Are the Bombay stock Exchange Sectoral indices of Indian stock market cointegrated? Evidence using fractional cointegration test

Krishnankutty, Raveesh and Tiwari, Aviral Kumar

ICFAI University Tripura

26 September 2011

Journal of Emerging Financial Markets, ***Vol. 2, No. 1: pp. 37-45 (2011).***

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By

Raveesh Krishnankutty and Aviral Kumar Tiwari

Management research scholar ICFAI University Tripura

Email: raveeshbabu@gmail.com, aviral.eco@gmail.com

Abstract

The present study is an attempt to test whether sectoral indices of Bombay stock Exchange have diversification benefits in the same. For the analysis, we used daily data spanning from 2/1/1999 to 3/31/2011. To test our hypothesis we used Fractional cointegration test. Study found that, in general, no evidence of cointegration in the sectoral indices of Bombay stock Exchange and hence conclude that there is benefit to domestic investors for sectoral diversification in the Bombay stock Exchange Sectoral indices of Indian stock market.

Keywords: *BSE stock Market, Fractional cointegration test, long memory returns, sectoral diversification benefits*

Journal of Emerging Financial Markets, ***Vol. 2, No. 1: pp. 37-45 (2011).***

1. Introduction

Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) are the two major stock exchange of India. In order to attract more and more investment as well as to induce trading both of these stock exchanges have maintained indices for different sector. In the present era, every investor wants to make portfolios, and they want to invest in growth-oriented sector. The importance of sector-oriented investment is popular in these days. In case of India to an extent year by year, growth in each sector is entirely depended on the government policies. In this paper, we are looking in to Sectoral indices of Bombay Stock Exchange (BSE). BSE Sectoral indices consist of 11 sectors whereas for analysis purpose we focused ourselves to only 7 indices as rest of 4 indices were recently started and therefore we do not have data for these 4 indices for the period we considered in our analysis.[1]

The main purpose of this study is to examine whether there is any long run dependency among the Sectoral indices of BSE of India. We examined whether movement of Sectoral indices are predictable based on other sector. This will help investors to identify whether there are any sectoral diversification benefits in the same.

2. A brief Literature review

Lobato and Savin (1997) tested the presence of long memory in daily stock returns and their squares using a robust semi- parametric procedure. They have addressed this problem by analyzing sub- periods of returns and using individual stocks. The result indicates that no evidence of long memory in the levels of the returns. For the squared returns, the result favors long memory and furthermore their result suggests that the evidence in favor of long memory is real, not spurious. Cheung and Lai (1993) provides an empirical evidence from the perspective of long memory analysis on the behavior of stock returns over long as opposed to short run. The study has been used Morgan Stanley Capital Internal stock index data for eighteen countries for

[1] 11 sectors are: Auto, Capital Goods, Consumer Durables, IT, Healthcare, Oil and gas, Metal, Power, Tech, FMCG and Reality. And excluded sectors are: Power, Tech, FMCG and Reality.

the analysis. Their study finds little support for long memory, in general, in international stock returns. Moreover, their findings are robust to inflation adjustments in stock returns, data source, and statistical methods used. Ding, Granger and Engle (1993) studied the long memory property of stock market returns. They found that there is a substantial correlation between absolute return than return them and the power transformation of the absolute returns also has quite high autocorrelation for long lags. Ganger and Hyung (2004) compare two time series models, an occasional- break model and an *I(d)* model to analysis S&P 500 absolute stock returns. The paper shows that occasional breaks generate slowly decaying autocorrelations and other properties of *I(d)* process, where *d* can be a fraction. In general, they found that an occasional – break model provides less competitive forecast, but not significantly. However, their result suggests a possibility such that, at least, part of long memory may be caused by the presence of neglected break in the series. Henry (2002) suggests those long horizons are forecastable. While this phenomenon is usually attributed to time varying expected returns, or speculative fads, it may also be due to long memory in the return series. He has tested the long-range dependence on a sample of nine international stock index returns using parametric and semi-parametric estimators. The author founds the evidence of long memory in the German, Japanese, South Korean, and Taiwanese market. Bilel and Nadhem (2009) examined the presence of long memory property in monthly and quarterly stock returns of seven countries, namely Japan, France, UK, Italy, Canada, Germany, and the USA. The finds some evidence for positive long memory in 5 of the 7 series considered. Mishra, Sehgal and Bhanumurthy (2011) have tested the presence of nonlinear dependence and deterministic chaos in the rate of return series for six Indian stock market indices. The overall result of the analysis suggests that the return is not following the random walk process. Furthermore, the study reveals that there is strong evidence of nonlinear dependence in daily increments of all equity analyzed. There are other various studies conducted for India and analyzed for different indices of BSE or NSE. However, there is no such study for sectoral indices in case of India wherein sectoral diversification benefits have been analyzed. Therefore, to the best of our knowledge, we are the first in this direction.

