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Financial Integration for India Stock Market, a Fractional Cointegration Approach

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Abstract: The Indian stock market is one of the earliest in Asia being in operation since 1875, but remained largely outside the global integration process until the late 1980s. A number of developing countries in concert with the International Finance Corporation and the World Bank took steps in the 1980s to establish and revitalize their stock markets as an effective way of mobilizing and allocation of finance. In line with the global trend, reform of the Indian stock market began with the establishment of Securities and Exchange Board of India in 1988. This paper empirically investigates the long-run equilibrium relationship and short-run dynamic linkage between the Indian stock market and the stock markets in major developed countries (United States, United Kingdom and Japan) after 1990 by examining the Granger causality relationship and the pairwise, multiple and fractional cointegrations between the Indian stock market and the stock markets from these three developed markets. We conclude that Indian stock market is integrated with mature markets and sensitive to the dynamics in these markets in a long run. In a short run, both US and Japan Granger causes the Indian stock market but not vice versa. In addition, we find that the Indian stock index and the mature stock indices form fractionally cointegrated relationship in the long run with a common fractional, nonstationary component and find that the Johansen method is the best reveal their cointegration relationship.

Keywords: *unit root test, cointegration, Error Correction Model, Vector Autoregression Model, Johansen Multivariate Cointegration, Fractional Cointegration*

1. INTRODUCTION

One of the most profound and far-reaching financial phenomenon in the late twentieth century and the forepart of this century is the explosive growth in international financial transactions and capital flows among various financial markets in developed and developing countries. This phenomenon in international finance is not only a result of the liberalization of capital markets in developed and developing countries and the increasing variety and complexity of financial instruments, but also a result of the increasing relativity of the developing and developed economies as developing countries become more integrated in international flows of trade and payments. More freedom in the moving of capital flows improves the allocation of capital globally, allowing resources to move to areas with higher rates of return. Contrarily, attempts to restrict capital flows lead to distortions of capital structure that are generally costly to the economies imposing the controls. Thus, the boost in international capital flows and financial transaction is an underway and, to certain extent, irreversible process.

Since the work from Grubel (1968) on expounding the benefits from international portfolio diversification, the relationship among national stock markets has been widely studied. The relationship among different stock markets has great influence on investment because diversification theory assumes that prices of different stock markets do not move together so that investors could buy shares in foreign as well as domestic markets seek to reduce risk through global diversification.

In addition, the ever closer relationship among international capital markets and the increasing international portfolio investment have important implications for macroeconomic policies. While contributing to build-up of foreign exchange reserves, international portfolio investments can influence the exchange rate and could lead to appreciation of local currency. Thus, it has great influence on trade and fiscal imbalances among countries. Also, foreign portfolio investments are amenable to sudden withdrawals and therefore these have the potential for destabilizing an economy, with good examples from the Mexican and East Asian financial crisis in 1990s. Moreover, supported by technological advances in information and transaction, the growing internationalization of finance and the tremendous increase in the speed and volume of international capital flows have allowed much more rapid assessment of and response to the real growth possibilities in many countries.

Since its independence in 1947, a multitude of social and political problems have stood in India's way of realizing its true economic potential. However, it has recently made tremendous strides in the economic field through both economic and political reforms. The most significant policy should be the opening of the economy to foreign investment on very liberal terms for the first time in independent India's history. The policy soon harvested positive results as its industrial exports and foreign investment today are growing at the country's fastest rate ever. The country's foreign exchange reserves rose to US$51 billion in March 2002 from less than US$1 billion in June 1991. As now the globalization of capital flows has led to the growing relevance of emerging capital markets, India is one of the countries with an expanding capital market that is increasingly attracting funds from the foreign countries. Actually, in line with the global trend, reform of the Indian stock market began with the establishment of Securities and Exchange Board of India (SEBI) in 1988 to frame rules and guidelines for various operations of the stock exchange in India. Nevertheless, the reform process gained momentum only in the aftermath of the external payments crisis of 1991 followed by the securities scam of 1992.

Among the significant measures of opening up capital market, portfolio investment by foreign indirect investors (FIIs) such as pension funds, mutual funds, investments trusts, asset management companies, nominee companies and incorporated portfolio managers allowed since September 1992 have made the turning point for the Indian stock markets. As of now FIIs are allowed to invest in all categories of securities traded in the primary and secondary segments and in the derivatives segment. The ceiling on aggregate equity of FIIS including non-resident Indians and overseas corporate bodies in a company engaged in activities other than agriculture and plantation has been enhanced in phases from 24 percent to 49 per cent in February 2001. Attracting foreign capital appears to be the main reason for opening up of the stock markets for FIIs. Progressively the liberal policies have led to increasing inflow of foreign investment in India, both in terms of direct investment increasing from US$4 million in 1991 to US$2021 million in 2001, as well as portfolio investment increasing from US$1 million in 1992 to US$1505 million in 2001.[1]

In general, the deregulation and market liberalization measures and the increasing activities of multinational companies will continually accelerate the growth of Indian stock market. Given the newfound interest in the Indian stock markets, an intriguing question is how far India has gone down the road towards international financial integration, and whether the linkages exist among the stock indices of India and world's major stock indices. To answer these questions, we examine the interrelationship between Indian stock markets and major developed stock markets and study the underlying mechanism through which the Indian stock indices interact with international stock indices by analyzing empirically the long-run the pairwise, multiple and fractional cointegration relationship and short-run dynamic Granger causality linkage between the Indian stock market and the world major developed markets including US, UK and Japan in the post-liberalization period. We conclude that Indian stock market is integrated with mature markets and sensitive to the dynamics in these markets in a long run. In a short run, both US and Japan Granger causes the Indian stock market but not vice versa. In addition, we find that the Indian stock index and the mature stock indices form fractionally cointegrated relationship in the long run with a common fractional, nonstationary component and find that the Johansen method is the best reveal their cointegration relationship.

