace test to perform the cointegration tests.

Theory of Stationarity

Following are different ways of thinking about whether a time series variable X_t is stationary or has a unit root:

- In the AR(1) model, if $\Phi=1$, then X has a unit root. If $|\Phi| <1$ then X is stationary.
- If X has a unit root, then its autocorrelations will be near one and will not drop much as a lag length increases.
- If X has a unit root, then it will have a long memory. Stationary time series do not have long memory.
- If X has a unit root then the series will exhibit trend behavior.
- If X has a unit root, then ΔX will be stationary. For this reason, series with unit root are often referred to as difference stationary series.

The stationarity condition of the data series used in the study has been tested using Augmented Dickey Fuller Test. Consider a simple general AR(p) process given by

$$Y_t = m + f_1 * Y_{t-1} + f_2 * Y_{t-2} + ... + f_p * Y_{t-p} + e_t \qquad (14)$$

If this is the process generating the data but an AR(1) model is fitted, say

$$Y_t = m + f_1 * Y_{t-1} + n_t \qquad (15)$$

then $n_t = f_2 * Y_{t-2} + ... + f_p * Y_{t-p} + e_t$ (16)

and the auto correlations of v_t and v_{t-k} for k> 1 will be nonzero, because of the presence of the lagged Y terms. Thus an indication of whether it is appropriate to fit an AR(1) model can be aided by considering the autocorrelations of the residual from the fitted models. To illiustate how the DF test can be extended to autoregressive process of order greater than 1, consider the simple AR(2) process below

$$Y_t = m + f_1 * Y_{t-1} + f_2 * Y_{t-2} + e_t \qquad (17)$$

and the above is same as

$$Y_t = m + (f_1 + f_2) * Y_{t-1} - - f_2 * (Y_{t-1} - Y_{t-2}) + e_t \qquad (18)$$

and subtracting Y_{t-1} from both the sides give

$$\Delta Y_t = m + b * Y_{t-1} - a_1 \Delta Y_{t-1} + e_t \qquad (19)$$

where the following have been defined

$$b = f_1 + f_2 - 1$$

and $\alpha_1 = -\phi_2$

This means that if the appropriate order of the AR process is 2 rather than 1, the term ΔYt-1 should be added to the regression model. A test of whether there is a unit root can be carried out in the same way as for the DF test, with the test statistics provided by the t 'statistics of the β coefficient. If β = 0 then there is a unit root. The same reasoning can be extended for a generic AR(p) process. Therefore to perform an Unit Root test on a AR(p) model the following regression should be estimated.

$$\Delta Yt = m + bY_{t-1} - \sum_{j=1}^{p} a_j \Delta Y_{t-j} + e_t \qquad (20)$$

Here the standard Dickey-Fuller model has been augmented by ΔY_{t-j}. In this case the regression model and the t test are referred as ADF test.

Data

The first hand primary data was collected from the web sites of respective Stock Exchanges and via written communication from them. The data collected was the closing index values for the Nifty (India), TAIEX (Taiwan) and STI (Singapore). India is located at the time zone (GMT + 5.30) while the other two are located at the same time zone. The data is from January 1994 to November 2002. The cointegration analysis was done for the entire data from January 1994 to November 2002 as well as for the period from January 1995 to November 2002 when the stock market reforms took shape in Indian market and National Stock Exchange came into being, for the period from January 1997 to November 2002 when further institutional reforms took shape in India and from 2000-2002 when major reforms like compulsory rolling settlement with electronic book entry form, shortening of settlement cycle, etc.. The period has been split into the above time buckets, as we understand substantial market reforms were introduced after the onset of National Stock exchange of India.

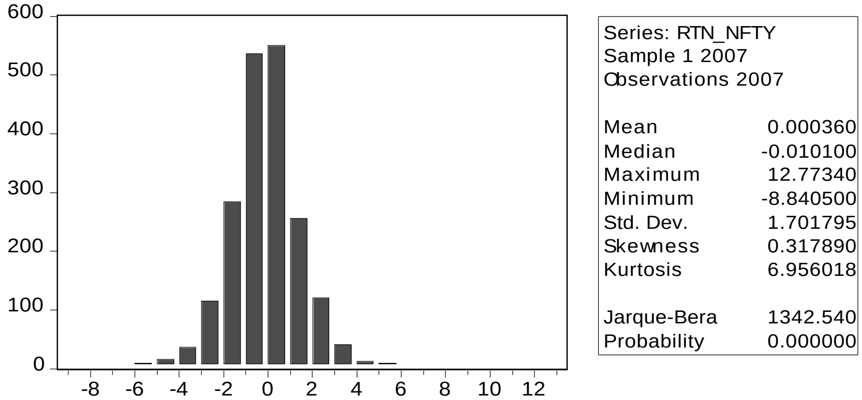
The simple correlation of these markets as well as the descriptive statistics of the three markets are given in Table 1, Table – 2 respectively and the returns, market movement as well as the market volatility are plotted in Chart 1, Chart 2 and Chart 3. The volatility estimates have been calculated using the formula $(\sigma_t)^2 = \lambda\ (\sigma_{t-1})^2 + (1 - \lambda\ )\ (r_t)^2$ where σ_t is the standard deviation, λ is assigned 0.94 and r_t is the daily logarithmic return. This formula has been used for calculation of volatility as the same is being used in the Indian market as given by Securities Exchnage Board of India. (Source www.sebi.gov.in). The above methodology is widely used in academic literature and has been put forward by RiskMetrics. (see RiskMetrics Technical Document for details)

