LONG-RANGE DEPENDENCE IN SECTORAL INDICES

Sanjay Rajagopal, Western Carolina University

ABSTRACT

This study tests for market efficiency in the Indian financial market by analyzing long-range dependence in sectoral equity index returns. It applies three fractal analysis techniques—the Classical Rescaled Range, Wavelets, and Roughness-Length relationship methods— to the complete range of equity price information available for each of the sectoral indices on the Bombay Stock Exchange and the National Stock Exchange. As many as 15 of the 30 indices studied in total exhibit persistence in returns, a finding consistent with recent studies of broader Indian market indices. The results point to the existence of pricing inefficiencies that may well offer exploitable opportunities for excess returns in significant sections of the Indian capital market.

INTRODUCTION

Over the last three decades, India has emerged as an important player in the global economy. Concomitantly, the country has attracted increasing capital inflows, and the question of informational efficiency in the pricing of assets in this emerging economy has assumed greater significance (Dicle et al, 2010). Not surprisingly, recent studies have sought to assess the informational efficiency of the country's capital markets. The results of these studies are not in perfect agreement, but on balance the evidence appears to suggest some degree of dependence in market returns (see, for example, Poshakwale, 2002; Sarkar & Mukhopadhyay 2005; and Mishra et al, 2011).

The present work extends the literature on market efficiency within the Indian context by analyzing the behavior of a total of thirty returns series for sectoral equity indices on the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). This contrasts with existing studies, which concern themselves primarily with broader market indices. A recent study by Palamalai & Kalaivani (2015) does conduct tests of weak-form efficiency for Indian sectoral indices, but in contrast to the aforementioned study, which tests for serial correlation and any departures from a random walk using autocorrelation, unit root, variance ratio, and the runs tests, the present work employs fractional integration models to check for the presence of long-range dependence or memory in the series. Further, in contrast to the prior study's focus on a 5 ½-year period beginning in 2009, we analyze returns behavior over the full window for which data are available, which amounts to between 11 to 18 years for the BSE indices and roughly 3 to 20 years for the NSE indices; the vast majority of the indices span a period of 11 to 20 years, or roughly two to three times that of the previous work cited. Further, we seek to ascertain whether each of the returns series studies can be classified as "persistent" or "antipersistent", based on its estimated Hurst exponent. The study by Hiremath & Kumari (2015) represents another recent assessment of pricing efficiency in the Indian context, and it tests for long memory in both sectoral and broader indices. However, that study also constrains itself to a relatively narrow window, focusing on the 9 years between 2003 and 2012. Further, it considers only about half of the sectoral indices (16 out of a total of 30 available indices) on the BSE and the NSE. In the absence of any compelling a priori reason to either exclude any available sectoral indices or any available price information on those indices, the present study applies three fractal analysis techniques, viz., the Classical

Rescaled Range (R/S), Wavelets, and Roughness-Length relationship methods, to the complete range of price information available for all sectoral indices on the BSE and NSE, ending on August 31, 2017. A later section details the contrasting results of this approach. In summary, our results show that returns for 15 of the 30 series studied behave in a manner that is inconsistent with efficient pricing, a finding that agrees with some recent studies of broader market indices (e.g. Mishra et al, 2011). Our results have significant practical implications. The existence of temporal dependencies suggests that traders who can exploit inefficiencies to generate excess returns through technical trading rules. These rules can be more effective if the precise nature of returns behavior (such as "persistence" or "antipersistence") can be identified.

The remainder of this study is organized as follows. The section below provides a brief review of the literature on market efficiency within the Indian context, with a focus on long memory. This is followed by a description of the data, a discussion of the methodology employed to study long-range dependence in returns, and a presentation of the empirical results. The concluding section discusses the results and implications of the study.

INFORMATIONAL EFFICIENCY OF INDIAN CAPITAL MARKETS

The evidence on market efficiency within the Indian context is mixed, though the balance of it appears to lie in favor of some predictability of returns. In an early study of Indian stock market efficiency, Poshakwale (2002) tests for linear and nonlinear dependence using an equally weighted portfolio of 100 stocks, and 38 of the most actively traded individual securities listed on the BSE for the period 1990-1998. The results reject the random walk hypothesis and are consistent with the presence of non-linear dependence and volatility persistence.