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[1] Source: India, Ministry of Finance, Economic Survey: 2002-2003

The rest of the paper is organized as follows: Section 2 presents a snapshot of the literature on stock market cointegration and Granger causality, Section 3 discusses the data and gives a sketch of the methodology being employed, Section 4 summarizes the findings and interprets the results and Section 5 concludes.

2. LITERATURE REVIEW

The financial markets, especially the stock markets, for developing and developed markets have now become more closely interlinked despite the uniqueness of the specific markets or the country profile. Literature has shown strong interest on the linkages among international stock markets and the interest has increased considerably after the loose of financial regulations in both mature and emerging markets, the technological developments in communications and trading systems, and the introduction of innovative financial products, creating more opportunities for international portfolio investments. The interest can also be attributed to the globalization which gives another impetus to the higher intertwinement of international economies and financial markets. In recent years, the new remunerative emerging equity markets have attracted the attention of international fund managers as an opportunity for portfolio diversification. This intensifies the curiosity of academics in exploring international market linkages.

Earlier studies by Ripley (1973), Lessard (1976), and Hilliard (1979) generally find low correlations between national stock markets, supporting the benefits of international diversification. The links between national stock markets have been of heightened interest in the wake of the October 1987 international market crash globally. The crash has made people realize that various national equity markets are so closely connected as the developed markets like the US stock market exert a strong influence on other markets. Applying the vector autoregression models, Eun and Shim (1989) find evidence of co-movements between the US stock market and other world equity markets. Cheung and Ng (1992) investigate the dynamic properties of stock returns in Tokyo and New York and find that the US market is an important global factor from January 1985 to December

1989. Lee and Kim (1994) examine the effect of the October 1987 crash and conclude that national stock markets became more interrelated after the crash and find that the co-movements among national stock markets were stronger when the US stock market is more volatile. Applying the VAR approach and the impulse response function analysis, Jeon and Von-Furstenberg (1990) show that the degree of international co-movement in stock price indices has increased significantly since the 1987 crash. On the other hand, Koop (1994) uses Bayesian methods to conclude that there are no common trends in stock prices across countries. Also, Corhay, et al (1995) study the stock markets of Australia, Japan, Hong Kong, New Zealand and Singapore and find no evidence of a single stochastic trend for these countries.

Only a few studies have examined the co-movement of Indian stock market with international markets. For example, Sharma and Kennedy (1977) examine the price behavior of Indian market with the US and UK markets and conclude that the behavior of the Indian market is statistically indistinguishable from that of the US and UK markets and find no evidence of systematic cyclical component or periodicity for these markets. Rao and Naik (1990) apply the Cross-Spectral analysis and find that for the Indian stock index, the gains estimates from either the US or the Japan indices are 'independent' and hence they conclude that the relationship of Indian market with international markets is poor reflecting the institutional fact that the Indian economy has been characterized by heavy controls throughout the entire seventies with liberalization measures initiated only in the late eighties.

Above studies were carried out over decade ago. As the Indian stock market becomes more open to the rest of the world since early 1990s, the relationship between the Indian market and the developed stock markets may change and hence our paper reexamine the nature of co-movement between Indian market and the others main stock indices.

3. DATA AND METHODOLOGY

Weekly indices of the stock exchanges from Datastream for India and the three most developed countries including the United States, the United Kingdom and Japan are used as proxies to measure the stock market for each country, specifically, BSE 200 (India)[2], S&P 500 (the United States), FTSE 100 (the United Kingdom) and Nikkei 225 Stock Average (Japan). Our sample covers the period from January 1, 1991 through December 31, 2003, a total of 13 years and the indices are adjusted to be in terms of US dollars for better comparison. The weekly indices as opposed to daily data is used to avoid representation bias from some thinly traded stocks, i.e., the problems of non-trading and non-synchronous trading and to avoid the serious bid/ask spreads in daily data. In addition, we use Wednesday indices to avoid the day-of-the-Week effect of stock returns (Lo and MacKinlay 1988).

To examine the co-movements between the Indian stock market and the developed markets, we first study their relationship by the simple regression:

$$y_t^I = a + b y_t^D + e_t \qquad (1)$$

where the endogenous variable y_t^I represents the India's stock index; the exogenous variable y_t^D is the stock index of any of the developed countries including the United States, the United Kingdom and Japan; and e_t is the error term. In order to study the joint effect from all the developed stock markets on the Indian market, we further study the following multiple regression:

$$y_t^I = a + b_1 y_t^{D1} + b_2 y_t^{D2} + b_3 y_t^{D3} + e_t \qquad (2)$$

where y_t^{Di} are the stock indices for the United States, the United Kingdom and Japan for i = 1, 2 and 3 respectively.

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[2] See detail introduction of BSE200 from http://www.bseindia.com/about/abindices/bse200.asp. We have analyzed other major Indian stock indices and the results are similar.

The validity and reliability of the regression relationship require the examination of the trend characteristics of the variables and cointegration test as the presence of unit root processes in the stock indices results in the spurious regression problem. Cointegration tests consist of two steps. The first step is to examine the stationary properties of the various stock indices in our study. If a series, say y_t, has a stationary, invertible and stochastic ARMA representation after differencing d times, it is said to be integrated of order d, and denoted by $y_t = I(d)$. To test the null hypothesis H_0: $y_t = I(1)$ versus the alternative hypothesis $H_1 : y_t = I(0)$, we apply the Dickey-Fuller (1979,1981) (DF) and the augmented Dickey-Fuller (ADF) unit root tests based on the following regression

$$\Delta y_t = b_0 + a_0 t + a_1 y_{t-1} + \sum_{i=1}^{p} b_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

