Long Memory in Indian Stock Market : An Empirical Analysis

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Abstract: This study aims at investigating the existence of long memory property in Indian stock market. We have chosen two leading indices SENSEX and NIFTY as proxy for the same. Standard econometric tests have been used including Rescaled-Range (R/S) analysis and its modified form in time domain and the Spectral Regression Method in the frequency domain. The results indicate presence of short memory in return series and long memory for volatility. The study also found the existence of Taylor's effect in Indian stock market. The findings are consistent in all the tests and are in line with the stylized facts of financial time series.

Key-words: Long memory, rescaled-range analysis, spectral regression method, Taylor's effect, volatility.

1. Introduction

The covert presence of stochastic long memory in stock market returns has been an imperative issue of both theoretical and empirical investigation. It is well known and accepted that some of the human and natural phenomena show long memory and there exists huge publications relating to long memory in areas such as finance (e.g. Lo, 1997), econometrics (e.g. Robinson, 2003), internet modelling (e.g. Karagiannis et al., 2004), hydrology (e.g. Painter, 1998), climate studies (e.g. Varotsos and Kirk-Davidoff, 2006), linguistics (e.g. Alvarez-Lacalle et al., 2006) or DNA sequencing (e.g. Karmeshu and Krishnamachari, 2004). Long range dependence and long memory are synonymous notions that have far reaching implications. Presence of stochastic long memory in stock market returns has a direct impact on the world of market efficiency and can pose a serious challenge to the proponents of random walk behavior of the stock returns. The studies related to long range dependence includes detection of long memory in the data, statistical estimation of parameters of long range dependence, limit theorems under long range dependence, simulation of long memory processes, and many others. Hurst (1951) possibly inspired the development of statistical long-memory processes. He proposed a method (Rescaled-Range analysis) for the quantification of long-term memory which is based on estimating a parameter for the scaling behaviour of the range of partial sums of the variable under consideration. Some early studies in long memory process in finance were carried out by Mandelbrot (1971, 1972) and Mandelbrot and Wallis (1969) who suggested that in the presence of long memory, arbitrage opportunities may exist as new market information cannot be absorbed quickly and martingale models of asset prices may not be justified. Mandelbrot (1997) contains many of the early papers that Mandelbrot wrote on the application of the Hurst exponent in financial time series. Since those days, the application of the long memory processes in economy has been extended from macroeconomics to finance. A good survey of the econometric approach to long-memory is given in Baillie (1996).

The study of possible long-memory properties of time series in finance is even more widespread. There has been a long-standing debate as to whether or not asset prices have long-memory properties. In case of long memory, linear pricing models and statistical inferences about asset pricing models based on standard testing procedures may not be appropriate (Yajima, 1985). Several authors have claimed that the time series of stock returns for stock prices or indices display long-memory (Mandelbrot, 1971; Greene and Fielitz, 1977). Lo (1991) re-examined these results and showed that the statistical Rescaled-Range (R/S) test used by Mandelbrot (1971) and Greene and Fielitz (1977) is too weak and unable to distinguish between long and short memory. By introducing a modified R/S test, Lo concluded that daily stock returns do not display long-memory properties. However, Willinger et al. (1999) showed that the modified R/S test leads to the rejection of the null hypothesis of short-memory when applied to synthetic time series with a low degree of long-memory. Since financial data typically display low degree of long-memory, they claim that the result of Lo (1991) may not be conclusive.

It is more widely accepted (though still not entirely uncontroversial) that the volatility of prices is a long-memory process. It is well known that asset price returns contain little serial correlation, in accord with the efficient markets hypothesis; however, their volatilities exhibit a much richer structure. There is a lot of evidence showing that conditional volatility of returns on asset prices displays long memory or long range dependence. Andersen and Bollerslev (1997), Ding et al. (1993) and Breidt et al. (1998) find evidence of long-memory stochastic volatility in stock returns, and Harvey (1993) finds evidence for this in exchange rates. These results led to the development of alternate models for volatility, such as Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) model.

In finance, the discussion as to whether or not the stock market prices display long memory properties still continues since this fact has important consequences on the capital market theories. So, if stock prices show long memory this means that predictability is not a dream but a possibility. The main implication of this circumstance is that an efficient market hypothesis is clearly rejected because stock market prices do not follow a random walk. The presence of long memory dynamics in asset prices would provide evidence against the weak form of market efficiency as it implies nonlinear dependence in the first moment of the distribution and hence a potentially predictable component in the series dynamics. It would also raise issues regarding linear modeling, forecasting, statistical testing of pricing models based on standard statistical methods, and theoretical and econometric modeling of asset pricing.