3. Data and Methodology: Fractional cointegration analysis

While the usual notion of integration has the strict $I(0)$ and $I(1)$ distinction, fractional cointegration allows the variables to be fractionally cointegrated.[2] A system of $I(1)$ variables $S = \{s_j, j = 1,..., n\}$ is said to be fractionally cointegrated if a cointegrating vector β exists such that $\beta' S$ is integrated of order d with $0 < d < 1$. A fractionally integrated process has long memory since its autocorrelations decay hyperbolically, in contrast to a faster, geometric decay of a finite order ARMA process (Granger and Joyeux, 1980; Hosking, 1981). Furthermore, an $I(d)$ process with $d < 1$ is mean-reverting (Cheung and Lai, 1993). Thus, if stock indices are fractionally cointegrated, then an equilibrium relationship among the stock indices in the system will prevail in the long run.

When testing fractional cointegration, we can adopt the Engle and Granger (1987) two-step cointegration approach, though a different method than the standard unit root test is preferred in the second step. Cheung and Lai (1993) suggest the use of Geweke and Porter-Hudak's (1983, henceforth GPH) method to detect the order of integration in the error correction term estimated from the ordinary least squares regression.

Consider the error correction term, $Z_t = (Z_1,..., Z_T)$ and its first difference, X_t, denoted $X_t = (1 - L)Z_t$, where L is the lag (or backward-shift) operator by way of an autoregressive fractionally-integrative moving-average (ARFIMA) process of order (p, d, q) becomes:

$$\Phi(L)(1 - L)^d Z_t = \Phi(L)(1 - L)^{d'} X_t = \Theta(L) \in_{t,} \in_t \sim iid(0, \sigma^2), \qquad (3)$$

where d is a fractional difference operator and possibly a non-integer; and $\Phi(L)$ and $\Theta(L)$ are the autoregressive and moving average lag polynomials of orders p and q, respectively, [i.e., $\Phi(L) = 1 - \phi_1 L - ... - \phi_p L^p, \Theta(L) = 1 + \phi_1 L + ... + \phi_q L^q, d = 1 + d', and\ (1 - L)^d$ is the fractional differencing operator defined by $(1 - L)^d = \sum_{k=0}^{\infty} \Gamma(k - d) L^k / \Gamma(k + 1)\Gamma(-d)$ with

[2] In this study we computed a modified form of the Geweke and Porter-Hudak (GPH, 1983) estimate of the long memory (fractional integration) parameter, d, of a time series, proposed by Phillips (1999a, 1999b). This is because if a series exhibits long memory, then distinguishing unit-root behavior from fractional integration may be problematic, given that the GPH estimator is inconsistent against d>1 alternatives. This weakness of the GPH estimator is solved by Phillips' (1999a, 1999b) Modified Log Periodogram Regression estimator, in which the dependent variable is modified to reflect the distribution of d under the null hypothesis that d=1. The estimator gives rise to a test statistic for d=1 which is a standard normal variate under the null. Phillips suggests (1999a, 1999b) that deterministic trends should be removed from the series before application of the estimator.