where $\Delta y_t = y_t - y_{t-1}$ and y_t can be y_t^I, y_t^D or y_t^{Di}, ε_t is the error term. Regression (3) includes a drift term (b_0) and a deterministic trend ($a_0 t$). Integer p is chosen in (3) to achieve white noise residuals for the ADF test and when p=0, the test is known as the Dickey-Fuller (DF) test. Testing the null hypothesis of the presence of a unit root in y_t is equivalent to testing the hypothesis that $a_1 = 0$. If a_1 is significantly less than zero, the null hypothesis of a unit root is rejected. In addition, we test the hypothesis that y_t is a random walk with drift, i.e. $(b_0, a_0, a_1) = (b_0, 0, 0)$ and y_t is random walk without drift, $(b_0, a_0, a_1) = (0,0,0)$ using the likelihood ratio test statistics Φ_3 and Φ_2 respectively. If the hypotheses that a_1 = 0, $(b_0, a_0, a_1) = (b_0, 0, 0)$ or $(b_0, a_0, a_1) = (0,0,0)$ are accepted, we can conclude that y_t is $I(1)$. If we cannot reject the hypotheses that y_t is $I(1)$, we need to further test the null hypothesis $H_0 : y_t = I(2)$ versus the alternative hypothesis $H_1 : y_t = I(1)$. Note that most series are integrated of order at most one.

In addition, we apply the PP test[3] developed by Phillips and Perron (1988) to detect the presence of a unit root. The PP test is nonparametric with respect to nuisance parameters and thereby is suitable for a very wide class of weakly dependent and possibly heterogeneously distributed data.

If both y_t^I and y_t^D (y_t^{Di}) are of the same order, say $I(d)$, with $d > 0$, we then estimate the cointegrating parameter in (1) or (2) by OLS regression. If the residuals are stationary, the series, y_t^I and y_t^D (y_t^{Di}) are said to be cointegrated. Otherwise, y_t^I and y_t^D (y_t^{Di}) are not cointegrated.

Cointegration exists for variables means despite variables are individually nonstationary, a linear combination of two or more time series can be stationary and there is a long-run equilibrium relationship between these variables. If the error term in (1) or (2) is stationary while the regressors are individually trending, there may be some transitory correlation between the individual regressors and the error term. However, in the long run, the correlation must be zero because of the fact that trending variables must eventually diverge from stationary ones. Thus the regression on the levels of the variables is meaningful and not spurious.

The most common tests for stationarity of estimated residuals are Dickey-Fuller (CRDF), and Augmented Dickey-Fuller (CRADF) tests based on the regression:

$$\Delta\hat{e}_t = \gamma\hat{e}_{t-1} + \sum_{i=1}^{p}\gamma_i\Delta\hat{e}_{t-1} + \xi_t \qquad (4)$$

where $\hat{e}_t$ are residuals from the cointegrating regression (1) or (2) and p is chosen to achieve empirical white noise residuals for CRADF and set to zero for CRDF test.

Engle and Granger (1987) pointed out that when a set of variables is cointegrated,

[3] Refer to Phillips and Perron (1988) for the detail of the test statistics.

a vector autoregression in first differences will be misspecified. The first differencing of all the nonstationary variables puts too many unit roots and any potentially important long-term relationship between the variables will be unclear. Thus, inferences based on vector autoregression in first differences may lead to incorrect conclusions (Granger, 1981, 1988 and Sims, *et al*, 1990). However, there exists an alternative representation, an error correction representation of such variables, which takes account of a short- and long-run equilibrium relationship shared by those variables.

If the Indian stock market and the other markets are not cointegrated, one can adopt the bivariate VAR model, see Granger *et al* (2000), to test for the Granger causality. When a set of variables is cointegrated, Engle and Granger (1987) point out that a vector autoregression in first difference will be misspecified because first differencing of all the nonstationary variables imposes too many unit roots and any potentially important long-term relationship between the variables will be obscured. Thus inferences based on this model may lead to incorrect conclusions (Granger 1981, 1988 and Sims et al. 1990). Nevertheless, there exists an alternative representation, an error correction model (ECM) to test for the Granger causality between these variables by taking account of a long-run equilibrium relationship shared by the variables.

As shown in the next section, the Indian market is cointegrated with other markets and hence we can only use the ECM model to test the Granger causality in the following equation:

$$\Delta y_t^I = \alpha_0 + ae_{t-1} + \sum_{i=1}^{n} \alpha_{1i} \Delta y_{t-i}^I + \sum_{i=1}^{m} \alpha_{2i} \Delta y_{t-i}^D + \varepsilon_{1t}$$

$$\Delta y_t^D = \beta_0 + be_{t-1} + \sum_{i=1}^{n} \beta_{1i} \Delta y_{t-i}^D + \sum_{i=1}^{m} \beta_{2i} \Delta y_{t-i}^I + \varepsilon_{2t}, \tag{5}$$

where e_{t-1} is the residual for equation (1) and ae_{t-1} and be_{t-1} are called the error correction terms.

According to Engle and Granger (1987), the existence of the cointegration implies a causality among the set of variables as manifested by $|a|+|b|>0$, so a and b actually denotes the speed of adjustment. An error correction model allows us to study the long-term relationship between y_t^I and y_t^D. Equation (7) incorporates both the short-run and long-run information in modeling the data. Failing to reject the H0: $\alpha_{21}=\alpha_{22}=\ldots=\alpha_{2m}=0$ and a=0 implies that y_t^D do not Granger cause y_t^I. Similarly, failing to reject the H0: $\beta_{21}=\beta_{22}=\ldots=\beta_{2n}=0$ and b=0 suggests that y_t^I do not Granger cause y_t^D.