In financial econometrics literature, different power transformations of absolute returns of various financial assets have been found to display different magnitudes of sample autocorrelations, a property referred to as the 'Taylor effect'. Taylor (1986) observed that the empirical sample autocorrelations of absolute returns are usually larger than those of squared returns. A similar phenomena is observed by Ding et al. (1993) and Granger and Ding (1994, 1995, 1996). Granger and Ding (1995) referred this phenomenon as the "Taylor effect" and since then this has been an area of interest in many studies.

This study aims at investigating the existence of long memory property in Indian stock market. Studies in long range dependence in Indian stock market are very limited. Nath (2001) found evidence of long memory property in the Indian stock market using data from BSE500 stock index. We have chosen two leading indices SENSEX and NIFTY as proxy for the same. The study also explores the existence of Taylor effect in Indian stock market.

In the present paper section 2 gives the definition of long memory process. Section 3 consists of the different methodologies used to test long memory process. Section 4 is completely devoted to the data analysis and findings of the paper. Finally, section 5 narrates the conclusion drawn from data analysis and findings.

2. Definition of Long Memory

The long memory describes the higher order correlation structure of a series. If a time series y_t is a long-memory process or exhibits long-range dependence, there is persistent temporal dependence between observations widely separated in time. Such series exhibits hyperbolically decaying autocorrelations and low frequency distributions. Mathematically, if λ_s= cov (y_t, y_{t+s}), s=0, ±1, ±2,..., and there exist constants k and α, $\alpha \in (0,1)$ such that

$\lim_{s\to\infty} k\lambda_s s^{-\alpha} = 1$ then y_t is a long-memory process. A long memory process can be regarded as a halfway between stationary and unit root process. Like a stationary process, it is also a mean reverting process with a finite memory, i.e., it comes back to equilibrium after experiencing a shock. But unlike an autoregressive stationary process, it shows a much slower hyperbolic rate of decay rather than exponential, and the process takes much larger time to adjust back to equilibrium. When a time series have unit root at level but its first-differences are stationary, it is said to be I(1) process (integrated of order one). A stationary process is said to be I(0) process (integrated of order zero). Using the same notation, long memory process is I(d) process, where d lies between 0 and 1, i.e., a fraction. Hence long memory is also known as 'fractionally integrated process'. In the frequency domain, long memory financial time series have typical spectral power concentration near zero or at low frequencies and then it is declining exponentially and smoothly as the frequency increases (Granger, 1966).

3. Methodology for Testing Long Memory Processes

The empirical determination of the long-memory property of a time series is a difficult problem. The basic reason for this is that the strong autocorrelation of long-memory processes makes statistical fluctuations very large. Thus tests for long-memory tend to require large quantities of data. In this paper we tested the stationary properties of all the data series using Dickey and Fuller (1979) (ADF) test, Phillips-Perron (1988) (PP) test and Kwiatkowski, et al. (1992) (KPSS) test. We have tried to capture the long memory property of financial data using Rescaled-Range (R/S) analysis introduced by Hurst (1951), modified Rescaled-Range (R/S) analysis introduced by Lo (1991) and the spectral regression method suggested by Geweke and Porter-Hudak (1983). The above tests were applied on return series, absolute return series and squared return series. The referred methods and the definition of long memory are detailed below.

3.1 Rescaled-Range (R/S) Analysis

R/S analysis provides a measure of long range dependence based on the evaluation of the Hurst's exponent of stationary time series introduced by English hydrologist H.E. Hurst in 1951. The Hurst exponent was built on Einstein's contributions regarding Brownian motion of physical particles and is frequently used to detect long memory in time series. R/S analysis in economy was introduced by Mandelbrot (1971, 1972, 1997) who argued that this methodology was superior to the autocorrelation, the variance analysis and to the spectral analysis. Let X(t) be the price of a stock on a time t and r(t) be the logarithmic return denoted by $r(t)=\ln\left(\frac{X_{t+1}}{X_t}\right)$. The R/S statistic is the range of partial sums of deviations of times series from its mean, rescaled by its standard deviation. Hence, if r(1), r(2),... r(n) denotes asset returns and $\bar{r}_n$ represents the mean return given by $\bar{r}_n=\frac{1}{n}\sum_{t=1}^{n}r(t)$, where 'n' is the time span considered, the rescaled range statistic is given by

$$\left(\frac{R}{S}\right)_n=\frac{1}{\sigma_n}\left[\max_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\bar{r}_n)-\min_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\bar{r}_n)\right] \quad \ldots (1)$$