$\Gamma(\cdot)$ denoting the gamma or generalized factorial function] with roots lying outside the unit circle. An integer value of $d = 0$ yields a standard ARMA process (i.e., the process exhibits short memory for $d = 0$, whereas $d = 1$ gives rise to the unit-root nonstationary process. For $d \in (0,0.5)$ and $d \neq 0$, the ARFIMA process is said to exhibit long memory and the autocorrelations of the ARFIMA process decay hyperbolically to zero as $k \to \infty$. For $d \in (-0.5,0)$, the ARFIMA process is said to exhibit intermediate memory (see Granger and Joyeux, 1980). Although for $d \in (0.5,1)$ the process implies mean reversion, however, it is not a covariance stationary process. Finally $d > 1$ implies that the process is not mean reverting. The fractional integration test due to GPH (1983) is used to detect the nature of stationarity. GHP (1983) demonstrate that the fractional differencing parameter d can be estimated consistently from the least squares regression at frequencies near zero:

$$\ln(I(\omega_j)) = \alpha + \beta \ln(4\sin^2(\omega_j / 2)) + v_j, \qquad j = 1,\dots, J \qquad (4)$$

where α is the constant term, $\omega_j = 2\pi j / T\,(j = 1,\dots,T-1)$ $J = T^{\eta} << T, T$ is the number of observations, and $I(\omega_j)$ is the periodogram of time series X_t at frequency ω_j. With a proper choice of *J*, the negative of the OLS estimate of β coefficient gives a consistent and asymptotically normal estimate of the order of integration d.

Moreover, this is true regardless the orders and the estimates of the parameters of the ARMA process. While $\eta = 0.5$ is suggested in the empirical analysis, we set η also equal to 0.475 and 0.525 for checking the sensitivity of the results to the selection of η.[3] To ensure that stationarity and invertibility are achieved, we conduct the GPH test on the first-differenced series, i.e., X_t. As d of the level series equals $1 + d'$, a value of d' equal to zero corresponds to a unit root in Z_t. Thus, the GPH test is used as a unit root test as we apply it to the first differences of the relevant series. The unit root null hypothesis $d = 1\ (d' = 0)\, d$ can be tested against the one-sided,

[3] Cheung and Lai (1993) conducted a Monte Carlo experiment and found better performance for η = 0.55, 0.575, and 0.6. In another investigation, Cheung (1993) used η = 0.5 (which is commonly used to test for fractional integration), and also reports results for η = 0.45 and 0.55 to check the sensitivity of the estimates. Overall, it may be inferred that, irrespective of sample size, a value of η, between 0.5 and 0.6 appears to be the ideal choice.

long-memory, fractionally integrated alternative $d < 1$ $(d' < 0)$. The rejection of the unit-root null hypothesis would suggest the existence of fractional integration.

As with the GPH approach, there is a substantial amount of evidence documenting the poor performance of the Robinson's semiparametric estimator in terms of bias (see Baillie, 1996). Therefore, to examine further the characteristics of long-memory and mean-reversion in the cointegrating series of stock markets, we employ the rescaled range (R/S) test. The R/S statistic is formed by measuring the range between the maximum and minimum distances that the cumulative sum of a stochastic random variable has deviated from its mean and then dividing this by its standard deviation. An unusually small (large) R/S statistic signifies mean-reversion (mean-aversion). Mandelbrot (1972) demonstrates that the R/S statistic can uncover not only periodic dependence but also non-periodic cycles. He further shows that the R/S statistic is a more general test of long-memory in time series than examining either autocorrelations (i.e., the variance ratio test) or spectral densities.

Lo (1991) points out that the original version of the R/S analysis (which may be termed as classical R/S test) has limitations in that it cannot distinguish between short and long-term dependence, nor is it robust to heteroskedasticity. Lo (1991) developed a test for short memory versus long memory based on a simple modification of the rescaled range or RS statistic introduced by Hurst (1951). The modified RS statistic is

$$Q_n = \frac{1}{\hat{\omega}}\left\{ \underset{1\le k\le T}{Max} \sum_{t=1}^{k} (X_t - \overline{X}) - \underset{1\le k\le T}{Min} \sum_{t=1}^{k} (X_t - \overline{X}) \right\}, \qquad (8)$$