The minimum final prediction error criterion (FPE), see Hsiao (1979 and 1981), is then used to determine the optimum lag structures for the equations in (5). In these two equations n and m denotes the numbers of lags in the explained variable and explanatory variable respectively; and ε_{1t} and ε_{2t} are disturbance terms obeying the assumptions of the classical linear regression model. The final prediction error statistic of Δy_t^I for n lags of Δy_t^I and m lags of Δy_t^D is

$$FPE_{\Delta y_t^I}(n,m)=\frac{(N+n+m+1)\sum(\Delta y_t^I-\Delta\hat{y}_t^I)^2}{(N-n-m-1)N} \tag{6}$$

where N is the number of observations. The FPE statistic for Δy_t^D is found by the same way. To determine the minimum $FPE_{\Delta y_t^I}$, the first step is to run the regressions in (5). But the terms for the lags of Δy_t^D should be excluded, and only the lags of Δy_t^I are included, which means the calculation begins from m=0 and n=1. The same step is repeated until n=n* where FPE value is minimized for m=0. Then by fixing on n=n*, FPE value for different m will be calculated until m=m* which companied by a minimum FPE value. The same procedure is repeated with equation (9) where n=n** and m=m** minimize $FPE_{\Delta y_t^D}$.

We further apply the multivariate cointegrated system developed by Johansen (1988a,b). Assume each component $y_{i,t}$ i=1,…, k, of a vector time series process y_t is a unit root process, but there exists a k×r matrix β with rank r<k such that $\beta' y_t$ is stationary. Clive Granger has shown that under some regularity conditions we can write a cointegrated process y_t as a Vector Error Correction Model (VECM):

$$\Delta y_t = \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + ... + \Gamma_{p-1} \Delta y_{t-(p-1)} - \Pi y_{t-p} + \varepsilon_t , \tag{9}$$

where the ε_t's are assumed to be independent and identical distributed as multi-normal distribution with mean zero and variance Ω. The core idea of the Johansen procedure is simply to decompose Π into two matrices α and β, both of which are k×r such that $\Pi = \alpha\beta'$ and so the rows of β may be defined as the r distinct cointegrating vectors. Then a valid cointegrating vector will produce a significantly non-zero eigenvalue and the estimate of the cointegrating vector will be given by the corresponding eigenvector[4]. Johansen proposes a trace test for determining the cointegrating rank r. such that:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i), r = 0,1,2,...,n-1 . \tag{10}$$

and proposes another likelihood ratio test to test whether there is a maximum of r cointegrating vectors against r+1 such that:

$$\lambda_{\max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1}) . \tag{11}$$

with critical values given in Johansen (1995).

At last, we apply a generalized form of cointegration, known as fractional cointegration, as a characterization of the long run dynamics of the system of the stock indices in our study. In fractional cointegration context, the integration order of the error correction term is not necessarily 0 or 1, but it can be any real number in between. This allows obtaining more various mean reverting[5]. More specifically, a fractionally

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[4] See Johansen (1995) for more detail.

[5] see Chou and Shih (1997) for detail discussion.

integrated error correction term implies the existence of a long run equilibrium relationship, as it can be shown to be mean reverting, though not exactly I(0). Despite its significant persistence in the short run, the effect of a shock to the system eventually dissipates, so that an equilibrium relationship among the system's variables prevails in the long run.

A series is said to be integrated of order *d*, denoted by I(*d*), if it has a stationary, invertible autoregressive moving average (ARMA) representation after applying the differencing operator $(1-L)^d$. The series is said to be fractionally integrated if *d* is not an integer. A system of variables $y_t = \{y_{1t}, y_{2t}, ..., y_{nt}\}$ is said to be cointegrated of order I(*d*, *b*) if the linear combination αy_t is I(*d*-*b*) with *b*>0. So our interest is to find out the characteristic pattern of the error correction term. A flexible and parsimonious way to model short term and long term behavior of time series is by means of an autoregressive fractionally integrated moving average (AFIMA) model. A time series *y* follows an AFIMA process of order (*p*, *d*, *q*), if

$$\Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t, \varepsilon_t \sim i.i.d.(0, \sigma_\varepsilon^2) \tag{12}$$

where L is the backward-shift operator, $\Phi(L) = 1 - \phi_1 L - ... - \phi_p L^p$, $\Theta(L) = 1 + \upsilon_1 L + ... + \upsilon_q L^q$. The stochastic process y is both stationary and invertible if all roots of $\Theta(L)$ and $\Phi(L)$ are outside the unit circle, and -0.5<*d*<0.5. The process is nonstationary but mean-reverting for 0.5< *d* <1.

Cheung and Lai (1993) use this method and extend the alternative hypothesis to all order if integration less than one. In this paper, we follow the way by Cheung and Lai (1993) to analyze the dynamic relationship by applying the fractional testing methodology suggested by Geweke and Porter-Hudak (GPH, 1983) to obtain an estimate of *d* based on the slope of the spectral density function around the angular frequency $\xi = 0$. More specifically, let $I(\xi)$ be the periodogram of *y* at frequency ξ defined by

$$I(\xi) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} e^{it\xi}(y_t - \bar{y})\right|^2,$$

where $i = \sqrt{-1}$. Then the periodogram can be transformed to:

$$I(\xi) = \frac{1}{2\pi}\left\{\frac{1}{T}\sum_{t=1}^{T}(y_t - \bar{y})^2 + 2\sum_{k=1}^{T-1}\left[\frac{1}{T}\sum_{j=1}^{T-k}(y_j - \bar{y})(y_{j+k} - \bar{y})\right]\cos(\xi k)\right\},$$

which can be easily obtained based one T observations. Then the spectral regression is defined by

$$\ln\{I(\xi_\lambda)\} = \beta_0 + \beta_1 \ln\left\{\sin^2\left(\frac{\xi_\lambda}{2}\right)\right\} + \eta_\lambda, \qquad \lambda=1, \ldots, v \tag{13}$$

where $\xi_\lambda = \frac{2\pi\lambda}{T}$ ($\lambda=0,\ldots,T-1$) denotes the Fourier frequencies of the sample, and $v = T^u$ is the sample size of the GPH spectral regression (u is usually set as 0.55, 0.575 and 0.60). The negative of the slope coefficient in (19) provides an estimate of d. The theoretical asymptotic variance of the spectral regression error term in known to be $\pi^2/6$.

