Long Range Dependence And Market Efficiency : Evidence From The Indian Stock Market

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ABSTRACT

This empirical investigation examines the long memory or long range dependence in the Indian stock market vis-à-vis market efficiency. The researcher examined the daily data of the major indices and large, liquid common stocks using the Rescaled range (R/S) analysis to measure the Hurst exponent using both static and dynamic approach. The researcher evidences significant long range dependence in all the tested indices and many individual stocks. The results are not consistent with weak form efficiency in the Indian stock market. The dynamic approach evidences time dependence and rejects both the notion of evolving efficiency through the passage of time and permanent increase in efficiency subsequent to both market reforms and improved trading practices in the Indian stock market. The results are robust to alternate time domain and frequency domain measures of Hurst exponent.

Keywords : Long Range Dependence, Indian Stock Market, Hurst, Market Efficiency
JEL Classification: G10,G14.

INTRODUCTION

A number of studies have examined the presence of long memory or long range dependence in asset prices. A stationary process with slowly decaying or long range correlations is said to be long range dependent[1]. Baillie (1996) defined the presence of long memory for empirical studies as persistence of observed correlations. The auto correlations of such processes decay hyperbolically (slow) and not exponentially (fast). According to Barkoulos et al. (1996), asset returns with long range dependence exhibit correlations between observations widely separated in time. The implication is that the asset prices in the remote past can be used to predict future prices, and is a direct challenge to the Efficient Market Hypothesis. In the Efficient Market Hypothesis (EMH) paradigm, asset prices follow a martingale process, which requires any new information to be quickly arbitraged away. According to Mandelbrot (1971), in the presence of long range dependence, the arrival of new information cannot be fully arbitraged away, and the martingale model does not hold. Thus, the presence of long range dependence in asset returns is a direct challenge to the weak form Efficient Market Hypothesis (EMH), which contends that past returns cannot be used to predict future returns.

Greene and Feilitz (1979) outlined the implication of long memory for the existing risk return models. They stated that in the presence of long range dependence, the ranking of stocks and portfolios and construction of efficient portfolios depend on the differencing interval and have implications for the widely used Capital Asset Pricing Model (CAPM). Mandelbrot (1971) contended that in the presence of long range memory, pricing derivatives with the widely used martingale assumption are not valid. A number of studies have focused on the long-range dependence in stock prices in the developed markets with mixed results. Such studies are few and far in between in the Indian stock market. The importance of these studies in the Indian stock market can be appreciated based on the fact that the Indian equity market stood 13th in the world and 4th in Asia in terms of both traded value ($ 1050 bn during 2008) and market capitalization ($ 645 bn at the end of year 2008). Further, most economists feel that the emerging economies of India and China will be the major drivers of the world economy in the coming decades. The increasing international portfolio investment and participation provides a perfect platform for gathering information about the market structure, efficiency and evidence of the integration mechanism with the developed markets.

OBJECTIVES OF THE STUDY

The objective of this study is to examine the long range dependence for major indices and large, liquid stocks in the Indian stock market using the Hurst exponent calculated by the widely used range scale statistic in the recent period. The Hurst exponent is used as the market efficiency indicator as in many other similar studies. Further, a 'Rolling

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sample' approach was also used to test the assertion that market efficiency evolves over time. The Indian financial markets witnessed significant reforms, since the year 1992, which not only resulted in increased participation, but also improved trading practices. SEBI had initiated various measures to improve Reporting, Corporate Governance, etc. Further, 'Derivatives' trading was introduced in 1999. In order to check the robustness of the results, this study uses both the time domain and the frequency-domain measures.

REVIEW OF LITERATURE

The long memory properties have been observed in natural phenomena since 1950s. Mandelbrot (1969,1971,1972) introduced the concept of long memory in economics, and since then, numerous studies have examined the financial time series for long memory using the Hurst exponent. The Hurst exponent is used in several areas of applied mathematics, including fractals and chaos theory, long memory processes and spectral analysis. Hurst exponent estimation is being used in areas like biophysics, economics, computer networking, etc. to measure long range dependence.