Table 1 Correlation of Markets

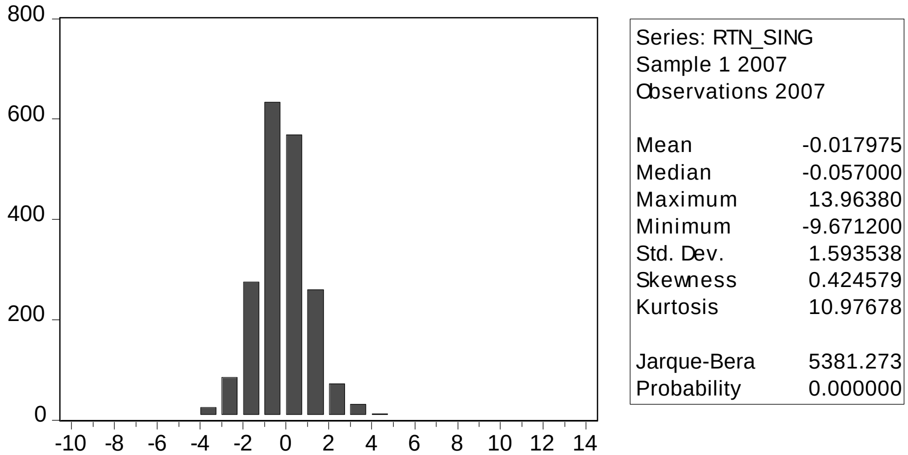
	RET_NIFTY	RET_SING	RET_TAI
RET_NIFTY	1	0.198405	0.112699
RET_SING		1	0.298679
RET_TAI			1

Figure - 2: Descriptive Statistics

NIFTY



SINGAPORE



TAIWAN

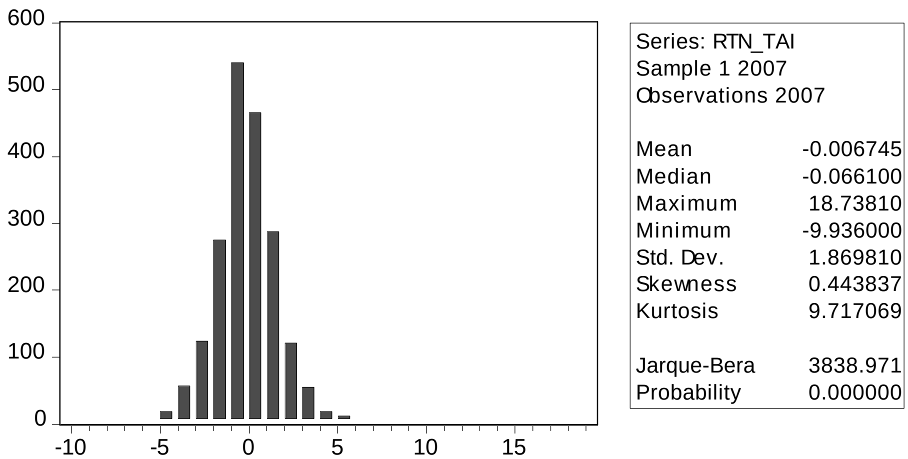


Chart 1: Movement of Returns

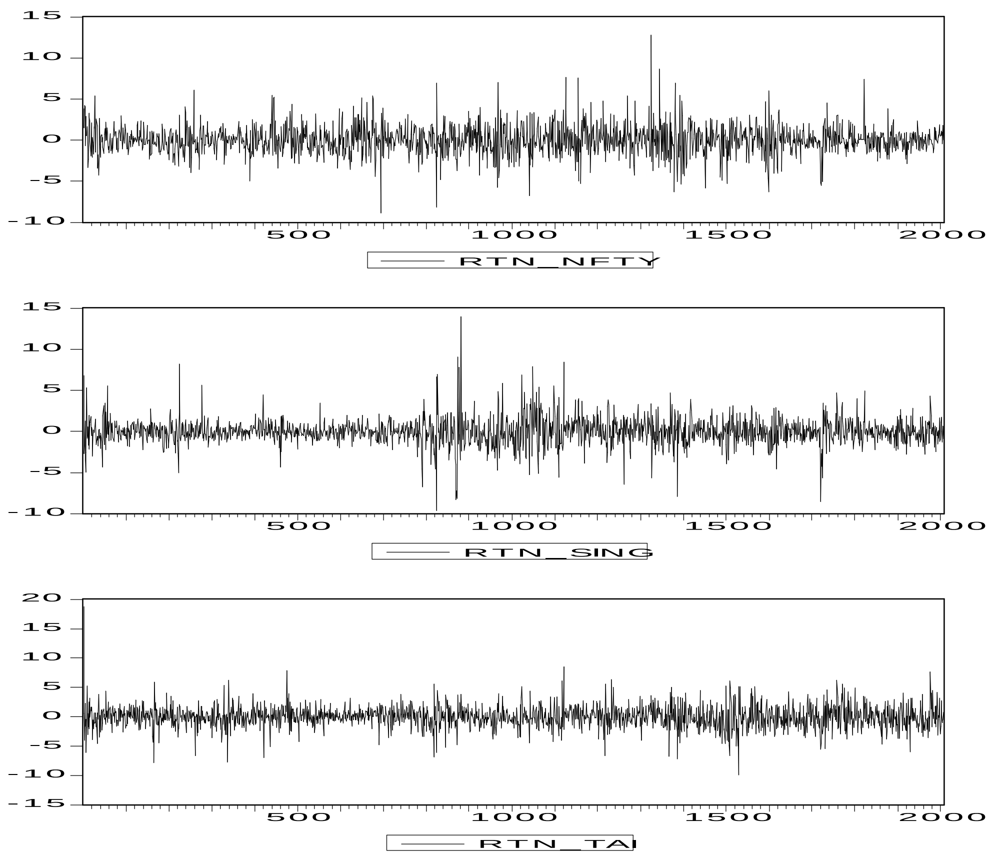


Chart 2: Movement of Markets Indices (1994-2002)