The GPH test can also be used as a test of the unit root hypothesis with I(1) processes imposing a test on d(GPH) from the first-differenced form of the series being significantly different from zero. The differencing parameter in the first-differenced data is denoted by $\tilde{d}$ in which case the fractional differencing parameter for the level series is $d = 1 + \tilde{d}$. In this respect, the GPH procedure poses an alternative viewpoint from which to scrutinize the unit root hypothesis. To test the statistical significance of the $\tilde{d}$ estimates, we have imposed the known theoretical variance of the spectral regression error $\pi^2/6$ in the construction of the t-statistic for $\tilde{d}$ and it is well-known that the asymptotic result are:

$$\sqrt{T}(\hat{d} - d) \Rightarrow N(0, \frac{6}{\pi^2}). \tag{14}$$

Therefore, the asymptotic standard deviation of $\tilde{d}$ is given by $\sqrt{6/T\pi^2}$.

4 Empirical Results and Interpretation

The weekly stock indices of India (BSE 200), US (S&P 500), UK (FTSE 100) and Japan (NIKKEI 225) are plotted in Figure 1[6] and their stationarity property are reported in Table 2 by the unit root tests including (augmented) Dicky-Fuller tests (DF, ADF), Likelihood Ratio tests ($\Phi_{2,}$ Φ_3) and Phillips-Perron test (PP) tests.

Figure 1 Normalized BSE 200, FTSE 100, NIKKEI 225 and S&P 500 Index

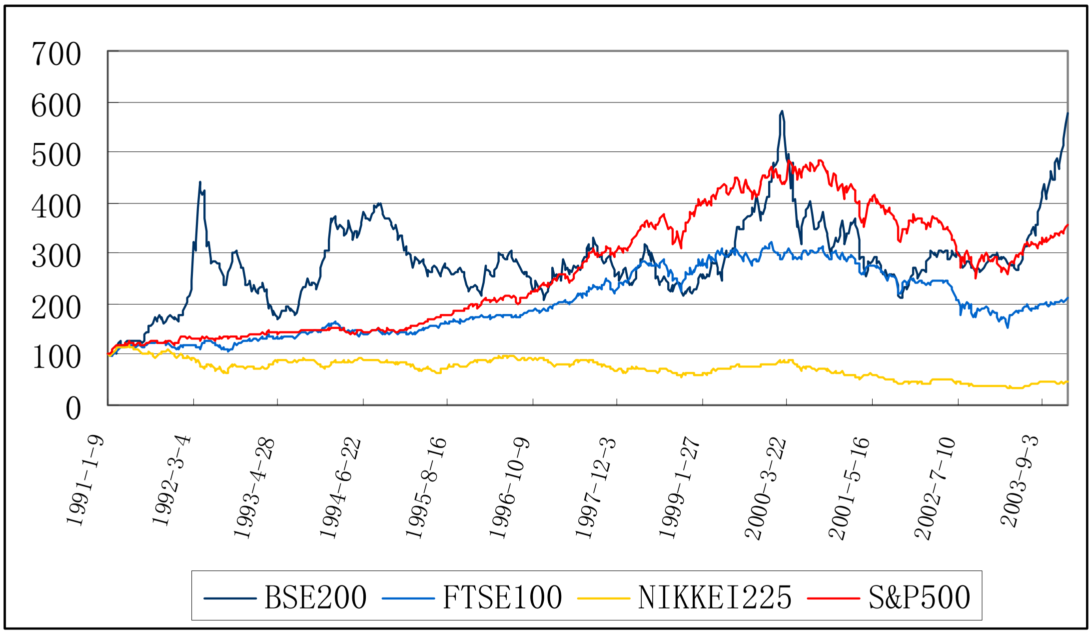

Figure 1 shows that basically all series are moving together in a long run, this suggests there may have a common trend for all the series. The results of the unit root tests in Table 2 do not reject all the four series for the period of January 1, 1991 to December 31, 2003 are I(1) but reject any of the series to be I(2) and hence we conclude that the all the series are I(1). We then study the cointegration relationship between Indian stock market and each market from the developed countries in equations (1) and (2) by examining the residuals in equation (6). The results are in Table 3.

[6] All series are normalized at 100 as of January 9, 1991 in the plot for easy comparison.

Table 2: Unite Root Tests for the Weekly Stock Indices of India, US, UK and Japan

Variable	DF	ADF	ADF lag	Φ_2	Φ_3	$Z(\hat{\alpha})$
BSE	-2.79	-3.38	2	0.10	4.36	-16.88
S&P	-0.66	-0.66	0	0.14	0.96	-1.88
FTSE	-0.62	-0.31	1	0.52	1.38	-2.23
NIKKEI	-2.39	-2.39	0	0.99	2.95	-0.32
ΔBSE	-23.57**	-15.31**	1	275.51**	277.69**	-307.739**
ΔS&P	-28.04**	-28.04**	0	384.71**	393.15**	-302.651**
ΔFTSE	-29.10**	-29.10**	0	416.28**	423.43**	-313.546**
ΔNIKKEI	-26.36**	-26.36**	0	347.91**	347.40**	-318.554**

* p < 5%, ** p < 1%

Note that DF is the Dickey-Fuller t-statistic; ADF is the augmented Dickey-Fuller statistic; Φ2 and Φ3 are the Dickey-Fuller likelihood ratios; and $Z(\hat{\alpha})$ is the Phillips-Perron test statistic. All series are in log form. Δ is the differencing operator.