The R/S analysis developed by Hurst is a widely used measure to study long memory using the Hurst exponent. Greene and Feilitz (1977,1979) used the original range scale analysis or R/S analysis to examine 200 daily stock returns in the US market and found evidence of long memory in many stock returns. Aydogan and Booth (1988) also studied 200 stocks from the US market using weekly returns for the period 1962 to 1980, and concluded that the evidence was not overwhelmingly in favor of long memory. Lo (1991) introduced the modified R/S statistic to discriminate between short term and long term dependencies and evidenced lack of long memory properties in the US market. Generally, researchers have opined that this modified statistic is too restrictive and consistently underestimates the Hurst exponent.

Various measures like Higuchi (1988), Peng et al. (1994) etc. in the time domain, and wavelet based estimation in the frequency domain to test long term dependence have been surveyed in Taqqu et al. (1995), Clegg (2006) and Rea et al. (2007). The general inference from their analysis is that almost all the estimators have their drawbacks, and consistent estimation from more than one estimator would avoid spurious results.

The empirical results in the developed markets are : Nawrocki (1995) analyzed the CRSP monthly index and the S&P 500 daily index, and found persistence or long memory based on R/S Hurst exponent, and the Lo modified R/S statistic and opined that the dependence arises due to economic cycles. Barkoulas and Baum (1996) applied the spectral regression method and found no evidence of long memory in either aggregate or sectoral stock indices, but found evidence of long memory in some of the stocks of the Dow Jones Industrial companies.

Barkoulas and Baum (2000) studied the Greek stock market using the same spectral regression method and evidenced significant long range dependence. Lillo and Farmer (2008) studied individual stocks in the London stock market, and found mixed evidence of long range dependence. Carles (2000) studied the Spanish stock market for long memory and found little evidence for stock returns. He evidenced significant long memory in squared and absolute returns.

In the other markets, Cajueiro and Tabak (2004) using classical R/S statistic found that the markets of Hong Kong, Singapore and China exhibited long-range dependence. They also evidenced that the Hurst component is time dependent using 'rolling sample' approach and used the results to rank the countries based on their efficiency as measured by the Hurst parameter. Oh, Um and Kim (2006) studied a number of stock market indices and foreign exchange rates using both - high frequency and daily data in order to examine the long term memory. Generally, significant long-term memory was not evidenced in the return series, but significant persistence was evidenced in the volatility series. Sadique and Silvapulle (2001) examined the presence of long memory, using classical, modified R/S statistic etc., in weekly stock returns of seven countries, namely Japan, Korea, New Zealand, Malaysia, Singapore, the USA and Australia. They found evidence for long-term dependence in Korea, Malaysia, Singapore and New Zealand.

In the Indian stock market, Nath (2001) studied the NSE data from 1990 to 2001, and found indications of long-term memory in the Indian stock market using R/S analysis, but suggested that a more rigid analysis should be used for confirmation.

DATA AND METHODS

❖ **Data :** The National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) are the two major stock exchanges in the Indian stock market. This study used the daily data of the major indices from both the stock markets based on the

Table 1: The Characteristics Of The Stock Indices				
INDEX SERIES	**DESCRIPTION**	**DATA**	**% Market Capitalization**	**% Traded value**
CNX 500(NSE)	Broad based benchmark index consisting of top 500 stocks in NSE and can be considered as the representative of the Indian stock market.	Jun 99 - Dec 10	92%	81%
BSE 500	Broad based BSE index	Jan 99 - Dec 10	93%	80%
BSE 200	Top 200 firms in BSE	Jan 99 - Dec 10	80%	56%
BSE 100	Top 100 firms in BSE	Jan 99 - Dec 10	68%	45%
CNX 100 (NSE)	Top 100 firms in NSE	Jan 03 - Dec 10	74%	58%
NIFTY(NSE)	Consists of 50 large, liquid stocks in NSE. The premier index of the NSE and India.	Jul 90 - Dec 10	63%	44%
SENSEX(BSE)	Consists of 30 large, liquid stocks in BSE. The oldest index in India and next only to the Nifty in popularity.	Jan 91 - Dec 10	42%	29%
The NSE represents the National Stock Exchange and the BSE represents the Bombay Stock Exchange in the Indian stock market. While the NSE is the leader in terms of traded value, the BSE is the oldest. The indices were chosen as they represent the broader market and have adequate observations. The data is as on December 2010. The approximate percentage values represent the value in relation to the total market value in NSE and BSE respectively.				
Source : NSE and BSE official websites				