Under the null hypothesis, Lo (1991) showed that

$$RS = \frac{Q_n}{\sqrt{n}} \Rightarrow U_{RS} = \max_{1\le k\le n} W^0(t) - \min_{1\le k\le n} W^0(t).$$

The distribution function of the random variable U_{RS} was derived by Feller (1951) and has the formula

$$F_{U_{RS}}(x) = 1 + 2\sum_{k=1}^{\infty} (1 - 4k^2x^2)e^{-2k^2x^2}.$$

This distribution function is used to calculate the critical values of the modified RS test. Critical values at various significance level are available in Table 2 in Lo (1991). Further, for estimation in our analysis we considered two lag truncation procedures: a lag truncation equals to zero and the Andrews' formula.[4]

4. Results

Table 1 displays the results of the GPH estimates of *d*, the degree of fractional integration, [5] along with F-statistics for the null hypotheses of $d = 1$. A concern in the application of the GPH estimator is the choice of J (as in most cases, the results vary across the different values of η), the number of spectral ordinates from the periodogram of X_t, to include in the estimation of *d*. Here results are presented for $J = T^{\eta}$; where $\eta = 0.5, 0.55, 0.6$, where T represents the sample size (i.e., number of observations).

Table 1: Results of the Geweke-Porter-Hudak (GPH) test for fractional integration and Robinson estimates[6]

Modified LPR estimate of fractional differencing parameter											
	0.5			**0.55**			**0.6**			Rescaled range (R/S) analysis of long memory	
Variable	**d**	**d=0**	**d=1**	**d**	**d=0**	**d=1**	**d**	**d=0**	**d=1**	Lag=0	Lag=1
auto –cd	0.847888	10.1806*	-1.759***	0.962598	11.8832*	-0.5282	1.030209	15.5711*	0.5203	1.26	11.9
cd- auto	0.845323	10.6298*	-1.789***	0.960361	12.1736*	-0.5597	1.040926	0.7049*	15.8915	1.52	14.2
auto –cg	1.180851	17.0904*	2.0915**	1.201516	18.9674*	2.8456*	1.21258	21.0557*	3.6615*	1.5	14.3

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[4] In practice, however, a bandwidth value *q* has to be selected in the construction of the tests. Consequently, the finite sample performance of these tests depends on the choice of the bandwidth. The most popular bandwidth choice is probably the data-dependent automatic bandwidth $q = \mu_k \hat{\delta}(f,k) n^{1/(2p+1)}$ where μ_k is a constant associated with the kernel function *k*, $\delta(f,k)$ is a function of the unknown spectral density and is estimated using a plug-in method, and *p* is the characteristic exponent of *k*. This bandwidth choice has been studied by Andrews (1991) in the estimation of a covariance matrix for stationary time series and is now widely used in econometrics applications. It has the advantage that it partially adapts to the serial correlation in the underlying time series through the data-dependent component $\hat{\delta}(f,k)$. Lima and Xiao (2010) find that the problem of choosing the optimal q is not solved yet, but providing a bandwidth procedure that is robust against both the null and alternative models may help practitioners in their investigation on the presence of long memory in financial time series.

[5] Diebold and Rudebusch (1991) demonstrate that the standard unit root tests have low power against fractional alternatives.

[6] Agiakloglou et al. (1993) suggest that the estimate of the order of fractional integration from the GPH method could be biased for a model with large ARMA parameters. However, if the estimates *d* remain stable for different η 's, there is no hint of a bias due to ARMA parameters (Hassler and Wolters, 1995).