Table 3: Cointegration Results for Stock Indices of India and Major Developed Countries

Model[7]	R^2	CRDF	CRADF
BSE=3.96381+0.28985(S&P)	0.2338	-3.27**	-3.63**
BSE=-2.33003+0.42716(FTSE)	0.2566	-3.26*	-3.52**
BSE=8.25127-0.24414(NIKKEI)	0.0558	-3.42**	-3.65**
BSE=1.97107-0.47417(S&P)+ 1.02958(FTSE)-0.15568(NIKKEI)	0.2716	-3.31**	-3.39**

CRDF and CRADF are cointegrating regression Dickey-Fuller and augmented Dickey-Fuller statistics. All equations are in log form, allowing easy interpretation of the coefficients.
* p < 10%, ** p < 5%.

[7] The heteroskedasticity consistent covariance matrix estimator developed by White (1980) are used to correct estimates of the coefficient covariances in the presence of heteroskedasticity of unknown form.

From the table, we find that both CRDF and CRADF statistics are significant at the 5% level except the CRDF value for the pair of BSE and FTSE being slightly less than the 5% critical value. These results lead us conclude that the Indian stock market has been integrating with US, UK and Japan's markets. We note that the beta coefficients in the multiple regression are not very meaningful as their variance inflation factor (VIF) [8] are very high.

Table 4: Granger Causality Results for BSE 200 VS the Three Mature Stock Indices

Variable	Causality	Lag from FPE	ECM p-value	Error correction term p-value
S&P 500	S&P500 → BSE200	6:3	0.0220*	0.1084
	BSE200→ S&P500	4:2	0.2829	0.6011
FTSE 100	FTSE100 → BSE200	6:2	0.1246	0.0055**
	BSE200 → FTSE100	4:1	0.6635	0.8066
NIKKEI 225	NIKKEI225 → BSE200	6:1	0.0469*	0.0018**
	BSE200 → NIKKEI225	1:6	0.0525	0.7982

→ denotes the direction of the Granger causality, e.g. S&P → IBOM implies Indian market is Granger caused by US market.
* p < 5%, ** p < 1%

With the cointegration relationship, Indian stock market is moving along with US, UK and Japan stock markets in a long run. Herewith we further study the short run relationship by examining the Granger causality relationship between India and any of the three developed stock markets. As the Indian market is cointegrated with these markets, the ECM model but not the VAR model is appropriate for testing granger causality and the results of the ECM model[9] are shown in Table 4 in which the optimal lag numbers are suggested by the minimum final prediction criterion in (6).

[8] The VIF is 45.25 for US and 39.69 for UK.

[9] The test results of the VAR model are available on request.

The results in Table 4 conclude that there are unidirectional causality runs from both the US stock market and the Japan stock market but not from the UK stock market to the Indian stock market and there is no causality run from the Indian stock market to any of the market from the US, UK or Japan.

The results between the US and Indian stock markets are rather intuitive as the US stock market is the world's foremost securities market and has heavy influence on other stock markets. Hence, we are not surprised that US Granger causes the Indian stock market in a short run (Table 4) and leads the Indian stock market in a long run (Table 3). More rationally, several macroeconomic factors may give good explanation to the causal relationship between the two stock markets. They include economic connection, regulatory structures similarity, exchange rate policy and trade flows. Coincided with the start of the liberalization of the Indian economy, there is a steady improvement in India-US trade relations during last decade. US government has identified India as one of the 10 major emerging markets. The volume of India-US bilateral trade also started to grow at a steady pace with the export from India to the US grows from US$2922 million in 1991 to US$11,318 million in 2002.[10]

On the other hand, the India-US trade volume still remains a small fraction of US's global trade. While US's exports to India account for over 10% of India's non-oil imports and US is the destination of one-fifth of India's exports, US's trade turnover with India constitutes less than 1% of its global trade. India's percentage share in US imports has remained stable over the last few years; it was 0.88% during 2000. In 2000, India ranked 21st among countries that export to the US.[11] These economic figures show that US economy is very important to Indian economy, but not conversely. This is consistent with our finding of unidirectional causality from S&P 500 to BSE 200.

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[10] Data are quoted from ADB http://ww.adb.org/Documents/Books/Key_Indicators/2003/pdf/IND.pdf

[11] All data cited here is from India-US embassy http://www.indianembassy.org/indusrel/trade.htm

The results in Table 3 indicate that in the long run UK stock market leads Indian stock market at the 1% significant level, but no evidence of short-run impact from UK stock market to Indian stock market can be found from Table 4. Simultaneously, Indian stock market almost cannot exert any long-run or short-run influence on UK stock market. Except the centuries-long colonial economic connection, India-UK bilateral trade volume has been increasing constantly since India's economic opening up since 1991.

From the data of bilateral trade and FDI[12], UK continues to be India's second largest trading partner after US and continues to be the largest cumulative investor in India, and the third largest investor post-1991. As Indian economy is linked with UK's economy closely, it is not surprised that Indian stock market has long-run lead-lag relationship with UK stock market. But, unlike the US and Japan stock markets, there is no impact from the UK stock market to the Indian stock market in a short run. One possible reason could be due to the fact that the UK market opens after the Indian market.