While Poshakwale (2002) tests for structural breaks in volatility due to regulatory changes in the sample period 1990-1997, a later study of the BRIC countries (for the period 1990-2007) by Kasman (2009) suggests that incorporating sudden variance shifts due to domestic and global economic and political events into the model reduces the estimated volatility persistence by as much as 34% for the Indian stock market. Using a similar sample period of 1990-2007, Badhani (2008) studies the CNX Nifty Index for the presence of long memory in returns and returns volatility. The study suggests that the volatility of returns (but not the returns themselves), are characterized by persistence. Such volatility persistence was not observed for the 2001-2007 sub-period, however, and the author concludes that the results are more consistent with structural breaks in the volatility process.

Sarkar & Mukhopadhyay (2006) analyze four broader market indices for a period between six and fifteen years (depending upon the index) ending in the year 2000. Using daily returns, they find nonlinear dependencies in the returns series and dynamics beyond the second moment that contribute to inefficiency in these markets. Mishra et al (2011) study two sectoral (Banking and IT, both from the NSE), and four non-sectoral indices roughly over the period 1991-2010. Their findings are similar to those of Sarkar & Mukhopadhyay (2006). Variance Ratio tests lead them to reject the random walk hypothesis in the case of all the six indices they consider. They also find evidence of nonlinear dependence in returns, and the results of a rescaled range (R/S) analysis suggest some persistence (long memory) in returns.

A recent work by Bhat & Nain (2014) also tests for persistence, though its focus is on the volatility of returns on four sectoral indices—the BSE Bankex, Information Technology (IT), Metal, and Public Sector Undertakings (PSU) indices. That study finds evidence of volatility persistence in the BSE Bankex and IT indices. Similarly, Mukherjee et al (2011) find evidence of persistence in return volatility (but not returns) for the BSE Sensex index over the period 1997-2009.

Mishra & Mishra (2011) test the random walk hypothesis in the presence of nonlinearities for two market indices belonging to the National Stock Exchange (NSE) and ten individual stocks. Their findings suggest that the series of returns for both indices and most of the individual stocks studied follow a random walk, a finding that stands in contrast to those from some of the studies mentioned above (e.g., Poshakwale, 2002; Sarkar & Mukhopadhyay, 2006; and Mishra et al, 2011).

The question of persistence has also been addressed for returns on individual securities, as against equity indices. For example, Rajagopal (2011) employs classical R/S analysis to study returns on 25 infrastructure stocks. He finds evidence of antipersistence in most of the series; in these returns series, the dependency between two sets of returns is such that an up-trend in one set is more likely to be followed by a down- trend in the next set of the same length. Another study of weak-form efficiency in the Indian markets is that by Hiremath & Kamaiah (2012). They use a non-parametric variance ratio test and analyze the behavior of several non-sectoral BSE indices, among others, for a period roughly covering 1998—2009 (the data for some of the indices originate later than 1998). They find evidence consistent with weak-from inefficiency, especially in the case of mid-and small-cap equities. In an earlier study, Hiremath & Kamaiah (2010), the authors document a mean-reverting tendency among India stock returns.

Studies have addressed the issue of long memory in returns and volatility in the context of markets other than equities as well. For example, Kumar (2014) is a recent study that documents the existence of long-range dependence in returns and volatility in the market for foreign exchange, specifically the Indian Rupee-USD market. The results are inconsistent with weak-form efficiency in this market, and suggest that models incorporating long-range dependencies will likely possess greater forecast accuracy than would short-memory models.

Palamalai & Kalaivani (2015) and Hiremath & Kumari (2015) are the two studies of which we are aware that assess informational efficiency in Indian sectoral indices. The first of these studies uses a sample of daily returns for about 5 ½ years beginning in 2009 and 2010, and tests for efficiency based on autocorrelation, unit roots, the variance ratio, and runs in return signs. The results suggest significant autocorrelation in returns (reported for lags of up to 12 days), and the existence of unit root, pointing to weak-form inefficiency. Taking a different approach to the question of market efficiency, the present work assesses whether there is long memory/long-range dependence in the returns series. The Hiremath & Kumari (2015) study focuses on a window of nine years ending in March 2012, and tests for long memory in 16 sectoral and 13 broader indices traded on the BSE and the NSE. In contrast, the present study uses self-affine fractal analysis methods to estimate the Hurst exponent, seeking to identify each series as exhibiting persistent/trend-reinforcing behavior, antipersistent/mean-reverting behavior, or Brownian motion. The existence of such patterns would contradict efficient pricing and suggest the possibility of establishing profitable trading strategies based on historical market information.