length of observation. The indices analyzed in this study are described in the Table 1. This study also analyzed the top 30 large and liquid stocks in the Indian stock market. All the data were taken from the NSE and BSE official websites. The testing of long term dependence needs large amounts of data, and hence, the maximum available data was used for accuracy. The data from July 1990 to December 2010 was used for the present study.

Daily return R_t is calculated as :

$$R_t = Ln\ (P_t) - Ln\ (P_{t-1}) \qquad \text{-----------} (1)$$

Where,

P_t is the stock/index closing price at time t ;

P_{t-1} is the stock/index closing price at time t-1.

The daily prices are adjusted for capitalization changes like bonus and splits.

- **Measures of Long Range Dependence**
- **Rescaled Range Analysis:** The rescaled range analysis developed by Hurst for use in hydrology to measure long range dependence is used in this study. Mandelbrot later used this test for asset prices. Unlike other correlation tests, R/S analysis can detect both periodic and non-periodic long term dependence. The range scale analysis involves dividing the range of the values exhibited in a portion of the time series by the standard deviation of the values over the same sub period of the time series. The R/S statistic is given by :

$$(R/S)_t = R_t/S_t \quad \text{for} \quad t = 1,2,\ldots..\ n \qquad \text{-----------} (2)$$

Where, the range :

$$R_t = \max(Z_1, Z_2, \ldots, Z_t) - \min(Z_1, Z_2, \ldots, Z_t) \text{ for } t = 1, 2, \ldots, n \qquad \text{-----------} (3)$$

and is calculated using the following steps, a mean adjusted series Y_t is created,

$$Y_t = X_t - m \text{ for } t = 1, 2, \ldots, n \qquad \text{-----------} (4)$$

Then accumulative series Z is calculated and using this range is calculated;

$$Z_t = \sum_{i=1}^{t} Y_i \text{ for } t = 1, 2, \ldots, n \qquad \text{-----------} (5)$$

The standard deviation S_t is calculated using :

$$S_t = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(X_i - u)^2} \text{ for } t = 1, 2, \ldots, n \qquad \text{----------- (6)}$$

Hurst established the relation between rescaled range R/S with the 'Hurst' exponent 'H' as :

$$(R/S)_t = (t/2)^H \qquad \text{---------- (7)}$$

Hurst exponent 'H' measures long range dependence and H = 0.5 suggests random walk, 0.5> H > 1 implies long memory and 0 > H >0.5 suggests anti-persistent behavior. Similar to many other studies, the Hurst exponent 'H' is used as the efficiency indicator in this study. Lo (1991) demonstrated that the R/S statistic is sensitive to small 'n' and to the heteroskedasticity of the underlying process, and hence, is biased towards over estimating the Hurst parameter. The R/S statistic used in this study is largely devoid of such short range dependencies, and the reported results are a conservative estimate of long range dependence. Further, the researcher has also used Weron (2002) simulation based confidence intervals to measure the significance of his results. The researcher used a methodology similar to Cajiueiro and Tabak (2004) to analyze the long term dependence using R/S statistic. In addition to calculation of Hurst exponent for the whole series, the researcher also used a 'Rolling sample' approach for the Sensex[2] index data for the period 1991-2010. He used a five year daily data from 01-01-1991 to 31-12-2005 and calculated the Hurst exponent. The researcher then dropped the first three months data and still used the five years data from 01-04-1991 to 31-03-2006. He continued with this approach till he reached the last five years from 01-01-2006 to 31-12-2010 and got 61 Hurst exponents. This 'rolling sample' methodology helps us to find out whether the market efficiency is time dependent in the Indian stock market.