Table 4 also shows that there exists unidirectional causality from Japanese stock market to Indian stock market. This could be attributed to Japan-India economic relations which have been expanding both in quality and quantity notably since early nineties, keeping pace with the progress in economic liberalization in India. For example, exports from India to Japan stood at US$1.9 billion in 1998 which accounted for 4.9 per cent of India's total exports. Japan is the 6th largest importer from India after the US, Germany, UAE, UK and Hong Kong. As for India's imports from Japan, they stood at US$2.7 billion in 1998, an increase of 25.8 per cent over the previous year, accounting for 5.5 per cent of India's total imports. Japan is the 5th largest exporter to India after the US, Switzerland, Belgium and UK. Thus Japan is an important trading partner for India. While the bilateral trade is maintaining a steady growth in the recent years, Japanese direct investment in India has been increasing quite significantly. On approval basis,

[12] Data are obtained from High Commission of India, London
http://www.hcilondon.net/business-with-india/india-uk-economic-relations.html

Japan occupies 4th position after US, Mauritius and UK among the major FDI providers. With the opening up of the Indian economy, Japanese investments in India have been steadily increasing. Deregulation of foreign capital by India has been progressing smoothly and India has emerged as an attractive investment destination for Japanese investors. According to a survey by the EXIM Bank of Japan on promising FDI destination figured by the industries in 1999, India ranked fourth on the medium term (next three years) and third on the long term (next 10 years). As the bilateral economic relations are strengthened year by year, the stock markets of these two countries should also be connected more and more closely. These support there are both long-run lead-lag effect and short-run lead-lag effect from Japanese stock market to Indian stock market by using the Nikkei 225 and BSE 200 data of the 1991-2003 period.

As Johansen (1988) is a powerful way of analyzing complex interaction of causality and structure among variables in a system, this process is further applied to determine whether any cointegrating relationship exists among Indian, US, UK and Japanese stock markets as all the indices from these markets are integrated of order one (Table 1). As the stock indices exhibit a trend, a constant is included in this model. Lag structures are chosen according to the both Schwarz-Bayes criterion (SBC) and Akaike's information criterion (AIC) and the results are shown in Table 5A.

From Table 5A, the hypothesis of zero cointegrating vectors against the alternative of one or more cointegrating vectors is rejected while the hypothesis of one cointegrating vector is rejected by Johansen Trace test but cannot be rejected by Lamda-max test. These results show strong evidence that there is at least one set of cointegrating vector existing in four-variable system. The cointegrating vector, whose coefficients are normalized on the Indian stock market for both the MLE and OLS estimation methods given in Table 5B shows significant difference between the estimates from the two methods. It might be interesting to compare the performance of the two methods. A comparison of two residuals plotted in Figure 2 shows that the fit of the Johansen MLE model and the stationarity of the Johansen MLE residual have improved dramatically from that of the OLS model. The stationarity property of the residuals from MLE and OLS estimation are further tested and stated in Table 5C which shows that the MLE residuals are stationary at the 1% significant level for all the statistics while the OLS residuals, however, show much less evidence of stationarity. This further confirms that the MLE is a better estimation.

Table 5A: Johansen Cointegration Tests for the US, UK, Japan and Indian Stock Markets

Hypothesis		Trace Test	Lamda-max Test	Eigenvalue
H_0	H_1			
r≤0	r>0	43.5699**	21.3203**	0.032564
r≤1	r>1	22.2495**	11.4267	0.017587
r≤2	r>2	10.8228	9.6905	0.014935
r≤3	r>3	1.1323	1.1323	0.001757
Conclusion		r = 1	r = 1	r = 1
* p < 5%, ** p < 1%				

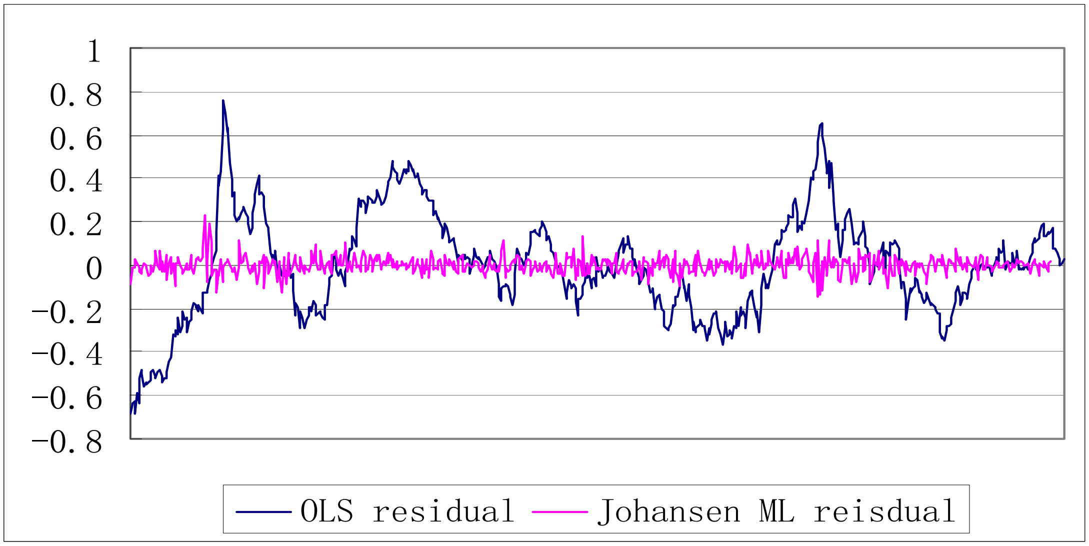
Table 5B: Normalized Johansen Cointegrating Vector of MLE and OLS Estimation

	BSE 200	S&P 500	FTSE 100	NIKKEI 225	Constant
MLE	-1	2.7378	-3.3663	1.5079	1.3812
OLS results	-1	-0.47417	1.02958	-0.15568	1.9711
Both the equations are in log form.					

Table 5C: Unit Root Tests for the MLE and OLS residuals

Variable	DF	ADF	Φ_2	Φ_3	$Z(\hat{\alpha})$ (PPT)
ML residual	-25.28**	-25.28**	320.01**	319.51**	-314.456**
OLS residual	-3.26	-3.35*	5.50	5.81*	-17.3783
* p < 5%, ** p < 1%					

Figure 2: Plot of the OLS and Johansen MLE Residuals



As the unit root tests employed above allow for only integer orders of integration, the four stock indices are each checked for a fractional exponent in the differencing process using the GPH test. The unit root hypothesis is tested by determining if the GPH estimate of $\tilde{d}$ [13] from the first-differenced stock indices series is significantly differently from zero. Table 6A reports the empirical estimates for the fractional differencing parameter $\tilde{d} = 1 - d$ as well as their corresponding GPH test statistics.[14]

[13] Refer to the Data and Methodology Section for the explanation.