DATA, METHODOLOGY, & EMPIRICAL RESULTS

We consider the returns on a total of 30 sectoral equity indices on the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), employing the entire price series available for each index on the BSE and NSE sites (bseindia.com; nse.com), ending on August 31, 2017. Some additional information (that for the NIFTY Pharma index) has been collected from

Investing.com. Table 1 below shows the time period over which each of the 19 BSE sectoral index price series is available. The data for the BSE indices span a period of roughly 11 to 18 years.

Table 1
BSE Sectoral Index Date Range ending August 31, 2017

Index	**Data Start Date**	**N**
Auto	01/02/1999	4628
Bankex	01/01/2002	3901
Basic Materials	16/09/ 2005	2962
Capital Goods	01/02/1999	4628
Consumer Discretionary	16/09/ 2005	2962
Consumer Durables	01/02/1999	4628
Energy	16/09/2005	2962
FMCG	01/02/1999	4628
Finance	16/09/2005	2962
Healthcare	01/02/1999	4628
Industrials	16/09/2005	2962
IT	01/02/1999	4628
Metal	01/02/1999	4628
Oil and Gas	01/02/1999	4628
Power	03/01/2005	3142
Realty	02/01/2006	2891
Teck	31/01/2000	4380
Telecom	16/09/2005	2962
Utilities	16/09/2005	2962

Table 2 below provides some descriptive statistics for the daily returns on the BSE indices. The returns data are non-normal, and, except for the Auto index, Metal index and, to some extent, the Telecom index, return distributions are quite significantly leptokurtic. Also, virtually all return series are negatively skewed to some degree.

Table 2
BSE Sectoral Index Returns Descriptive Statistics

Index	N	Mean %	St Dev	Skewness	Kurtosis
Auto	4628	0.068	0.016	-0.299	3.36
Bankex	3901	0.085	0.019	-0.066	6.25
Basic Materials	2962	0.039	0.018	-0.397	5.17
Capital Goods	4628	0.062	0.018	-0.029	6.42
Consumer Discretionary	2962	0.045	0.014	-0.671	7.20
Consumer Durables	4628	0.062	0.019	-0.294	4.06
Energy	2962	0.045	0.017	-0.264	9.67
FMCG	4628	0.050	0.014	-0.045	5.03
Finance	2962	0.058	0.018	0.017	6.35
Healthcare	4628	0.056	0.014	-0.100	7.43
Industrials	2962	0.041	0.017	-0.083	6.16
IT	4628	0.050	0.023	-0.398	8.11
Metal	4628	0.056	0.022	-0.255	4.03
Oil & Gas	4628	0.059	0.018	-0.304	7.70
Power	3142	0.026	0.017	-0.095	8.00
Realty	2891	0.017	0.028	-0.464	7.08
Teck	4380	0.014	0.020	-0.544	7.60
Telecom	2962	0.012	0.020	-0.077	4.28
Utilities	2962	0.024	0.017	-0.438	10.90

Tables 3 and 4 below list the corresponding information for the sectoral indices on the NSE. Some price series, such as those for the Realty, PSU Banks, Metal, and Pharma indices are relatively short, especially in relation to what is available for BSE indices. A total of 11 sectoral indices are available on the NSE, and the data for these span a period of roughly 3 to 21 years. In general, the returns are characterized by varying degrees of negative skewness and are leptokurtic (with the exception of Pharma and PSU Banks).