❖ **Robustness Measures:** Clegg (2006), Rea et al. (2007) cautioned against using a single estimator for the 'Hurst exponent'. Generally, researchers have suggested that consistent estimations suggesting the presence of long memory from more than one estimator is needed to confirm long range dependence in a time series. In this study, the robustness of the results from R/S analysis was tested using both time domain and frequency domain estimators. Los (2003) stated that, unlike the traditional methods, wavelet methods might detect and measure non-linear long range dependence. Though the Istas and Lang (1997) method is not based on the wavelet methodology, it still uses quadratic or second order variations, which might be useful in unearthing nonlinear long range dependence.

Rigorous mathematical treatment of the robustness measures can be appreciated from the referenced articles. Taqqu et al. (1995) and Rea et al. (2007) compared various measures estimating the Hurst exponent and had concluded that the wavelet based estimations give unbiased results for large 'N'. Istas and Lang (1997) [3] estimator (hereafter, W1) is based on discrete second order derivative, which uses generalized quadratic variations to estimate the local holder index of a time series or the Hurst exponent. The researcher also used wavelet based adaptation (Daubechies 4 wavelet variation) as the next robustness measure (hereafter, W2). The other frequency-domain measure used is also wavelet based, proposed by Flandrin (1992) and later extended by Abry et al. (2003)[4]. This wavelet estimate uses the slope of the log - log plot of the detail variance versus the level to estimate the Hurst parameter (hereafter, W3). Generally, wavelet based estimations have a minimum bias with increasing number of observations. In this study, all the indices were chosen to have at least 2000 daily observations.

ANALYSIS AND FINDINGS

The Table 2 represents the results of the rescaled range analysis of returns of the major indices in the Indian stock market. It also presents the summary results of the rescaled range analysis of the top 30 large and liquid stocks in the Indian stock market.

Lo(1991) and other researchers have pointed out that due to the small 'n' effect (in equation (1) ; in relation to number of observations 'N'), the range scale analysis might over estimate the Hurst exponent. The researcher analyzed the Hurst exponent analysis with n= N/2, N/4, N/6, N/8 etc. using the Nifty and Sensex data to analyze the sensitivity of his analysis. The sensitivity analysis shows that the chosen R/S statistic gives a conservative estimate of the Hurst exponent[5]. Further, the researcher used the confidence intervals developed by Woren (2001) to test the significance of his results. The results in Table 2 evidence that all the tested indices exhibit significant long memory or long range dependence. The Indian stock market represented by the broad-based NSE CNX 500 and the BSE 500 index exhibited

Table 2 : Estimate of Hurst Exponent Based On R/S Range Analysis				
Index Series	**Length N**	**HURST Exponent based on R/S analysis**	**HURST Exponent of top 30 large, liquid common stocks**	**Number of common stocks**
CNX 500	2891	0.60**	< 0.50	1
BSE 500	3001	0.60**	0.50 -0.54	9
BSE 200	3001	0.60**	0.54 - 0.58	10
BSE 100	3001	0.60**	> 0.58	10
			Total	30
CNX 100	1997	0.59*	**Overall statistics**	
			Nifty Stocks	HURST
NIFTY	4908	0.57*	Mean	0.56
SENSEX	4794	0.58**	Median	0.57

All the major indices representing size based portfolio in both NSE and BSE were analyzed using R/S analysis adjusted for small 'n' bias. As long term dependence is the focus of study, the index with the maximum number of observations was chosen in each category of index. eg: CNX 500 and BSE 500 consist of almost similar stocks in NSE and BSE respectively. CNX 500 was chosen as the number of observations were larger. Further, top 30 stocks in the Indian stock market based on market capitalization representing the large, liquid segment were also studied. 30 stocks each over 1500 observations[6] were chosen. This study uses the simulation based confidence intervals suggested by Weron (2002) to test the significance of the results. *, **, *** represent significance level at 1%, 5% and 10% level respectively.