cg- auto	1.232133	13.4683*	2.6846*	1.242237	16.9989*	3.4206*	1.250588	18.9681*	4.3162*	1.92	18.4
cd- cg	0.80497	8.7092*	-2.2555**	0.907593	12.5425*	-1.3049	1.080993	16.6189*	1.395	1.45	13.2
cg- cd	0.847094	9.6628*	-1.768***	0.960442	12.9335*	-0.5586	1.126481	16.3749*	2.1785**	1.93	17.7
auto – hc	0.899774	11.1319*	-1.1591	0.913788	13.1952*	-1.2174	0.97493	16.2655*	-0.4318	1.23	10.8
hc –auto	0.870828	10.5021*	-1.4938	0.898058	12.7688*	-1.4395	0.965871	15.9183*	-0.5878	1.3	11.2
auto-it	0.882661	10.345*	-1.357	0.970153	12.6033*	-0.4215	1.102973	17.386*	1.7736***	1.66	15.3
it-auto	0.883098	9.9942*	-1.3519	0.959514	13.471*	-0.5717	1.099999	19.171*	1.7224***	1.39	12.2
auto -metal	1.215363	11.5806*	2.4906**	1.140633	15.1506*	1.9859**	1.172001	19.1069*	2.9626*	1.29	12
metal -auto	1.156399	11.5185*	1.8087***	1.079141	15.6231*	1.1175	1.160903	19.1889*	2.7714*	1.76	16.3
cd- hc	1.010867	10.479*	0.1257	1.097629	14.3309*	1.3786	1.039163	17.7918*	0.6745	1.33	12.1
hc –cd	0.969478	10.4611*	-0.353	1.067512	14.8513*	0.9533	1.024245	17.8662*	0.4176	1.34	12.1
cd-it	0.752353	7.0805*	-2.864*	0.877236	10.7071*	-1.734***	0.963833	16.0014*	-0.6229	1.67	15
it –cd	0.878024	8.9952*	-1.4106	0.977615	12.1731*	-0.3161	1.046319	17.6819*	0.7978	1.29	11
cd-metal	0.987996	10.2171*	-0.1388	1.088026	13.7001*	1.243	1.097389	18.1773*	1.6774***	1.37	12.5
metal-cd	0.983426	10.8849*	-0.1917	1.050785	15.282*	0.7171	1.092185	19.8418*	1.5878	1.49	13.5
cd- og	0.931506	11.4036*	-0.7921	0.983763	14.3246*	-0.2293	1.064633	16.8092*	1.1132	1.41	13.2
og-cd	0.919041	11.2566*	-0.9363	0.966058	13.7763*	-0.4793	1.043813	16.707*	0.7546	1.92	18.1
cg-hc	1.099139	12.8607*	1.1465	1.130569	17.5638*	1.8438***	1.089082	21.6674*	1.5344	1.68	15.7
hc-cg	1.01706	11.9424*	0.1973	1.078126	16.5111*	1.1032	1.080128	20.2839*	1.3801	1.2	11.1
cg-it	0.912875	10.6708*	-1.0076	0.986995	14.2847*	-0.1836	1.105077	19.3062*	1.8099***	1.86	12.2
cg-metal	0.843504	9.6919*	-1.809***	0.836546	13.3618*	-2.3081**	1.009341	17.7542*	0.1609	1.69	14.9
metal- cg	0.844929	9.9824*	-1.793***	0.834336	13.6908*	-2.3393**	1.011945	18.1187*	0.2057	1.36	11.8
cg- og	0.884812	10.5287*	-1.3321	0.914349	12.9246*	-1.2095	0.987927	15.7288*	-0.208	1.4	12.2
og- cg	0.855712	10.2523*	-1.669***	0.887486	12.6052*	-1.5888	0.958704	16.2598*	-0.7113	1.51	13.2
hc- it	0.809348	9.4947*	-2.2048**	0.9418	12.5023*	-0.8218	1.089113	15.0141*	1.5349	1.77	16.4
it- hc	0.871272	11.0913*	-1.4887	0.987375	13.2268*	-0.1783	1.104572	18.1316*	1.8012***	1.32	11.8
hc- metal	1.043541	11.0685*	0.5035	1.018169	14.7558*	0.2566	1.020457	18.6137*	0.3524	1.04	9.39
metal-hc	1.04235	10.3876*	0.4898	1.004711	13.6422*	0.0665	1.007531	17.665*	0.1297	1.49	13.4
hc- og	1.061305	11.8004*	0.709	1.068843	14.9173*	0.9721	1.057163	16.8799*	0.9846	1.42	13.3
og-hc	1.067993	10.2439*	0.7863	1.05885	13.212*	0.831	1.022426	15.9736*	0.3863	1.92	18.2
it-metal	0.93155	15.3071*	-0.7916	1.021074	16.1585*	0.2976	1.157628	20.3193*	2.715*	1.35	12.1
metal- it	0.859653	9.47*	-1.6231	0.917436	12.9336*	-1.1659	1.083687	17.0595*	1.4414	1.66	15.5
it-og	0.925835	12.0631*	-0.8577	1.002385	15.275*	0.0337	1.102277	20.361*	1.7616***	1.38	12.5
og- it	0.958628	12.2534*	-0.4785	1.00167	15.1735*	0.0236	1.086107	18.4339*	1.4831	1.91	18.1
metal-og	0.929456	8.8478*	-0.8158	1.020585	12.0775*	0.2907	1.010839	15.3614*	0.1867	1.49	13.5
og-metal	0.938995	9.1632*	-0.7055	1.022832	13.1838*	0.3224	1.008088	16.4487*	0.1393	1.8	16.4