Where σ_n is the maximum likelihood estimate of sample standard deviation: $\sigma_n^2=\frac{1}{n}\sum_{t=1}^{n}(r(t)-\bar{r}_n)^2$. The first term in the bracket is the maximum of the partial sums of the first k deviations of r(t) from the sample mean, which is nonnegative. The second term in the bracket is the corresponding minimum of the partial sums, which is nonpositive. Therefore, the difference of these two quantities, called "range" is always nonnegative, so that the rescaled range, $\left(\frac{R}{S}\right)_n\ge 0$. The advantage of the classical R/S analysis is that the results are reliable regardless of whether the distribution of the series is normal or nonnormal. The null hypothesis of the test is that there is no long-range dependence in the series. This test is performed by calculating the confidence intervals with respect to some significance level, and to see whether the rescaled range statistic lies in or outside the desired interval. The critical values for the above two tests are given in Lo, 1991, Table II.

A drawback of the R/S analysis is that its measure of long range dependence is affected by short range dependence that may be presented in the financial data. Hence we consider estimating modified R/S statistic proposed by Lo (1991).

3.2 Modified Rescaled-Range (R/S) Analysis

The modified R/S test suggested by Lo (1991) for long memory examines the null hypothesis of a short memory and possibly heteroskedastic process against long memory alternatives. Lo's modified version of the statistic takes account of short-range dependence by performing a Newey and West (1987) correction to derive a consistent estimate of the long-range variance of the time series. Lo's modified R/S statistic, denoted by Q_n is defined as:

$$Q_n=\frac{1}{\sigma_n(q)}\left[\max_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\bar{r}_n)-\min_{1\le k\le n}\sum_{t=1}^{k}(r(t)-\bar{r}_n)\right] \quad \ldots (2)$$

where $\sigma_n^2(q)$ is the Newey and West (1987) estimate of long run variance of the series defined as $\sigma_n^2(q) = \frac{1}{n}\sum_{t=1}^{n}(r(t)-\bar{r}_n)^2 + 2\sum_{j=1}^{q}\omega_j(q)\gamma_j$, where γ_j represents the sample autocovariance of order j, and $\omega_j(q)$ represents the weights applied to the sample autocovariance at lag j (1,2,...q). $\omega_j(q)$ is defined as: $\omega_j(q) = 1 - \frac{j}{q+1}$

The second term in the long run variance equation intended to capture the short term dependence. The lag length q used to estimate the heteroskedasticity and autocorrelation corrected (HAC) standard deviation is extremely crucial for modified R/S test of long memory. We have used bandwidth selection procedures suggested by Lo (1991) to find the lag length.

3.3 The Spectral Regression Method

A stationary long memory process can be characterized by the behaviour of the spectral density f(λ) function which takes the form $f(\lambda) \sim c\left|1-e^{-i\lambda}\right|^{-2d}$, as $\lambda \to 0$ with $d \neq 0$, where $c \neq 0$, d is the long memory parameter (or fractional differencing parameter) and $0 < |d| < 0.5$. In order to estimate the fractional differencing estimator d, Geweke and Porter-Hudak (GPH) (1983) proposed a semi-parametric method of the long memory parameter d which can capture the slope of the sample spectral density through a simple OLS regression based on the periodogram, as follows:

$$\log I(\lambda) = \beta_0 - d \log\{4\sin^2(\lambda_j/2)\} + \upsilon_j, \qquad j = 1, 2, \ldots, M \qquad \ldots (3)$$

where $I(\lambda)$ is the j^{th} periodogram point; $\lambda_j = 2\pi j/T$; T is the number of observations; β_0 is a constant; and υ_j is an error term, asymptotically i.i.d, across harmonic frequencies with zero mean and variance known to be equal to $\pi^2/6$. $M = g(T) = T^{\mu}$ with $0 < \mu < 1$ is the number of Fourier frequencies included in the spectral regression and is an increasing function of T. As argued by GPH the inclusion of improper periodogram ordinates M, causes bias in the regression which results in an imprecise value of d. To achieve the optimal choice of T, several choices need to be established in terms of the bandwidth parameter M = $T^{0.45}$; $T^{0.5}$; ..., $T^{0.7}$. The GPH fractional differencing test is performed on the stock return aiming at a prospective gain in estimation efficiency. The fractional distinction test tends to find out fractional constitution in a time series based on spectral investigation of its low-frequency dynamics.