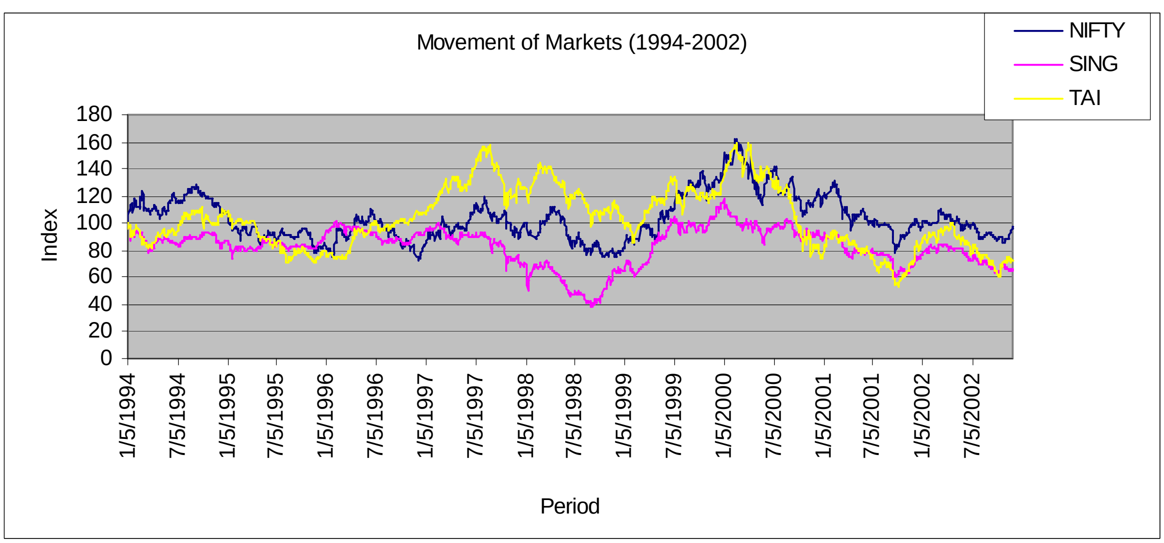
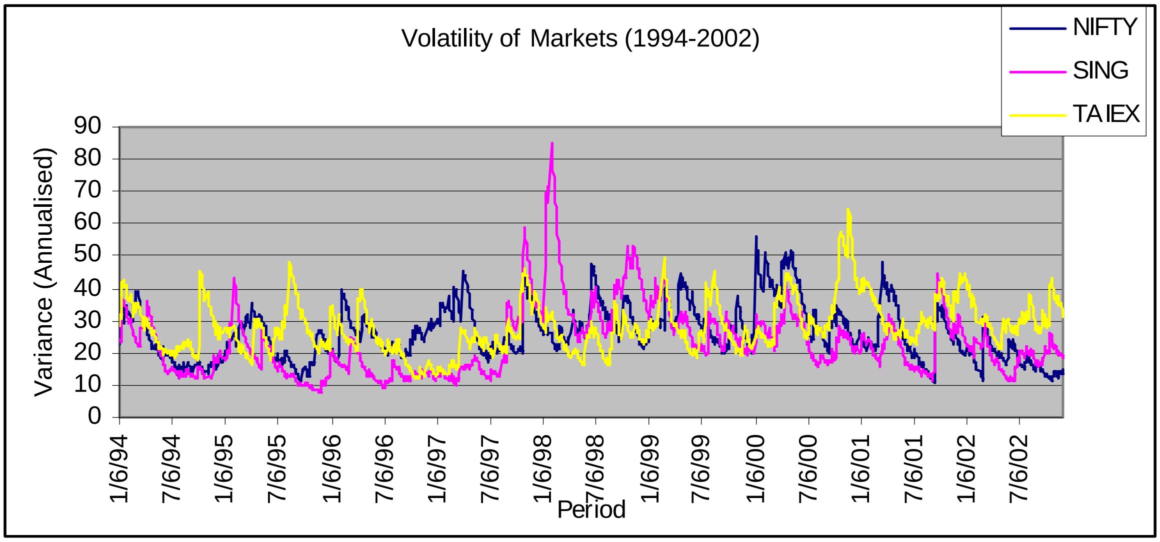


Chart 3: Volatility of markets



Empirical Study& Results

Initially we tried to find out the relationship through a linear equation as follows to see the significance of the relationship suing the log values of the indices for three countries. For 1994-2002, the relationship looks as

LNIFTY = 1.851281 + 0.432838*LSING + 0.219829*LTAI
(0.13221)# (0.01376)# (0.01164)#

For 2000-2002, the relationship looks as

LNIFTY = 0.040849+ 0.717465*LSING + 0.192962*LTAI
(0.1123) (0.02734)# (0.01519)#

# indicates significant at 1% and (figures in bracket gives the standard error)
From the above we see the signs of the coefficients have not undergone change.

The time series properties of the models need to be studied first such as presence of unit roots, visual properties of the charts, cyclicity, trends etc. Unit root tests were run for each series. As can be studied from the above graphs there is a presence of trend and hence the test results from the ADF test are evaluated only where a trend and intercept are included. The order for Augmented Dickey Fuller (ADF) tests were ascertained on minimum Schwarz Information Criterion (SC). Table 3 gives the results of the unit root test.

Table 3: Results of ADF Test for Unit Root

Variable	Optimal P@	Test Statistics#
NIFTY	1	-2.7789
SING	1	-1.8516
TAIEX	1	-1.8424
ΔNIFTY	13	-12.3676*
ΔSING	18	-10.9020*
ΔTAIEX	21	-10.6717*

@ Optimal P is selected based on minimum Schwarz Information Criterion
# Critical values of ADF test statistics for 1%, 5% and 10% level of significance are –3.9676, 3.4144 and –3.1290, respectively
* Significance at 1% level

Having satisfied with the results of ADF test, we proceed to conduct the Johansen's cointegration test for the variables. Though lag of 1 would have been sufficient for testing the cointegration as given by minimum AIC criteria as shown in the Table - 4, we have tested for various lags upto 5 and reported the results for lag 5 as the results are not significantly different.