Table 3 NSE Sectoral Index Date Range, ending August 31, 2017		
Index	**Data Start Date**	**N**
Auto	01/01/2004	3396
Bank	04/01/2000	4399
Energy	01/01/2001	4149
Financial Services	01/01/2004	3396
FMCG	01/01/1996	5397
IT	01/01/1996	5397
Media	30/12/2005	2892
Metal	13/07/2011	1518
Pharma	01/02/2011	1630
PSU Banks	02/08/2012	1255
Realty	23/07/2014	764

Table 4 NSE Sectoral Index Returns Descriptive Statistics					
Index	**N**	**Mean %**	**St Dev**	**Skewness**	**Kurtosis**
Auto	3396	0.070	0.015	-0.247	5.25
Bank	4399	0.071	0.019	-0.156	5.62
Energy	4149	0.062	0.017	-0.451	8.85
Financial Services	3396	0.068	0.019	-0.092	7.06
FMCG	5397	0.060	0.015	-0.142	4.59
IT	5397	0.087	0.023	-0.331	6.65
Media	2892	0.038	0.017	-0.198	4.80
Metal	1518	-0.065	0.017	0.052	1.58
Pharma	1630	0.040	0.011	-0.491	2.96
PSU Banks	1255	0.076	0.020	0.193	2.14
Realty	764	0.014	0.020	-0.650	4.80

To test for persistence, we estimate the self-affinity index (or Hurst exponent, H) for the index returns series using Mandelbrot's (1972) rescaled-range (R/S) analysis methodology, which has its origins in Hurst's (1951) study of the Nile river. We begin by defining a time series **Y** with n consecutive values **Y** = $Y_1, Y_2, \ldots, Y_n$. The mean and standard deviation, Y_m and S_n , are defined as usual:

$$Y_m = \frac{\sum_{i=1}^{n} Y_i}{n} \tag{1}$$

$$S_n = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - Y_m)^2}{n}} \tag{2}$$

The range, R, is defined here as the difference between the highest and lowest cumulative deviation values of Y over the n observations:

$$R = \mathrm{Max}[\textstyle\sum_{i=1}^{n}(Y_i - Y_m)] - \mathrm{Min}[\textstyle\sum_{i=1}^{n}(Y_i - Y_m)] \tag{3}$$

That is, successive deviations from the mean are cumulated through the series of Y values, the minimum and maximum cumulated values are identified, and the difference is taken between those two values. As Y has been redefined to a mean of 0, the maximum cumulated deviation would be at least 0, and the minimum at most zero. Hence, R will be non-negative. Now, the range can be viewed as the distance traveled by the series in time n. For systems following Brownian motion, distance covered is proportional to the square root of time, so that for $R = T^{0.5}$ for such systems. A general form of this rule for systems with dependence rather than Brownian motion would be (Hurst, 1951):

$$\frac{R}{S_n} = k \cdot n^H \tag{4}$$

In the equation above, k is a constant, and H is the "Hurst exponent". The left hand side of the equation shows the rescaled range, R/S ("range scaled by standard deviation"), and the relationship captures how the range of cumulated deviations scales over the time increment, n. For random series, we would expect the exponent (H) to be 0.5. Taking the log of each side, we get:

$$\log\left(\frac{R}{S_n}\right) = \log k + H \cdot \log n \tag{5}$$

As such, we can estimate the Hurst exponent, H, as the slope of the plot of log (R/S_n) against log (n). In practice, the Y series is divided into contiguous sub-periods and H is estimated by OLS (see Peters, 1994, pages 61-63). Consider, for example, a series consisting of 680 logarithmic returns. This series is divided successively into periods of length n, with n assuming values of whole integer factors of 680 (i.e. 2, 4, 5, 8, 10, 17, etc.). In the case of each n, an average range and standard deviation can be calculated. For instance, for n of 2, there will 340 windows, for n of 4 there will be 170 windows, and so on). The logarithm of the average R/S value obtained for the window length is regressed on the logarithm of the window length, n. The coefficient of log n is the estimated Hurst exponent, or scaling exponent, H. The value of H is 0.50 for a random series, or independent process; if $0.50 < H \leq 1$, the elements in the series influence other elements in the series, and the series is "persistent". The series is "anti-persistent" if $0 \leq H < 0.50$; in this case, the process reverses itself more frequently than a random process would.

A second method we use to estimate the Hurst exponent is that of the Roughness-Length relationship (R/L), which is similar to the R/S method described above, except that the vertical range is replaced with the root-mean-square roughness of the data. Thus, where the average range and standard deviation were calculated in the R/S approach, the root-mean-square roughness is calculated (after adjusting for local linear trend) under the R/L approach. This yields the average root-mean-square roughness for each interval length, denoted say, by *s (w)*. If the trace is self-affine, the roughness measure, *s(w)* is related to the Hurst exponent, *H*, as $s(w) = w^H$, and the Hurst exponent is estimated as in the case of the R/S approach through a regression.