4. Data Analysis and Findings

The series studied in this analysis include two stock indices, BSE SENSEX and NSE CNX NIFTY at daily frequencies in India. The period of study is from April 1999 to March 2008. The daily closing values of the individual indices were taken and daily index returns were calculated using the relation $r(t) = \ln(p_{t+1}) - \ln(p_t)$ where r(t) is the return on the index on t-th day, $\ln(p_{t+1})$, $\ln(p_t)$ represents natural logarithm of index value on t+1 day and t-th day respectively. We test for long memory on return, absolute return (mod value) and squared return series from SENSEX and NIFTY.

4.1 Descriptive Statistics

The statistical summaries of logarithmic return, absolute return and squared return series of both NIFTY and SENSEX are reported in Table1 below which shows that the sample means of all series are positive. The returns series of both the indices are negatively skewed and leptokurtic. This along with high value of Jarque and Bera (1987) statistic clearly suggests that return series of both the indices cannot be regarded as normally distributed. However, both absolute return series and squared return series are positively skewed and leptokurtic indicating non normal distribution.

Table 1: Descriptive Statistics

	NIFTY			SENSEX		
	Return	**Absolute return**	**Squared return**	**Return**	**Absolute return**	**Squared return**
Mean	0.00065	0.01159	0.00026	0.00066	0.011633	0.000262
Median	0.00154	0.00852	0.00007	0.00147	0.008661	0.000075
Maximum	0.07969	0.13053	0.01704	0.07931	0.118092	0.013946
Minimum	-0.13053	0	0	-0.11809	0.000013	0
Std. Dev.	0.01624	0.01139	0.00068	0.01618	0.011274	0.000628
Skewness	-0.57131	2.53266	10.2081	-0.49453	2.297102	8.152873
Kurtosis	7.81647	14.3644	187.717	6.8137	11.64986	123.3157
Jarque-Bera	2307.46	14577.6	3252277	1459.122	9017.121	1385724
Probability	0	0	0	0	0	0

4.2 Unit Root Tests

The results of unit root tests are displayed in the Table 2 given below.

Table 2: Unit Root Tests

	NIFTY			SENSEX		
	Return	**Absolute return**	**Squared return**	**Return**	**Absolute return**	**Squared return**
ADF	-34.2977*	-12.845*	-17.63*	-44.75*	-12.527*	-16.73*
PP	-44.481*	-36.427*	-28.99*	-44.75*	-37.536*	-31.27*
KPSS	0.204	0.3886	0.285	0.279	0.6998	0.497

a) The critical values are those of Mackinnon (1991).

b) * represent the rejection of null hypothesis at 1% level of significance.

The null hypothesis of presence of unit root in ADF test and PP test is rejected at 1% level of significance for logarithmic return, absolute return and squared return series of both NIFTY and SENSEX indicating all the data series are stationary. The same is further confirmed by KPSS test where the null hypothesis of stationary data series could not be rejected at 1% level of significance for logarithmic return, absolute return and squared return series of both NIFTY and SENSEX.

4.3 Visual Interpretation: Autocorrelation Function (ACF)

The Autocorrelation function was plotted against the time lag for logarithmic return, absolute return and squared return series of both NIFTY and SENSEX. The lag was taken upto 40 days. The autocorrelation is found to decay quickly and is insignificant in the logarithmic return series of both the indices (Fig. 1 and Fig. 2). However in case of absolute and squared return series, a slow decay in autocorrelation is observed (Fig. 3, Fig. 4, Fig. 5 and Fig. 6).

The ACF of the data series clearly indicates short memory in returns but long range dependence or persistence for absolute and squared return series in Indian stock market.