Table 4: Lag Length Criteria Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-11534.60	NA	20.811	11.549	11.557*	11.552
1	-11503.33	62.419	20.352*	11.526*	11.560	11.539*
2	-11496.08	14.443	20.388	11.528	11.587	11.550
3	-11491.65	8.8261	20.482	11.533	11.617	11.5640
4	-11485.24	12.727	20.535	11.535	11.645	11.575
5	-11481.18	8.0516	20.637	11.540	11.675	11.590
6	-11473.60	15.021	20.666	11.542	11.701	11.600
7	-11470.01	7.1093	20.778	11.547	11.732	11.615
8	-11461.11	17.569*	20.780	11.547	11.757	11.624

LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information Criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion and * indicates significant at 5% Level.

We now employ Johansen's (1991) maximum likelihood method to examine whether or not the logarithms of indices in question are cointegrated. The same has been performed with a lag of 5 as we feel that the same is sufficient to transmit all relevant information among the markets. The Table – 5 reports the relevant results. As can be seen in the table, there is no cointegration vector between the underlying series and hence no long run equilibrium relationship. Consequently an error term need not be included in the Granger Causality test equation.

Table 5: Johansen's Cointegration Test Results with lag of 5

Period	Eigen Values (Descending Order)	Null Hypothesis#	Trace Statistics*	Critical Value	
				5%	1%
1994 - 2002	0.009194	r=0	26.54633	29.68	35.65
	0.002846	r=<1	8.064138	15.41	20.04
	0.001179	r=<2	2.361089	3.76	6.65
1995-2002	0.009490	r=0	24.10111	29.68	35.65
	0.002852	r=<1	7.013508	15.41	20.04
	0.001057	r=<2	1.895299	3.76	6.65
1997-2002	0.018695	r=0	28.38088	29.68	35.65
	0.002503	r=<1	4.790431	15.41	20.04
	0.001326	r=<2	1.65818	3.76	6.65
2000-2002	0.027086	r=0	26.81349	29.68	35.65
	0.009066	r=<1	8.086340	15.41	20.04
	0.002746	r=<2	1.875193	3.76	6.65

- 'r' indicates number of cointegrating relationship.

The next step was to examine whether three markets are pair wise cointegrated with each other for the later period (1997-2002). As mentioned above, we have employed Johansen cointegration approach to test for the interdependence among these stock markets. The Table - 6 presents the results of the pair wise cointegration tests for the entire sample period. We also find that these markets are not cointegrated.

Table 6: Pairwise Cointegration Tests based on Johansen approach (Trace test with Lag 5)

Period	Eigen Values (Descending Order)	Null Hypothesis#	Trace Statistics*	Critical Value	
	NIFTY-SING			5%	1%
1997 - 2002	0.009194	r=0	14.82720	15.41	20.04
	0.002622	r=<1	3.281924	3.76	6.65
1997 - 2002	NIFTY-TAIEX				
	0.004946	r=0	7.924787	15.41	20.04
	0.001381	r=<1	1.727287	3.76	6.65
1997-2002	SING-TAIEX				
	0.004239	r=0	8.314969	15.41	20.04
	0.002401	r=<1	3.005104	3.76	6.65

- r’indicates number of cointegrating relationship.

Linear Granger Causality Test Results

The test results of Granger Causality between various markets are presented in Table-7. We experimented with a lag of 5-days from the consideration that 5 days period would be adequate to get effects of one market to another under the assumption of substantial informational efficiency.

<u>Table 7: Pairwise Granger Causality Tests between DLog(NIFTY), DLog SING and DLog TAIEX</u>

Period	Null Hypothesis	F-Statistics#	Probability
1997-2002	RTN_SING NOT=> RTN_NFTY	0.71354	0.61328
	RTN_NFTY NOT=> RTN_SING	1.45541	0.20163
	RTN_TAI NOT=> RTN_NFTY	0.87945	0.49406
	RTN_NFTY NOT=> RTN_TAI	3.85043	0.00181*
	RTN_TAI NOT=> RTN_SING	1.84829	0.1006
	RTN_SING NOT=> RTN_TAI	4.67467	0.00031*
1997	RTN_SING NOT=> RTN_NFTY	1.28481	0.27164
	RTN_NFTY NOT=> RTN_SING	0.76903	0.57305
	RTN_TAI NOT=> RTN_NFTY	2.33361	0.04341**
	RTN_NFTY NOT=> RTN_TAI	0.21478	0.95596
	RTN_TAI NOT=> RTN_SING	2.16289	0.05948***
	RTN_SING NOT=> RTN_TAI	1.74846	0.12497
1998	RTN_SING NOT=> RTN_NFTY	0.42105	0.83377
	RTN_NFTY NOT=> RTN_SING	1.09778	0.3627
	RTN_TAI NOT=> RTN_NFTY	0.54265	0.74381
	RTN_NFTY NOT=> RTN_TAI	1.77426	0.11943
	RTN_TAI NOT=> RTN_SING	2.88083	0.01542**
	RTN_SING NOT=> RTN_TAI	0.79678	0.55307
1999	RTN_SING NOT=> RTN_NFTY	2.4957	0.03202**
	RTN_NFTY NOT=> RTN_SING	0.8847	0.49217
	RTN_TAI NOT=> RTN_NFTY	1.42402	0.21677
	RTN_NFTY NOT=> RTN_TAI	1.2231	0.29933
	RTN_TAI NOT=> RTN_SING	0.93257	0.46074
	RTN_SING NOT=> RTN_TAI	1.97854	0.08305
2000	RTN_SING NOT=> RTN_NFTY	1.60297	0.16047
	RTN_NFTY NOT=> RTN_SING	0.19356	0.96477
	RTN_TAI NOT=> RTN_NFTY	0.42663	0.82983
	RTN_NFTY NOT=> RTN_TAI	2.48295	0.03273**
	RTN_TAI NOT=> RTN_SING	0.21336	0.95659
	RTN_SING NOT=> RTN_TAI	1.40449	0.22375
2001	RTN_SING NOT=> RTN_NFTY	1.81333	0.11139
	RTN_NFTY NOT=> RTN_SING	1.1135	0.35414
	RTN_TAI NOT=> RTN_NFTY	1.79851	0.11433