Third, we employ the Wavelets method to estimate the Hurst exponents. This approach exploits the fact that transforms of self-affine traces are themselves self-affine. We decompose the series to be analyzed in time frequency space and assess variations in power. Should the wavelet power spectrum be related to frequency by a power law function, we would infer the existence of fractal properties. As noted by Mulligan (2004), the method is applicable in the case of non-stationary series. The application of this method is briefly described below[1].

T wavelet transforms are taken, each with a distinct scaling coefficient, K_i. Let S_i denote the standard deviations from 0 of those scaling coefficients. Now, let R_i be the T-1 ratios of the standard deviations. So, $R_1 = S_1/S_2$, $R_2 = S_2/S_3$, etc. Next, estimate the average of the R_i as:

$$R_{AVG} = \frac{\sum_{i=1}^{T-1} R_i}{T-1} \quad (6)$$

Finally, estimate the Hurst exponent as $H = \Phi\ (R_{AVG})$; where Φ is a heuristic function that approximates H by R_{AVG} for stochastic self-affine series. In the present estimation process, T is varied up to a value of 4, and i takes the values of 0, 1, 2, and 3 for the scaling coefficients. As such, we estimate H using the first three dominant wavelet functions, a process also followed in Mulligan (2004). The wavelet method does not yield a standard error for hypothesis testing.

Table 5 below presents the results of the R/S analysis, the Wavelets method, and the R/L method for all thirty sectoral indices included in the study. The results for the **BSE indices** may be summarized as follows (summary results for both sets of indices under all three methods are tabulated in Table 6 below).

- There is agreement between all three methods that **persistence** appears to characterize the returns in **11 sectoral indices**: Auto, Basic Materials, Capital Goods, Consumer Discretionary, Consumer Durables, Healthcare, Industrials, IT, Metal, Realty, and Utilities.
- There are **3 sectors** in which the R/L method suggests the presence of **anti-persistence**, and for which the R/S approach does not return an exponent significantly different from 0.50. These sectors are Energy, Fast Moving Consumer Goods (FMCG), and Telecom.
- There are **2 sectors**, Oil & Gas, and Power, for which the R/S method does not lead to the rejection of the null, but for which the R/L and Wavelets methods suggests the existence of returns **persistence**. There is **1 sector**, Finance, for which the R/S method suggests **persistence**, but the R/L method fails to reject the null.
- For **1 sector**, TECK, the R/S and Wavelets methods on the one hand, and the R/L method on the other, suggest opposite returns behavior; the first two indicate returns **persistence**, while the third suggests the **antipersistent** behavior.
- Finally, under neither the R/S method nor the R/L approach is the null rejected for **1 sector**, Bankex.

For the eleven **sectoral indices on the NSE**, the results are as follows:

- The **4 sectors**, IT, Media, Metal, and PSU Banks are shown to have **persistence** in returns based on all three methods.
- For the **3 sectors**, Bank, Energy, and FMCG, **persistence** is indicated by the Wavelets and R/L methods, but the null is not rejected under the R/S method.

[1] The Wavelets method derives from the work of Beylkin (1992), Coifman et al (1992), and Daubechies (1990).

- Under neither the R/S method nor the R/L approach is the null rejected for **1 sector**, Financial Services.
- For **2 sectors**, Pharma and Realty, the R/L method suggests **antipersistent** behavior, but the null is not rejected under the R/S method.
- Finally for **1 sector**, Auto, the R/S and Wavelets methods suggest **persistence** in returns, but the null is not rejected under the R/L method.