Source : NSE and BSE official websites

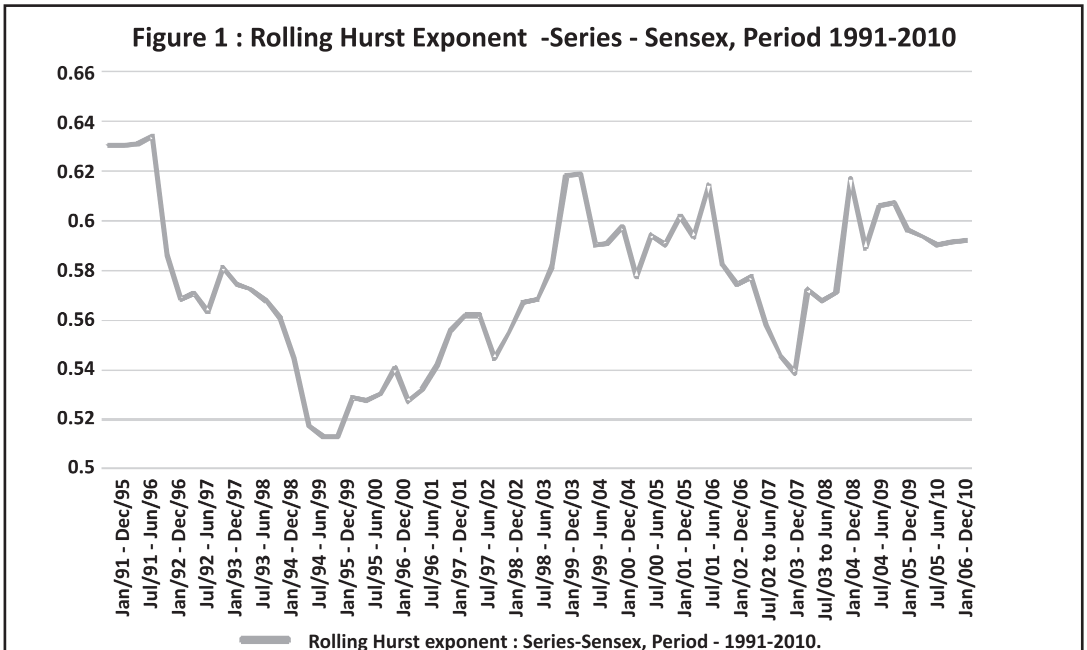
significant long memory with the Hurst exponents at 0.6, which is statistically significant at the 5% level. Even the premier indices[7], Nifty and Sensex, exhibit significant long range dependence and the Hurst parameter is 0.57 and 0.58 respectively. All the other measured indices like BSE 200, BSE 100 and NSE 100 exhibit significant long memory. Hence, all the major indices on the Indian stock market exhibit significant long memory.

Though the results of the thirty large, liquid stocks are not as strong as the indices, nearly 50% of the tested stocks evidenced significant long memory. The results in the developed markets have generally evidenced lack of long range dependence for the common stocks, but the results in the Indian stock market evidence the presence of long range dependence in nearly 50% of the tested large, liquid stocks in the Indian stock market. Further, Aydogan and Booth (1988) used 19 years' data to enable the non-periodic cycles to reveal themselves. Not only very few stocks in the large capitalization space will have data for such a long period in the Indian stock market, but also all the indices, barring the Sensex and the Nifty index, have data only for 11 years. Hence, the results evidencing significant long range dependence in nearly 50 % of large, liquid stocks and all the tested indices are all the more interesting in the Indian stock market as the large, liquid stocks are expected to be informationally efficient.