Note: *, **, and *** denotes significance at 1%, 5% and 10% level.

Source: Authors' calculation

Results reported in Table 1 of the GPH estimates suggest that the results are very much sensitive to the choice of η. The null hypothesis of d=0 is rejected in all cases irrespective of the value of η. However, the null hypothesis of d=1 is rejected in only three cases (i.e., Auto-cg, cg-auto and auto–metal)[7] irrespective of the value of η, implying that the error correction in those three cases clearly are fractionally integrated (i.e., long memory), suggesting that the stock indices of Auto-cg, cg-auto and auto–metal are fractionally cointegrated. Further, there are 18 cases[8] where we find that null hypothesis of d=1 is not rejected at any value of η. This implies the absence of long-memory in the error correction term of the sectoral BSE indices. Further, for the cases where the value of $d \in (0.5,1)$ despite the choice of the value of η implies that though the stock indices is mean reverting (i.e., cointegrated), however, it is not a covariance stationary process. Further, if we see the results of R/S analysis we find very interesting results in that when lag truncation procedures is set equal to zero value of d is between 1 to 2 whereas when lag truncation procedures assumes the Andrews' formula the value of d is very high in all cases. This shows the complete absence of cointegration of the sectoral stock indices. Hence, it provides evidence that diversification benefits in Indian sectoral indices are enormous.

5. Conclusion:

The study used the techniques of fractional cointegration of the modified GPH test, along with the Rescaled Range approach for India's BSE sectoral indices for the time period 1997 to 2011. We find that GPH estimates are very much sensitive to the choice of η. However, the null hypothesis of d=1 is rejected in only three cases (i.e., Auto-cg, cg-auto and auto–metal) irrespective of the value of η, implying that the error correction in those three cases clearly are fractionally integrated (i.e., long memory), suggesting that the stock indices of Auto-cg, cg-auto and auto–metal are fractionally cointegrated. Importantly, in most of cases we find that null hypothesis of d=1 is not rejected at any value of η. This implies the absence of long-memory in the error correction term of the sectoral BSE indices. Further, the results of R/S analysis show the complete absence of cointegration of the sectoral stock indices. Hence, it provides evidence

[7] In the Table cg, og, hc and cd denotes capital goods, Oil and gas, healthcare and consumer durables respectively.
[8] These 28 cases are: auto–hc, hc-auto, cd-hc, hc-cd, it–cd, metal-cd, cd-og, og-cd, hc-cg, cg-og, hc-metal, metal-hc, hc-og, og-hc, metal-it, og-it, metal-og and og-metal.

that diversification benefits in Indian sectoral indices are enormous. The results could be specifically used for both fundamental and technical analysis of stock markets. Since stock markets are a barometer for the economy, the results can also help us examine the overall economic situation and the existence of problems in the financial system.

It should be remarked that the use of daily would mean that the limits for daily price would be affected by the closing price of the previous day. There are chances that the data would have hit a circuit breaker and distort the data. Even then, daily price data is necessary to understand the behavior of the series. It should be pointed out that relations among stock markets are also affected by macroeconomic variables such as trade and levels of foreign exchange. Further studies could look into incorporating these to give more insightful results.

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