Table 5
Estimated H for BSE & NSE Sectoral Indices

		R/S Analysis		Wavelets	R/L Analysis	
BSE Sectoral Indices	**# In Trace**	**Est. H**	**p-value**	**Est. H**	**Est. H**	**p-value**
Auto	4620	0.582	0.0000	0.589	0.566	0.0060
Bankex	3780	0.528	0.4987	0.571	0.507	0.1966
Basic Materials	2520	0.568	0.0009	0.613	0.559	0.0000
Capital Goods	4620	0.571	0.0069	0.608	0.580	0.0000
Consumer Discretionary	2520	0.572	0.0008	0.632	0.548	0.0000
Consumer Durables	4620	0.583	0.0000	0.610	0.574	0.0000
Energy	2520	0.503	0.9118	0.575	0.484	0.0254
FMCG	4620	0.503	0.9602	0.583	0.473	0.0000
Finance	2520	0.548	0.0044	0.581	0.503	0.4700
Healthcare	4620	0.555	0.0469	0.597	0.546	0.0000
Industrials	2520	0.571	0.0000	0.629	0.556	0.0000
IT	4620	0.558	0.0001	0.588	0.530	0.0394
Metal	4620	0.564	0.1018	0.596	0.581	0.0000
Oil & Gas	4620	0.521	0.5295	0.582	0.523	0.0014
Power	2520	0.547	0.1603	0.578	0.542	0.0000
Realty	2520	0.569	0.0248	0.614	0.559	0.0000
Teck	4320	0.529	0.0024	0.585	0.479	0.0613
Telecom	2520	0.496	0.9003	0.581	0.464	0.0019
Utilities	2520	0.548	0.0926	0.604	0.533	0.0000
NSE Sectoral Indices	**# In Trace**	**Est. H**	**p-value**	**Est. H**	**Est. H**	**p-value**
Auto	3360	0.531	0.0744	0.576	0.508	0.2274
Bank	4320	0.53	0.4825	0.572	0.513	0.0000
Energy	3960	0.526	0.4452	0.545	0.519	0.0000
Financial Services	3360	0.526	0.2775	0.569	0.505	0.5782
FMCG	5040	0.497	0.952	0.563	0.461	0.0000
IT	5040	0.579	0.0000	0.588	0.558	0.0000
Media	2520	0.575	0.0000	0.576	0.531	0.0000
Metal	1440	0.531	0.0257	0.556	0.480	0.0036
Pharma	1440	0.462	0.4895	0.625	0.460	0.0000
PSU Banks	1080	0.549	0.0013	0.568	0.518	0.0054
Realty	720	0.503	0.5552	0.621	0.431	0.0000

Table 6
Summary of Results

	R/S		Wavelets		R/L	
BSE Sectoral Indices	Persist.	Anti-Pers.	Persist.	Anti-Pers.	Persist.	Anti-Pers.
Auto	▯		▯		▯	
Bankex			▯			
Basic Materials	▯		▯		▯	
Capital Goods	▯		▯		▯	
Cons. Discretionary	▯		▯		▯	
Consumer Durables	▯		▯		▯	
Energy			▯			▯
FMCG			▯			▯
Finance	▯		▯			
Healthcare	▯		▯		▯	
Industrials	▯		▯		▯	
IT	▯		▯		▯	
Metal	▯		▯		▯	
Oil & Gas			▯		▯	
Power			▯		▯	
Realty	▯		▯		▯	
Teck			▯			▯
Telecom			▯			▯
Utilities	▯		▯		▯	
NSE Sectoral Indices						
Auto	▯		▯			
Bank			▯		▯	
Energy			▯		▯	
Financial Services			▯			
FMCG			▯		▯	
IT	▯		▯		▯	
Media	▯		▯		▯	
Metal	▯		▯		▯	
Pharma			▯			▯
PSU Banks	▯		▯		▯	
Realty			▯			▯

DISCUSSION OF RESULTS & IMPLICATIONS OF STUDY

Our analysis of long memory in Indian sectoral equity indices includes estimating the Hurst exponent for the 30 returns series associated with the BSE and NSE sectoral indices using the rescaled range (R/S), Wavelets, and Roughness-Length relationship (R/L) methods. As the results in Table 5 and Table 6 above indicate, as many as 15 of the 30 series are characterized by persistence, or long-range dependence. For every sector, the Wavelets method yields estimates that are greater than 0.50, in many cases quite close to 0.60, and in roughly a third of the cases even higher than 0.60. The R/S analysis confirms significant persistence in the case of 17 of these returns series. Among the indices for which significant persistence is observed, the estimated Hurst exponents range between a low of 0.529 and a high of 0.583 (based on R/S), between a low of 0.556 and a high of 0.632 (based on Wavelets), and between a low of 0.513 and a high of 0.581 (based on the R/L method). Only for the BSE Bankex and NSE Financial Services sectoral indices is there no evidence of pricing inefficiency based on the R/S and R/L methods.