The results evidence that the Indian stock market exhibits significant long range dependence both at the indices and at the common stock level. This result implies the possibility of superior long memory forecasts and economic profits, which are incompatible with the weak form market efficiency. The Figure1 presents the results of the 'Rolling sample' methodology. The rolling sample methodology[8] was carried out for a twenty years period from 1991 to 2010. The Hurst exponent is used as a measure of efficiency. The analysis starts from the year 1991 to coincide with the start of market reforms were introduced in the Indian economy.

The Figure 1 represents the rolling Hurst exponent for the period 1990-2010 for the Sensex. The Sensex index data for the period 1991-2010 is considered. The researcher used a five year daily data from 01-01-1991 to 31-12-2005 and calculated the Hurst exponent. The researcher then dropped the first three months data, and continued to use the five years data from 01-04-1991 to 31-03-2006. He continued with this approach till he reached the last five years from 01-01-2006 to 31-12-2010, and the researcher obtained 61 Hurst exponents plotted in Figure 1. The mean is 0.57.The median is 0.58.

This methodology is used to examine whether the Indian stock market experienced increased efficiency since the start of the capital market reforms initiated in the year 1992. The results show that even though market efficiency improved post 1991-1992, it follows a 'W' shape, suggesting a lack of permanent improvement in efficiency in the post



Source : NSE and BSE official websites

liberalization era. The result show that the 1990-1991, 2000-2001 and 2008-2009 periods exhibit the maximum long memory or long range dependency and consequently, exhibit lower efficiency, which requires further research[9].

The major implication of the 'Rolling Hurst' results is that there is no evidence of any permanent improvement in the market efficiency post the capital market reforms. The idea of evolving efficiency, where market efficiency improves over time due to increased participation, etc., does not explain the Indian stock market. The robustness of the earlier results evidencing significant long range dependency is verified in this section in order to confirm the long range dependence. The Table 3 presents the Hurst exponent of the major indices measured using both time domain and frequency domain[10] indicators. The Hurst exponent is not only greater than 0.5 for all the tested indices, but also remained in a narrow range for all the indices. While the Hurst exponent for the Sensex varies in the range of 0.57 to 0.60, it varies in the range of 0.60 to 0.62 for the NSE 500 index. The results confirm the findings based R/S analysis that the broader Indian stock market exhibits significant long term dependence. The results are more interesting due to the fact that the premier indices like Nifty and Sensex also evidence long range dependence for all the measures used. The results of the large, liquid common stocks are also robust due to the alternate measures used. Not only is there a remarkable agreement between the various estimators used, but also the results are similar [11] to the short run estimators in that the premier indices display the least long range dependence. The results in the Table 3 evidence that the earlier results are not spurious, and confirm the presence of significant long memory or dependence in the Indian stock market. Further, the stronger evidence of long memory using wavelets may be due to their ability to detect non-linear long range dependence unlike the other traditional tests.

FURTHER RESULTS

The results also give us an opportunity to evaluate the estimators. The wavelet estimator W2 gives the highest values. Of the two wavelet estimators, W2 results are consistently more than W3. For most indices, the Istas and Lang (1997) method (W1) is similar to the R/S statistic used X in this study. The R/S statistic and the other measures evidence significant long range dependence for the major indices in the Indian stock market. The results for the large, liquid common stocks in the Indian stock market also confirm the presence of long memory properties for the majority of the tested stocks. Generally, results in the developed markets do not evidence significant long range dependence, but nearly 50% of the top 30 stocks evidenced significant long range dependence. The results do not support the Efficient Market Hypothesis in the Indian stock market as they contradict the martingale model of the EMH. The reason for the

Table 3 : Estimate of Hurst Exponent Based On Other Measures					
Series	Length N	R/S	W1	W2	W3
CNX 500	2891	0.60	0.61	0.63	0.62
BSE 500	3001	0.60	0.61	0.63	0.66
BSE 200	3001	0.60	0.61	0.62	0.59
BSE 100	3001	0.60	0.60	0.62	0.58
CNX 100	1997	0.59	0.58	0.59	0.60
NIFTY	4908	0.57	0.58	0.58	0.57
SENSEX	4794	0.58	0.59	0.60	0.57