	RTN_NFTY NOT=> RTN_TAI	0.53704	0.74809
	RTN_TAI NOT=> RTN_SING	0.33258	0.8929
	RTN_SING NOT=> RTN_TAI	2.13763	0.06217***
2002	RTN_SING NOT=> RTN_NFTY	0.33535	0.89114
	RTN_NFTY NOT=> RTN_SING	0.6491	0.6625
	RTN_TAI NOT=> RTN_NFTY	1.33219	0.25192
	RTN_NFTY NOT=> RTN_TAI	1.54306	0.17794
	RTN_TAI NOT=> RTN_SING	0.9024	0.48049
	RTN_SING NOT=> RTN_TAI	0.98097	0.43042

- F values have been derived using lag 5 in the related equation without error correction term and *,**, *** indicates significant at 1%, 5% and 10% level and NOT => means does not Granger Cause.

Now we move to the estimate VAR for the dataset for various time periods and finally proceed to forecast error decomposition using VAR. For the full period, the error variances for each variable are explained by their own innovations. The VAR equation for 1994-2002 and 2000-2002 are given below (Figures in the bracket gives the t-statistics)

DLNFTY= 0.0077*DLSING(-1) + 0.0126*DLSING(-2) - 0.0184*DLTAI(-1) + 0.0478*DLTAI(-2) +

[0.30278] [0.49689] [-0.84455] [2.25190]

0.0884*DLNFTY(-1) - 0.0365DLNFTY(-2) - 0.0017

[3.88096] [-1.59946] [-0.04465]

DLSING = 0.1066*DLSING(-1) - 0.0189*DLSING(-2) - 0.0202*DLTAI(-1) + 0.0209*DLTAI(-2) +
[4.52008] [-0.79649] [-0.99549] [1.05602]
0.0403*DLNFTY(-1) + 0.0279*DLNFTY(-2) - 0.0177
[1.90040] [1.31080] [-0.50374]

DLTAI = 0.1218*DLSING(-1) + 0.0327*DLSING(-2) - 0.0277*DLTAI(-1) + 0.00317*DLTAI(-2) +
[4.50806] [1.20546] [-1.19012] [0.14011]
0.08219*DLNFTY(-1) + 0.0304*DLNFTY(-2) - 0.0138
[3.38313] [1.24717] [-0.34255]

The VAR equation for 2000-2002:
DLSING = 0.0509*DLSING(-1) + 0.0107*DLSING(-2) - 0.0278*DLTAI(-1) + 0.0178*DLTAI(-2) +
[1.20218] [0.25116] [-0.98626] [0.63938]
0.0247*DLNFTY(-1) + 0.0204*DLNFTY(-2) - 0.0751
[0.72479] [0.59858] [-1.35605]

DLTAI = 0.1548*DLSING(-1) + 0.0752*DLSING(-2) - 0.0367*DLTAI(-1) + 0.0043*DLTAI(-2) +
[2.52823] [1.21994] [-0.89914] [0.10720]
0.1380*DLNFTY(-1) + 0.0518*DLNFTY(-2) - 0.0634
[2.80434] [1.05310] [-0.79074]

DLNFTY = 0.1204*DLSING(-1) + 0.0262*DLSING(-2) - 0.0013*DLTAI(-1) + 0.0262*DLTAI(-2) +
[2.36921] [0.51256] [-0.03695] [0.78525]
0.0509*DLNFTY(-1) - 0.0821*DLNFTY(-2) - 0.0340
[1.24637] [-2.00803] [-0.51210]

Table-8 gives the decomposition of forecast error variance for the variables.

Table – 8 Variance Decomposition (1994-2002 & 2000-02)

Variance Decomposition of DLSING: 1994-2002					Variance Decomposition of DLSING: 2000-2002				
Period	S.E.	DLSING	DLTAI	DLNFTY	Period	S.E.	DLSING	DLTAI	DLNFTY
2	1.5872	99.7819	0.0406	0.1776	2	1.4442	99.8012	0.1219	0.0769
3	1.5886	99.6074	0.0887	0.3040	3	1.4456	99.6876	0.1898	0.1226
4	1.5886	99.6033	0.0900	0.3067	4	1.4456	99.6873	0.1899	0.1228
5	1.5886	99.6031	0.0902	0.3067	5	1.4456	99.6873	0.1900	0.1228
10	1.5886	99.6031	0.0902	0.3067	10	1.4456	99.6873	0.1900	0.1228
Variance Decomposition of DLTAI:					Variance Decomposition of DLTAI:				
Period	S.E.	DLSING	DLTAI	DLNFTY	Period	S.E.	DLSING	DLTAI	DLNFTY
2	1.8232	8.6564	90.7837	0.5599	2	2.1156	11.7533	87.1241	1.1226
3	1.8263	8.8237	90.4842	0.6921	3	2.1244	12.2878	86.4046	1.3076
4	1.8263	8.8252	90.4808	0.6940	4	2.1245	12.2957	86.3956	1.3087
5	1.8263	8.8253	90.4807	0.6940	5	2.1245	12.2962	86.3949	1.3090
10	1.8263	8.8253	90.4806	0.6940	10	2.1245	12.2962	86.3947	1.3091
Variance Decomposition of DLNFTY:					Variance Decomposition of DLNFTY:				
Period	S.E.	DLSING	DLTAI	DLNFTY	Period	S.E.	DLSING	DLTAI	DLNFTY
2	1.7002	3.7049	0.2324	96.0627	2	1.7434	11.8819	1.0776	87.0405
3	1.7030	3.7281	0.4442	95.8278	3	1.7484	11.8389	1.1036	87.0576
4	1.7031	3.7330	0.4452	95.8218	4	1.7484	11.8389	1.1039	87.0573
5	1.7031	3.7334	0.4454	95.8213	5	1.7484	11.8386	1.1038	87.0576
10	1.7031	3.7334	0.4454	95.8213	10	1.7484	11.8387	1.1038	87.0575