These results are qualitatively similar to those reported by Mishra et al (2011) for broader market indices in India. They find persistence in the case of the BSE 100, BSE 200, BSE Sensex, and CNX Nifty indices, with estimated Hurst exponents (for raw returns) ranging between 0.575 and 0.619. The estimated exponents are significantly different from the benchmark of 0.50 for a series consistent with a random walk. For the banking sector, however, our results are mixed; we find only mixed evidence of persistence in the BSE Bankex series as persistence is suggested by the Wavelets method but not the R/S and R/L approaches. Our finding in the case of Bankex is confirmed by Hiremath & Kumari (2015). Mishra et al (2011) find strong persistence (relative to the broader indices that they study) for the Nifty Bank index, and the Wavelets and R/L methods in our study confirm this finding. As noted above, we do find evidence of persistence in the NSE PSU Bank index as well, which is in contrast to Hiremath & Kumari (2015). Further, the existence of long memory in the IT and Realty sectors had been documented previously by Rajagopal & Hays (2012a; 2012b), *inter alia*; updated data in our study confirm their findings. Hiremath & Kumari (2015) find evidence of long memory in the BSE Realty index, but not in the case of the IT sector. Our results confirm, at least qualitatively, the findings of Palamalai & Kalaivani (2015), who document weak form inefficiency in the sectoral indices that they examine. While they find evidence that all the 23 sectoral indices in their study exhibit behavior inconsistent with weak form efficiency, our analysis of long-range dependence suggests that the behavior of half of the sectoral indices diverges from what would be expected of series that follow a Brownian motion, but that that divergence in not true for all the sectors.

The consistent evidence that Hiremath & Kumari (2015) find of long memory in the BSE Auto, Capital Goods, Consumer Durables, Health Care, Metal, and Realty sectors is confirmed here using a significantly wider time frame. Their finding of long memory in the NSE Auto and FMCG indices, however, does not receive the same degree of confirmation in our study, in that not all three of our methods support that conclusion.

Interestingly, there are 6 returns series—those for BSE Energy, FMCG, TECK, and Telecom; and NSE Pharma and Realty—that appear to be antipersistent. This is the only evidence of antipersistence observed in the study, and is suggested by the R/L method; the finding is not supported by either the Wavelets or the R/S methods. Chamoli et al (2007), who test for the relative effectiveness of the Wavelets, R/S, and R/L techniques (in addition to the Power Spectrum and Variogram methods) in estimating the Hurst exponent, demonstrate that the Wavelets and R/S methods provide superior estimates of H across varying lengths of synthetically generated fractional Brownian motion data with a given Hurst exponent[2]. In relation to other methods, including the R/L approach, the Wavelets and R/S methods are found to be more robust in the estimation of the Hurst exponent for time series of both long as well as short length. In light of this, and as there is a large variation in the data length across the 30 series considered here (from 764 to 5397), we are inclined to discount the finding of antipersistence which is suggested solely by the R/L method.

Further, there is some inconsistency in the results for the BSE and NSE Realty indices; R/S analysis suggests that the NSE Realty index does not exhibit long-range dependence, but that the BSE Realty index does. This discrepancy is likely due to the fact that the BSE Realty series covers a period of time that is roughly three times the period covered by the corresponding NSE series. It includes the period of the real estate crash of 2008, while the NSE series begins only in 2014, rendering the two series quite different qualitatively.

In summary, the conclusion of long-memory is consistently supported by all three methods for as many as 15 of the 30 sectoral indices on the BSE and NSE. In addition, some evidence of antipersistence is found for 6 returns series, though this finding is not supported by the Wavelets and R/S methods. The results of this study point to the existence of significant pockets of pricing inefficiency in the Indian market; there is evidence of exploitable opportunities in several sectors in addition to the IT and Realty sectors considered by previous studies of long memory in the Indian context. Trading strategies aimed at extracting excess returns may be effective in as many as half of the sectors studied.

REFERENCES

Badhani, K.N. (2008). Long memory in stock returns and volatility in India: A nonparametric analysis. *The ICFAI Journal of Applied Finance*, 14:12, 34-53.

Bhat, S. A & M. Z. Nain (2014). Modeling conditional heteroscedasticity and leverage effect in the BSE sector indices. *The IUP Journal of Financial Risk Management*, 11:2, 49-61.