Figures of Autocorrelation Functions (ACF)

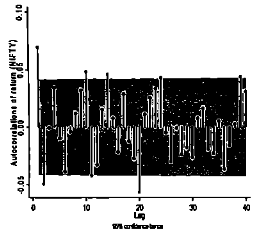

Fig. 1 - ACF of Return (NIFTY)

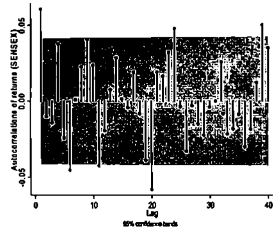

Fig. 2 - ACF of Return (SENSEX)

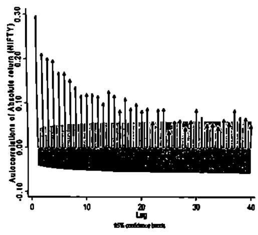

Fig. 3 - ACF of Absolute Return (NIFTY)

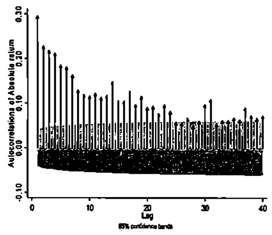

Fig. 4 - ACF of Absolute Return (SENSEX)

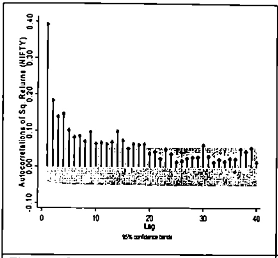

Fig. 5 - ACF of Squared Return (NIFTY)

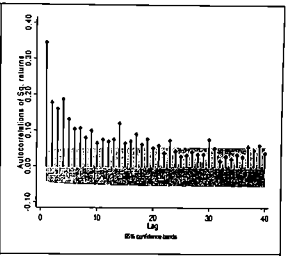

Fig. 6 - ACF of Squared Return (SENSEX)

4.4 Rescaled-Range (R/S) Analysis: Hurst-Mandelbrot's Classical R/S Statistic and Lo Statistic

The results of Rescaled-Range (R/S) Analysis are presented in the Table 3 obtained below where Hurst-Mandelbrot's Classical R/S Statistic and Lo Statistic are displayed.

Table 3: Hurst-Mandelbrot's Classical R/S Statistic and Lo Statistic

	NIFTY			SENSEX		
	Return	Absolute return	Squared return	Return	Absolute return	Squared return
Hurst-Mandelbrot's Classical R/S Statistic	1.51	4.58	3.52	1.61	5.19	4.13
Lo Statistic	1.47	2.63	2.05	1.56	2.93	2.44

Note: Critical values:

10% level of significance	[0.861, 1.747]
5% level of significance	[0.809, 1.862]
1% level of significance	[0.721, 2.098]

The estimated value of Hurst-Mandelbrot's Classical R/S Statistic suggests that the null hypothesis of no long-range dependence in case of return series of both NIFTY and SENSEX could not be rejected at 1% level of significance as estimated value of the statistic falls within the acceptance region. However, for both absolute and squared return, the null hypothesis is rejected at 1% level of significance. The critical values of the statistic are obtained from Lo (Table II, 1991). This clearly indicates that although logarithmic returns may not have long memory, returns without signs as well as volatility as measured by squared returns shows existence of longrun dependence in the series. Now since Classical R/S Statistic is sensitive to short range dependence and may give biased results in the case of short-range dependence, heterogeneities and nonstationary series, we also computed Lo's statistic which takes care of these shortcomings. The Lo statistic displayed in Table 4 also shows that the null hypothesis of no long-range dependence in case of return series of both NIFTY and SENSEX could not be rejected at 1% level of significance as estimated value of the statistic falls within the acceptance region. For squared return, Lo statistic rejects the null hypothesis at 1% level of significance for both NIFTY and SENSEX and in case of absolute return series, the null of no long range dependence is rejected for both NIFTY and SENSEX at 5% level and 1% level respectively. The results of both the tests are consistent and indicate short memory for return series and long memory for volatility.

4.5 The Spectral Regression Method (GPH statistic)

Table 4: GPH estimate of fractional differencing parameter (d)