[14] See equation (14) for its asymptotic standard deviation.

Table 6A: Empirical Estimates for the Fractional-Differencing Parameter $\tilde{d}$

Variable	$\tilde{d}$ (0.55)	$\tilde{d}$ (0.575)	$\tilde{d}$ (0.60)
BSE 200	-0.1699 (-5.534**)	-0.0823 (-2.681**)	-0.0490 (-1.596)
S&P 500	-0.0353 (-1.150)	-0.0254 (-0.827)	-0.0862 (-2.808**)
FTSE 100	0.0171 (0.558)	0.0384 (1.251)	0.0697 (2.270*)
NIKKEI 225	-0.0889 (-2.89**)	-0.0874 (-2.84**)	-0.0045 (-0.147)

$\tilde{d}$ (0.55), $\tilde{d}$ (0.575), and $\tilde{d}$ (0.60) give the empirical estimates for the fractional differencing parameter, where $\tilde{d} = 1 - d$. The superscripts **, * denote statistical significance for the null hypothesis $\tilde{d}$ =0 (d=1) against the alternative $\tilde{d} \neq 0$ ($d \neq 1$) at the 1% and 5% significant level.

Table 6B: Empirical Estimates for Cointegrating Parameter *d*

System of Stock Indices	d (0.55)	d (0.575)	d (0.60)
BSE 200 - S&P 500	0.8301	0.8332	0.8862
BSE 200 – FTSE 100	0.8264	0.8299	0.86944
BSE 200 – NIKKEI 225	0.9336	0.9211	0.9527
OLS Multivariate System	0.8911	0.8917	0.9007
Johansen Multivariate System	0.0284*	0.1262*	0.1631*

* denotes the residual of system is stationary.

The results in Table 6A show that the unit root null hypothesis is rejected for all the four indices by the GPH statistic. According to the results, differencing parameter of BSE

200, S&P 500, and NIKKEI 225 are slightly higher than integer one, and hence the integrated order of FTSE 100 is slightly less than one (but bigger than 0.5). Because the deviation of the integrated orders from one is miniature, we still think the four stock indices roughly follow a I(1) process.

We now turn to investigate the fractional cointegration in the error term of the system of stock indices. In the conventional cointegration framework, the system variables should be I(1) and the error correction term should be I(0). This criterion for cointegration relationship is strict and ad hoc as the error correction term can be mean reverting rather than exactly I(0). The hypothesis of fractional cointegration requires testing for fractional integration in the error correction term. The GPH test can be used for the used here, but the critical values for the GPH test derived from the standard normal distribution cannot be used in testing for fractional cointegration. This is due to the factor that the error term is not actually observed but estimated by minimizing the residual variance of the cointegration regression. So we only include the GPH statistics in our results. Table 6B reports the empirical results of the GPH test for cointegration in all the systems we have considered previously. The findings in Table 6B show that there is evidence of stationarity only for Johansen Multivariate System. The error terms of all other systems is not covariance stationary as $0.5<d<1$ but they are mean reverting. So there is evidence of fractional cointegration for all the systems in this study. Additionally, this GPH test seems to prove from another dimension that the performance of Johansen method is much better than that of OLS method.

5. CONCLUSION

We investigate the long run equilibrium relationship and short run dynamic inter linkages between the Indian stock market and world major developed stock market by using the weekly data of BSE 200 (India), S&P 500 (US), FTSE 100 (UK) and Nikkei 225 (Japan) from January 1991 to December 2003. Our main findings are as follows: First, Indian stock market is statistically significantly cointegrated with stock markets in United States, United Kingdom and Japan by using OLS estimation. Second, there exit unidirectional granger causality running from the US, UK and Japanese stock markets to the Indian stock market. Third, the Johansen ML estimation method suggests there is only one set of cointegrating vector for the four-variable system. Lastly, we reexamine the long run dynamics of all the stock indices systems by using the fractionally integrating technique and find that the Indian stock index and the mature stock indices form fractionally cointegrated relationship in the long run with the Johansen model generates a stationary error term and all other systems appear to possess a common fractional, mean-reverting component. In addition, the fact that only Johansen Multivariate model can generate stationary error term shows the superiority of Johansen method over others from another dimension. Generally speaking, long term equilibrium and short term dynamics have been detected in this study, which confirms Indian financial liberalization since 1991 has successfully opened up Indian stock market towards the outside world and hence its stock market is influenced by other markets.

Note that the cointegration and causality tests employed in our paper work well due to the large sample size. However, they may not be applicable when the sample size is small. In this situation, one may use the Modified Maximum Likelihood Estimator approach to modify the test (Tiku, et al 2000 and Wong and Bian 2005). Another alternative is to use the robust Bayesian sampling estimators (Matsumura, et al 1990 and Wong and Bian 2000) to improve the results. One can also use a 'distribution-free' approach to as an improvement for the test, for example, see Wong and Miller (1990) to improve the estimation and the test.

The cointegration and causality findings in our paper enable investors in their investment decision making in Indian stock market. Investors could further enhance their investment by incorporating our results with the findings in other approaches, like technical analysis (Wong et al 2001, 2003). Another way to improve the decision making on stock markets is to include the fundamental analysis (Thompson and Wong 1991, 1996, Wong and Chan 2004) or to incorporate the stochastic dominance approach (Wong and Li 1999, Li and Wong 1999) or a study on the economy situation (Manzur, et al 1999, Wan and Wong 2001) or on other financial anomalies (Fong et al 2005 and Wong, et al 2005).

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