It can be seen that variation in NIFTY and STI have greatly explanative by themselves for 1994-2002 while TAIWAN is explained by other markets. But in the later period of 2000-02 we see that there has been changed with respect to NIFTY while STI has remained more or less unaffected and explains itself. To further investigate the dynamic responses between the variables we also calculated the impulse response of the VAR system and results are given in Table-9. An impulse response function traces the effect of a one time shock to one of the innovations on current and further values of the endogenous variables. Innovations are usually correlated and may be viewed as having a common component that can not be associated with a specific variable in order to interpret the results. A shock to the *i*th variable not only directly affects the *i*th variable but is also transmitted to all of the other endogenous variables through the dynamic (lag) structure of the VAR. An important response function traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables.

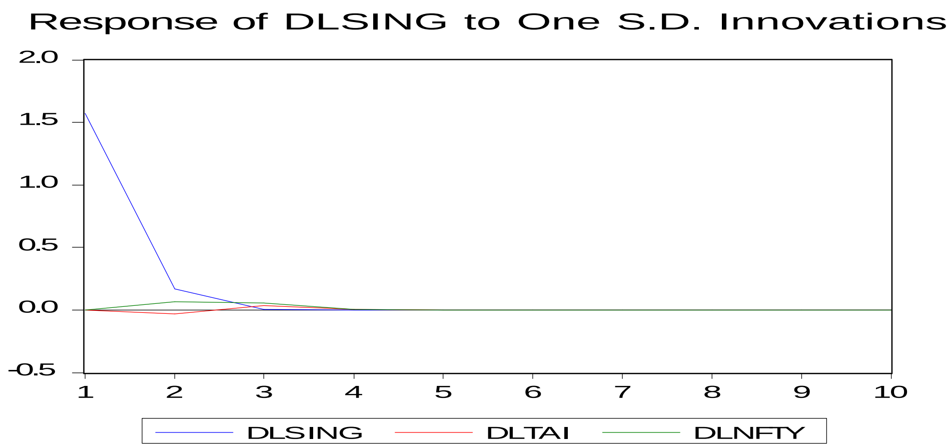
If the innovations ε_t are contemporaneously uncorrelated, interpretation of the impulse response is straightforward. The *i*th innovation$\varepsilon_{i,t}$ is simply a shock to the ith endogenous variable $y_{i,t}$. Innovation, however, are usually correlated, and may be viewed as having a common component which can not be associated with a specific variable.

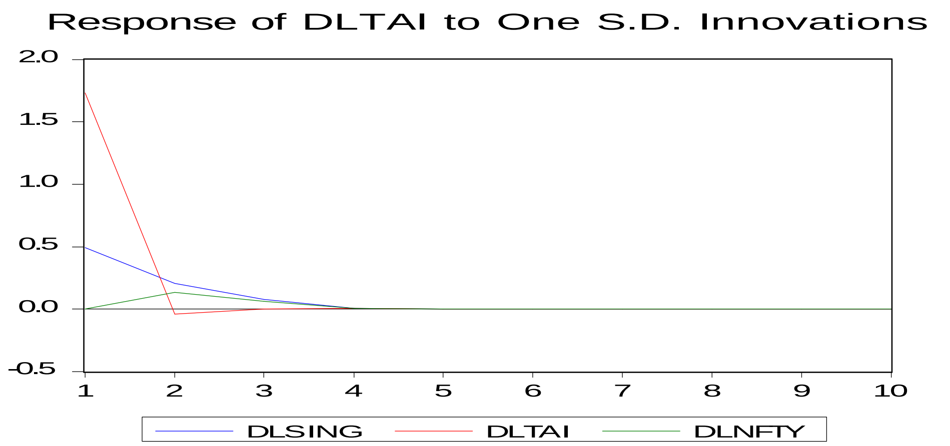
<u>Table – 9 Impulse Response (1994-2002 & 2000-02)</u>