Istas and Lang (1997) estimator (W1) is based on discrete second order derivative which uses generalized quadratic variations to estimate the local holder index of a time series or the Hurst exponent. We also use its wavelet based adaptation (Daubechies 4 wavelet variation) (W2). The fifth measure used is also wavelet based, proposed by Flandrin (1992) and later extended by Abry et al. (2003). This wavelet estimate uses the slope of the log - log plot of the detail variance versus the level to estimate the Hurst parameter (W3). Generally, the wavelet based estimations have a minimum bias with increasing number of observations. In this study, all the indices were chosen to have at least 2000 daily observations.

Source : NSE and BSE official websites

evidenced different results being different from some of the other results in the Indian stock market may be due to the period/length of the data used and the usage of wavelet methods, which can detect non-linear long range dependence unlike the traditional methods.

CONCLUSION

The researcher set out to investigate the long range dependence using daily data of the major indices and large, liquid stocks in the Indian stock market. Along with the normal approach of studying the whole series using the widely used R/S estimator, the researcher also used the 'Rolling sample' approach to analyze the evolving market efficiency ideas in the Indian stock market in the post liberalization era. The results in this study evidence significant long range dependence in the Indian stock market, and do not evidence any permanent increase in market efficiency. The researchers evidence that all the tested major indices are characterized by significant long range dependence. Many common stocks also evidence significant long memory. The results are robust to alternate measures of Hurst exponent. The 'rolling sample' study rejects both the notion of evolving efficiency through passage of time and increased efficiency subsequent to market reforms in the Indian stock market.

The significant evidence of long range memory in the Indian stock market is in contrast to the mixed results evidenced in the developed markets. Further, unlike some emerging markets, there is no evidence of any permanent improvement in efficiency after the market reforms. This result is rather interesting as the Indian economy in general, and the Indian stock market, in particular, has witnessed significant reforms over the past two decades resulting in increased participation, diverse financial products and increase in volume.

The results do not support the weak market efficiency in the Indian stock market as the potential for prediction of stock returns and economic profits exists. The long memory evidenced in the indices and common stocks has major implications for the derivative pricing models in vogue, which assumes Gaussian distributions. Further, the investment dynamics in the Indian stock market displaying long memory needs a different orientation as compared to other markets. The limitation of the study is that most of the indices and common stocks have data only from the year 2000.

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END NOTES

[1]www.long-memory.com for definition, discussion and existing literature regarding long memory in asset prices.

[2] Even though Nifty index is more broad based and representative, the Sensex was chosen because of the length of the series. Though Nifty series data is available from 1990, real data is available only from the year 1995.

[3] Istas and Lang (1997) for a detailed study and proof.

[4] Abry et al. (2003) for the uses of wavelet in estimation of long memory and for the detailed understanding of their estimate. This article also compares different wavelet methods used to test long memory.

[5] For various values of 'n' across the spectrum, the R/S statistics varied between 0.57 and 0.60 for both Sensex and Nifty.

[6] Except for two stocks , all the other 28 stocks have 3001 observations.

[7] The twenty year data of both the premier indices were bifurcated into two periods, and it was seen that both the periods evidenced significant long memory.

[8] Using the same Sensex series, a static approach of dividing the 20 year period into equivalent two, three and four periods and calculating the Hurst parameter for each sub-period was also attempted. The results also rejected the evolving efficiency paradigm in the Indian stock market.

[9] 2000 Recession due to dotcom bubble, 2001 - A major scam in the Indian stock market, 2008 Recession due to the sub - prime crisis.

[10] The researcher also calculated the Hurst exponent using Higuchi and Peng methods to verify the results. The results are similar to the results of the R/S method presented in the Table 3.

[11] Short run results not discussed for brevity, but can be had on demand.

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