Beylkin, G. (1992). On the representation of operators in bases of compactly supported wavelets. *SIAM Journal on Numerical Analysis*, 29:6, 1716–1740.

Chamoli, A., A. R. Bansal & V. P. Dimri (2007). Wavelet and rescaled range approach for the Hurst coefficient for short and long time series. *Computers and Geosciences*, 33, 83-93.

Coifman, R., M. B. Ruskai, G. Beylkin, I. Daubechies, S. Mallat, Y. Meyer, and L. Raphael (Ed.) (1992). *Wavelets and their applications*. Jones & Bartlett, Sudbury, MA.

Daubechies, I. (1990). The wavelet transform, time-frequency localization and signal analysis. *IEEE Transactions on information theory*, 36, 961-1005.

Dicle, M. F., A. Beyhan, & L. J. Yao (2010). Market efficiency and international diversification: Evidence from India. *International Review of Economics & Finance*, 19, 313-339.

Hiremath, G.S., & B. Kamaiah (2010). Do stock returns in India exhibit a mean-reverting tendency? Evidence from multiple structural breaks test. *Banking and Finance Letters*, 2, 4, 371-390.

Hiremath, G.S., & B. Kamaiah (2012). Variance ratios, structural breaks and non-random walk behavior in the Indian stock returns. *Journal of Business and Economic Studies*, 18, 62-81.

Hiremath, G.S., & J. Kumari (2015). Is there long memory in Indian stock market returns? An empirical search. *Journal of Asia-Pacific Business*, 16, 128-145.

[2] We are grateful to an anonymous referee for bringing the Chamoli et al (2007) study to our attention.

Hurst, H.E. (1951). Long-term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineers*,116, 770-799.

Kasman, Adnan (2009). The impact of sudden changes on the persistence of volatility: Evidence from the BRIC countries. *Applied Economics Letters*, 16, 759-764.

Kumar, A.S. (2014). Testing for long memory in volatility in the Indian forex market. *Economic Annals*, 59, 203, 75-90.

Lo, A. W. (1991). Long-term memory in stock market prices. *Econometrica*, 59, 5, 1279-1313.

Mandelbrot, B. (1972). Analysis of non-periodic long-run dependence using the robust statistic R/S. *Proceedings of the 1971 Princeton Conference on Information Sciences and Systems*, 155-159.

Mishra, A., & V. Mishra (2011). Is the Indian stock market efficient? Evidence from a TAR model with an autoregressive unit root. *Applied Economics Letters*, 18, 467-472.

Mishra, R.K., S. Sehgal, & N.R. Bhanumurthy (2011). A search for long range dependence and chaotic structure in Indian stock market. *Review of Financial Economics*, 20, 96-104.

Mukherjee, I., C. Sen, & A. Sarkar (2011). Long memory in stock returns: Insights from the Indian market. *The International Journal of Applied Economics & Finance*, 5, 1, 62-74.

Mulligan, R. F. (2004). Fractal analysis of highly volatile markets: An application to technology equities. *The Quarterly Review of Economics and Finance*, 44, 155-179.

Newey, W. & K. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), 703-708.

Palamalai, S.& M. Kalaivani (2015). Are Indian stock markets weak-form efficient?—Evidence from NSE and BSE sectoral indices. *The IUP Journal of Financial Risk Management*, 12, 4, 7—34.

Peters, E. (1994). *Fractal market analysis*. John Wiley & Sons, Inc.: New York.

Poshakwale, S. (2002). The random walk hypothesis in the emerging Indian stock market. *Journal of Business Finance & Accounting*, 29, 9/10, 1275-1299.

Rajagopal, S. (2011). Pricing of infrastructure equities: A test of efficiency in an emerging market. *Asia Pacific Journal of Finance & Banking Research*, 5, 5, 47-61.

Rajagopal, S. & Patrick Hays (2012a). Returns persistence in the Indian real estate market. *International Real Estate Review*, 15, 3, 283-305.

Rajagopal, S. & Patrick Hays (2012b). Long range dependence in stock returns: A study of US and Indian IT sectors. *International Research Journal of Applied Finance*, 3, 11, 1606-1623.

Sarkar, N. & D. Mukhopadhyay (2005). Testing predictability and nonlinear dependence in the Indian stock market. *Emerging Markets Finance and Trade*, 41, 6, 7-44.