Response of DLSING (1990-2002)				Response of DLSING ((2000-02)			
Pd	DLSING	DLTAI	DLNFTY	Period	DLSING	DLTAI	DLNFTY
2	0.170550	-0.031752	0.066234	2	0.067604	-0.049776	0.038490
	(0.03522)	(0.03514)	(0.03506)		(0.05488)	(0.05474)	(0.05459)
3	0.005225	0.034998	0.056466	3	0.039942	0.037890	0.030767
	(0.03499)	(0.03438)	(0.03522)		(0.05484)	(0.05401)	(0.05443)
4	0.002196	0.005821	0.008400	4	0.007842	0.001050	0.002168
	(0.00842)	(0.00425)	(0.00756)		(0.01117)	(0.00471)	(0.00878)
5	0.003042	0.002267	-0.000442	5	0.003802	0.001239	-0.000266
	(0.00261)	(0.00219)	(0.00260)		(0.00579)	(0.00272)	(0.00464)
10	3.48E-06	2.66E-06	1.67E-07	10	3.26E-06	1.04E-06	1.38E-06
	(5.7E-06)	(3.9E-06)	(5.0E-06)		(1.4E-05)	(5.2E-06)	(6.2E-06)
Response of DLTAI				Response of DLTAI			
Pd	DLSING	DLTAI	DLNFTY	Period	DLSING	DLTAI	DLNFTY
2	0.204781	-0.041698	0.136431	2	0.275498	-0.047361	0.223625
	(0.04044)	(0.04034)	(0.04021)		(0.08008)	(0.07959)	(0.07917)
3	0.080522	0.002992	0.066617	3	0.167461	0.012566	0.092792
	(0.04019)	(0.03952)	(0.04044)		(0.08047)	(0.07922)	(0.07976)
4	0.008211	0.008710	0.007981	4	0.020353	0.006144	-0.007738
	(0.00841)	(0.00627)	(0.00776)		(0.02120)	(0.01567)	(0.01866)
5	0.002437	0.004465	0.001090	5	0.005358	0.004864	-0.003462
	(0.00354)	(0.00291)	(0.00341)		(0.01110)	(0.00739)	(0.00946)
10	4.88E-06	2.85E-06	2.66E-06	10	8.30E-06	8.58E-07	1.57E-05
	(8.1E-06)	(4.9E-06)	(5.7E-06)		(3.3E-05)	(1.2E-05)	(2.9E-05)
Response of DLNFTY				Response of DLNFTY			
Pd	DLSING	DLTAI	DLNFTY	Period	DLSING	DLTAI	DLNFTY
2	0.031667	-0.025046	0.146392	2	0.200225	0.006738	0.082037
	(0.03783)	(0.03785)	(0.03772)		(0.06605)	(0.06571)	(0.06553)
3	0.032023	0.078382	-0.049594	3	0.026882	0.031174	-0.123985
	(0.03750)	(0.03683)	(0.03772)		(0.06631)	(0.06532)	(0.06579)
4	0.012184	0.005658	-0.003161	4	-0.001456	0.003025	-0.002560
	(0.00839)	(0.00405)	(0.00766)		(0.01551)	(0.00970)	(0.01600)
5	0.003690	-0.001894	0.005351	5	0.004084	-0.000961	0.013557
	(0.00288)	(0.00288)	(0.00345)		(0.00692)	(0.00541)	(0.01077)
10	2.81E-06	-1.80E-07	4.92E-06	10	1.16E-05	-2.40E-07	6.44E-06
	(5.6E-06)	(4.5E-06)	(6.6E-06)		(1.8E-05)	(8.3E-06)	(3.2E-05)

The following charts shows the impulse response of one of the variables on other variables.

<u>Chart (1994-2002)</u>





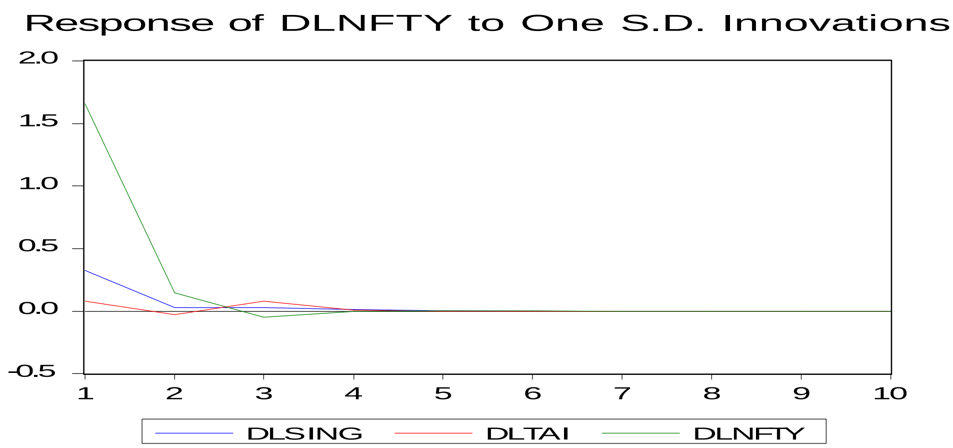
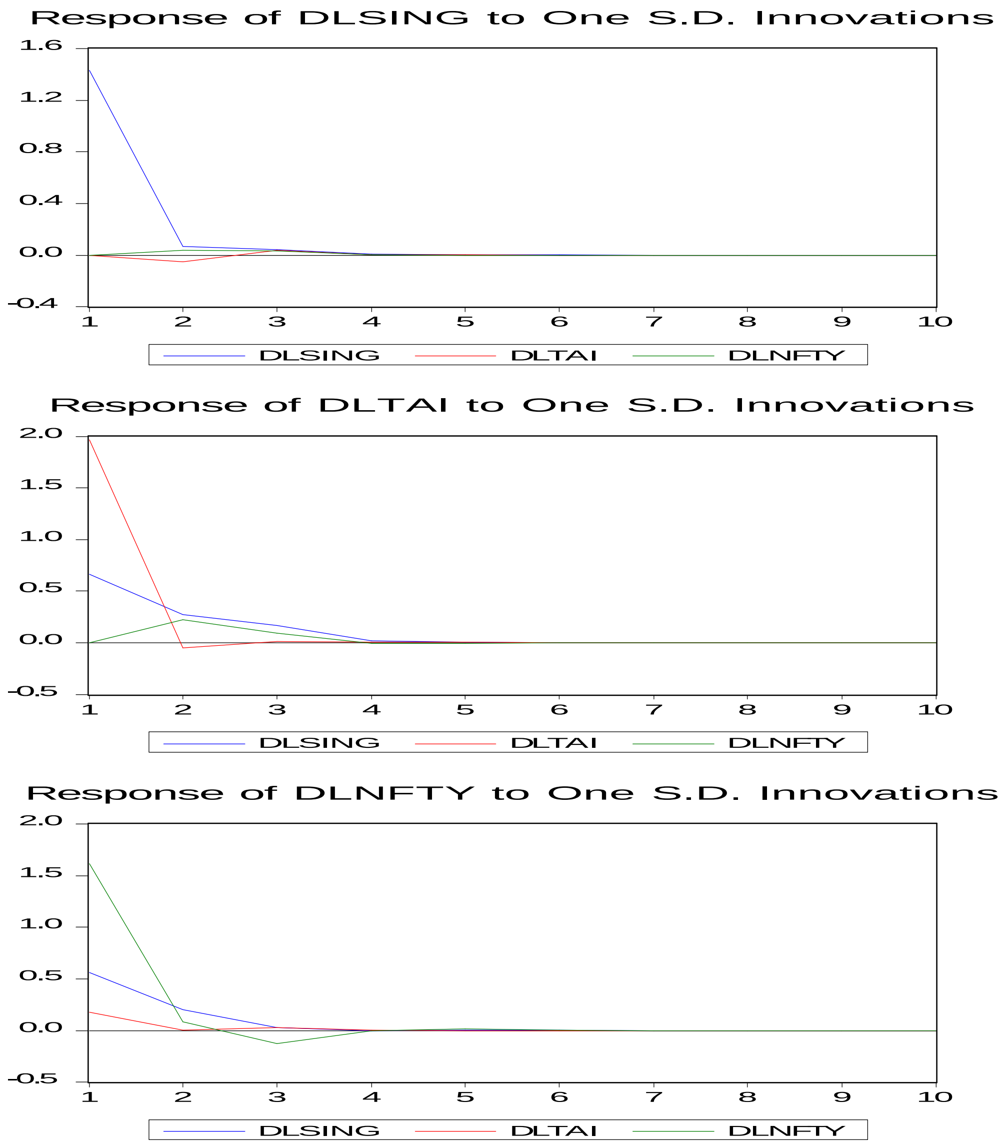