M	Fractional Differencing Parameter (d)					
	NIFTY			SENSEX		
	Return	Absolute return	Squared return	Return	Absolute return	Squared return
$T^{0.45}$	0.0514 [0.1289] (0.3992)	0.4161* [0.1104] (3.7678)	0.2703* [0.0940] (2.8746)	0.0860 [0.1115] (0.7714)	0.48110* [0.1112] (4.3250)	0.35473 * [0.0986] (3.5979)
$T^{0.50}$	-0.0581 [0.0965] (-0.6021)	0.3911* [0.0849] (4.607)	0.2759* [0.07767] (3.5529)	0.00509 [0.1038] (0.0491)	0.43453 * [0.0971] (4.4751)	0.35572* [0.0852] (4.1749)
$T^{0.55}$	0.0318 [0.08875] (0.3590)	0.3331* [0.0704] (4.7350)	0.2626* [0.0674] (3.8918)	0.0510 [0.0816] (0.6244)	0.33299* [0.07179] (4.6383)	0.29901* [0.06845] (4.3680)
$T^{0.60}$	0.0416 [0.0685] (0.6073)	0.3987* [0.06283] (6.3462)	0.2869* [0.0554] (5.1792)	0.05231 [0.0652] (0.8022)	0.42224* [0.06488] (6.5084)	0.35173* [0.06382] (5.5113)
$T^{0.65}$	0.0272 [0.0509] (0.5338)	0.3809* [0.05426] (7.0202)	0.2643* [0.0485] (5.4499)	0.06126 [0.0549] (1.1157)	0.33885* [0.05143] (6.5883)	0.30920* [0.05726] (5.4003)
$T^{0.70}$	0.0069 [0.0459] (0.1506)	0.3621* [0.0459] (7.8883)	0.2544* [0.0418] (6.0844)	-0.0021 [0.0435] (-0.0483)	0.33710* [0.04125] (8.1718)	0.29486* [0.04503] (6.5485)

a) * represents the rejection of null hypothesis at 1% level of significance.
b) Standard errors in [ ] and t-statistics in ( ).

The above Table 4 reports estimates of the fractional differencing parameter (d) for the daily logarithmic return, absolute return and squared return series of both NIFTY and SENSEX. The test examine the null hypothesis of short memory (H_0: d = 0) against long memory alternatives (H_1: $d > 0$). As shown in table 5, the estimates of d are insignificant for a range of bandwidth ($M = T^{0.45}; T^{0.5}; \ldots, T^{0.7}$) for the logarithmic return series of both the indices. However, the estimates of the parameter d range from 0.4811 to 0.2544 and are statistically significant at 1% level to reject the null of short memory in the absolute and squared returns of two Indian stock markets. These results indicate that a long memory property exists in the volatility of two Indian stock markets. Moreover, findings support the Taylor effect, because in general, the estimate of the parameter is higher for the absolute returns than that of squared returns. The evidence on the presence of long memory in absolute and squared returns is similar to that obtained in previous research from major capital markets.

5. Conclusion

According to the market efficiency hypothesis in its weak form, asset prices incorporate all relevant information, rendering asset returns unpredictable. When return series exhibit long memory, they display significant autocorrelation between distant observations. Therefore, the series realizations are not independent over time and past returns can help predict futures returns, thus violating the market efficiency hypothesis. Exploring long memory property is appealing for derivative market participants, risk managers and asset allocation decisions makers, whose interest is to reasonably forecast stock market movements. The study examined the evidence of long memory in the Indian equity market. We computed Hurst-Mandelbrot's Classical R/S statistic, Lo's statistic, semi parametric GPH statistic to test the presence of long-memory in asset returns. All the tests are consistent with long range dependence in the absolute return and squared return series. Findings also support the Taylor effect as the estimate of the fractional differencing parameter is higher for the absolute returns than that of squared returns. However, we find no evidence of long-term memory in historical Indian stock market returns indicating Indian equity returns follow a random walk. Absence of long memory in return series of both the indices shows there was no evidence against the weak form of market efficiency in stock returns. Also the relevance of linear pricing models and statistical inferences about asset pricing models based on standard testing procedures is not questionable in absence of long range dependence in stock returns. Given the financial economic environment, settlement cycles, strong regulatory authority like SEBI and market micro structure in Indian market, a possible explanation for absence of long memory in return series may be based on the grounds that Indian markets may be informationally efficient, prices tend to reflect all publicly available information and any new information is fully arbitraged away. An alternative explanation was suggested by Lo (1991) when he suggested that "…. we find little evidence of long-term memory in historical U.S. stock market returns. If the source of serial correlation is lagged adjustment to new information, the absence of strong dependence in stock returns should not be surprising from an economic standpoint, given the frequency with which financial asset markets clear. Surely financial security prices must be immune to persistent informational asymmetries, especially over longer time spans". Presence of long memory in squared returns indicate volatility of asset returns which can be modeled using returns from the recent as well as remote past and hence derivative instruments can now be more efficiently priced.

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