Chart (2000-2002)



Conclusions:

In this paper, we have analyzed the level of capital market integration by examining the transmission of market movements among three major stock markets in Asian region and during the period from 1994 to 2002. We have studied three important capital markets in Asian region which have attracted significant portfolio capital flows during last one decade. While the literature suggests the existence of significant interactions between the various equity markets, our empirical results show that generally returns in these three markets are not inter-related and there is no long term equilibrium, though in few cases the return in one stock market had causal influence on return in other stock markets though in very mild form (short-term influences). We have used a time lag of 5 for doing the analysis as we considered 5 days to be sufficient for any adjustment to take place considering significant informational efficiency. Our results suggest that international investors can achieve long term gains by investing in the stock markets as the market under study have been generally independent.

References:

1. **Basu & Morey**: *Stock Market Prices in India after Economic Liberalization*, EPW February 14, 1998
2. **Campbell, J.Y., A. W. Lo and A. C. MacKinlay, 1997**, *"The Econometrics of Financial Markets"*, Princeton University Press, Princeton, NJ.
3. **Engle, R.F., and C.W.J. Granger. 1987**. *Co-Integration, error correction: Representation, estimation and testing*. *Econometrica* 55:1251-1276.
4. **Engle, R.F., and C.W.J. Granger. 1991**. *Long-run economic relationships*. New York: Oxford University Press.
5. **Fuller, W.A. 1976.** *Introduction to Statistical Time Series*. New York: John Wiley.
6. **Gujrati, Damodar N.,:** *"Basic Econometrics"*, McGRAW – HILL International Edition, 1995.
7. **Geert Bekaerta, Campbell R. Harvey, Robin L. Lumsdaine,** *Dating the integration of world equity markets*, Journal of Financial Economics 00 (2002)
8. **Granger, C.W. 1986**. *Developemnts in the study of co-integrated economic variables*. *Oxford Bulletin of Economics and Statistics* 48:213-228.
9. **Granger, C.W.J. 1988**. Some recent developments in a concept of causality. *Journal of Econometrics* 39 (1/2):199-211.
10. **Johansen, S. 1988**. *Statistical analysis of cointegrating vectors*. *Journal of Economic Dynamic and Control* 12:231-254.
11. **Johansen, S. 1991**. *Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models*. *Econometrica* 59 (November):1551-1580.
12. **Johansen, S. 1992**. *Determination of cointegration rank in the presence of a linear trend*. *Oxford Bulletin of Economics and Statistics* 54 (3):383-397.
13. **Johansen, S., and K. Juselius. 1990**. *Maximum likelihood estimation and inference on cointegration with application to the demand for money*. *Oxford Bulletin of Economics and Statistics* 52:169-209.

14. **Johansen, S., and K. Juselius. 1994**. *Indentification of the long-run and the short-run structure: An application to the ISLM model. Journal of Econometrics* 63:7-36.

15. **Kanas, A. 1998**. *Linkages between the US and European equity markets: further evidence from cointegration tests. Applied Financial Economics.* 8: 607 - 614.

16. **Kasa K, (1992)** *Common Stochastic trends in International Stock Markets, Journal of Monetary Economics*, 29, 95-124

17. **Lo A & A Mac Kinlay (1988)** *Stock Market Prices do not Follow Random Walk: Evidence from a simple specification Test, review of Financial Studies. Vol I, No. 1, (41-66)*

18. **Nath, G C and Samanta, G P (2003)** *Dynamic Relation between Exchnage Rate and Stock Prices – A Case for India*, 39th Annual Conference paper of Indian Econometric Society also published in NSE News February 2003

19. **Nelson, Charles R**.: *"Applied time series analysis for managerial forecasting"*; Holden Day Inc.; 1973

20. **Osborne, M.F.M., 1964,** *"Brownian Motion in the Stock Market", in P.Cootner, ed., The Random Character of Stock Market Prices*, Cambridge: MIT Press.

21. **Risk Metrics – Technical Document (1996),** 4th Edition, (www.riskmetrics.com)

22. **Rocca E.D.** 1999. *Short-term and long-term price linkages between the equity markets of Australia and its major trading partners. Applied Financial Economics.* 9: 501-511

23. **Taylor, M.P. and Tonks, I. 1989**. *The internationalization of stock markets and abolition of UK exchange control, The Review of Economics and Statistics* 71: 332 - 336.